

Justus-Liebig-Universität Gießen

Fachbereich Agrarwissenschaften, Ökotropologie und Umweltmanagement

Institut für Landschaftsökologie und Ressourcenmanagement

**„The role of remote sensing and geospatial modelling in mapping ecosystem
condition und functioning“**

Habilitationsschrift
zur Erlangung der Lehrbefähigung für das Fach
Fernerkundung und Landschaftsökologie
im Fachbereich Agrarwissenschaften, Ökotropologie und Umweltmanagement
der Justus-Liebig-Universität Gießen

vorgelegt von

Dr. rer. nat. André Große-Stoltenberg

Gießen 2024

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Chapter 1

1 Introduction

1.1 Background

Degradation of ecosystems and subsequent decline of nature's contribution to people are a global challenge (IPBES, 2019). Future trends are negative, as the condition of ecosystems has deteriorated further since the Millennium Ecosystem Assessment (IPBES, 2019). Consequently, several initiatives and agreements such as the Aichi Biodiversity Targets (Hagerman & Pelai, 2016), the Kumming-Montreal Agreement (Obura, 2023) or the Sustainable Development Goals (SDGs) (Hák et al., 2016) address this challenge and emphasize the high relevance for society to sustain healthy ecosystems.

Main direct drivers of ecosystem degradation include, ordered by ascending importance, invasive alien species, climate change, and land-use change (IPBES, 2019). Invasive alien species (IAS) negatively affect various ecosystem services causing damages of more than US\$423 billion per year (for 2019) (IPBES, 2023), while the number of IAS is rising across the globe (Seebens et al., 2017). To tackle this problem, a global monitoring system has been suggested identifying alien species occurrence, status and impact as the most important variables to be collected (Latombe et al., 2017). Indeed, one main target of SDGs regarding IAS is to reduce their impact (IPBES, 2019). Therefore, the challenge is not only to map IAS, but also to estimate subsequent impacts as a proxy for ecosystem degradation.

Expansion of urban areas, infrastructure and agriculture are the dominating types of land-use change (IPBES, 2019). In agricultural landscapes, biodiversity and ecosystem functioning (e.g., related to carbon sequestration) could be promoted, and thereby ecosystem degradation alleviated, through agroforestry and other silvopastoral land-use

systems (IPBES, 2019), while in urban areas the urban green infrastructure is decisive for human well-being (García-Pardo et al., 2022; IPBES, 2019). Urban greens will be particularly important if climate change leads to pronounced heat waves, and thereby reinforces Urban Heat Island Effects (UHI) (Zhao et al., 2018), exemplifying the interaction between main drivers of ecosystem degradation. Another effect of climate change are an increased frequency and intensity of droughts (IPBES, 2019). Severe droughts recently affected forest ecosystems in Central Europe, and caused significant forest die-off (Haberstroh et al., 2022; Schuldt et al., 2020). As matter of fact, due to disturbance forests in Germany are turning from carbon sinks to carbon sources (BMEL, 2024).

Generally, natural ecosystems and “hotspots” of endemic species experienced a larger decline regarding condition and extent at a faster pace compared to other types of terrestrial ecosystems (IPBES, 2019). Concurrently, particularly sensitive ecosystems can important ecosystem services related to biodiversity and water cycling (IPBES, 2019). One example could be *páramos* ecosystem, which are high-mountain tropical grasslands with wetland and peatland components (Díaz-Granados Ortiz et al., 2005; Rangel, 2005). They are highly relevant regarding climate-related services such as water storage and carbon sequestration (Brück et al., 2023; Hofstede, 2003). At the same time, they are increasingly impacted by land-use changes caused by agricultural intensification (Brück et al., 2023). Another example of a natural ecosystem that is suffering from a combination of factors are dryland rangelands in Iran, where droughts and overgrazing led to noticeable Land-Use/Land Cover changes (Safaei et al., 2022). Thus, main drivers of ecosystem degradation affect a wide range of different ecosystems in many different ways.

These changes of the biosphere with negative effects on ecosystem services across the globe occur across spatio-temporal scales (IPBES, 2019). One way of producing basis data regarding ecosystem condition across spatio-temporal dimensions, e.g., related to the Aichi Biodiversity Targets, would be the use of earth observation coupled with ancillary geospatial data and modelling approaches (Guo, 2020; O’Connor et al., 2015). As there is no “one-size-fits-all” remote sensing solution for all challenges of ecosystem degradation, a broad set of tools is required.

In the following, I will briefly illustrate how remote sensing and geospatial modelling could promote progress in this field of research. I will first present a general view on one of the main drivers of ecosystem degradation, namely invasive alien species. Then I will comment in more detail on the role of remote sensing and geospatial modelling

for different types of ecosystems, namely temperate-continental urban ecosystems, temperate forests, temperate agroforestry systems, temperate forests, agroforestry systems, high Andean tropical grasslands, and dryland rangelands, in the context of land-use and climate change.

1.1.1 Invasive alien species (IAS) as an example of a main driver of ecosystem degradation

There is an increasing interest in using remote sensing approaches to investigate IAS (Bolch et al., 2020; Saranya et al., 2024; Vaz et al., 2018, 2019). As sensor technological and data analytics are fast-paced field of research (Li et al., 2023), it raises the questions which novel advancements could contribute to progress regarding remote sensing of IAS, and which methodological approaches have been applied to practice or which obstacles hinder transfer to practical application.

One limitation could be that remote sensing approaches to investigate IAS are too case-specific, and finding from such studies are difficult to generalise. In invasion ecology, comparative, multi-site studies using model species and model system haven been suggested to identify mechanisms of invasions and to improve generalisability of single-case studies (Kueffer et al., 2013). This approach could also enhance the interpretation value of remote sensing-based studies on IAS. However, such baseline data at species or species' group level is missing. At the same time, certain species' groups are widespread such as the legume genus *Acacia*, which includes global, high-impact invaders (Richardson, 2018). An overview focussed on such a well-studied species group from an invasion ecological perspective (Richardson et al., 2023) could give insights into the evolution of remote sensing approaches in the field of biological invasions and set the basis for comparative studies in the future.

While most remote sensing-based research is likely focussed on mapping IAS occurrence (Bolch et al., 2020; Saranya et al., 2024; Vaz et al., 2018, 2019), which is indeed a main aspect for global monitoring of invasive species, impact is another crucial parameter regarding invasions (Latombe et al., 2017), which remains underexplored. Impact is often related to abundance (Sofaer et al., 2018), but its context-dependency is still a major challenge in invasion ecology (Ricciardi et al., 2021). Several case studies aiming to map the impact of invasive plant species using remote sensing exist (Bolch et al., 2020; Saranya et al., 2024; Vaz et al., 2018, 2019), but the challenge of context-dependency of impact also applies to remote sensing-based approaches. However, many tools exists to map landscape structure and function (Crowley & Cardille, 2020; Senf,

2022), and thereby to map the context. Therefore, remote sensing-based approaches to map the spatial impact after plant invasion considering the environmental context still need to be conceptualised, and proofs-of-concept could lead to further progress in this field.

1.1.2 Temperate-continental urban ecosystems

Urban greens are an important LULC type in urban areas because they are the basis for various urban ecosystem services linked to human well-being, biodiversity and carbon storage (Basnou, 2015; García-Pardo et al., 2022; McPhearson et al., 2016). At the same time, they are increasingly affected by environmental pressures arising from air pollution and the urban heat island effect (UHI) (Weber et al., 2014). These pressures can lead to degradation of urban vegetation (Smithers et al., 2018), which, at the same time, can lessen such negative effects, e.g., by reducing the UHI (Georgi & Zafiriadis, 2006; Smithers et al., 2018; Weber et al., 2014) and by filtering harmful pollutants (Meerow & Newell, 2017; Nowak et al., 2018). Therefore, both demand for and pressure on these services is high (Bastian et al., 2012; Nastran et al., 2019), and urban vegetation needs to be in a healthy condition to provide such ecosystem services (Lausch et al., 2016; Vieira et al., 2018). Thus, monitoring of urban vegetation health is required to support the provision of urban ecosystem services.

Remote sensing provides useful tools to map urban vegetation health over large extents in a timely manner (Buchanan et al., 2015), and open access data is available to map urban ecosystem services provided by urban vegetation (García-Pardo et al., 2022). For example, freely available data from the Landsat 8 mission includes data collected by thermal sensors to estimate land surface temperature, which is extremely useful to examine the effect of UHI on urban vegetation (García-Pardo et al., 2022). Such data can be combined with freely available data from the Sentinel 2 mission for vegetation monitoring purposes (Crowley & Cardille, 2020). The advantage of the Sentinel 2 data (Drusch et al., 2012) is the existence of several bands located in the Red-Edge part of the spectrum that can be linked to chlorophyll content (Delegido et al., 2011; Frampton et al., 2013; Ramoelo et al., 2015) and, thus, have high potential to map vegetation health. The challenge to map vegetation condition and potential stress factors in an urban context is that urban ecosystems are complex, and stress factors might interact and add up (McPhearson et al., 2016; Zhao et al., 2018), but identifying and disentangling different stress factors remains understudied. Therefore, monitoring of vegetation health in urban areas could be improved if remotely sensed information on

vegetation health would be combined with ancillary geospatial data sets on potential stress and alleviating factors, e.g., road maps, surface sealing, presence of irrigation systems, using adequate modelling approaches that exploit the urban-rural gradients of the UHI (Nastran et al., 2019), or that account for the heterogeneity of complex urban ecosystems.

1.1.3 Temperate forests

Central Europe including Germany was affected in recent years by severe drought events with effects across ecosystems (Beloïu et al., 2022; Senf & Seidl, 2021; Thonfeld et al., 2022). One consequence is that forests are changing from carbon sinks to carbon sources (BMEL, 2024), and the drought of 2018 heavily affected coniferous tree species (Haberstroh et al., 2022; Schuldt et al., 2020). A simple and straightforward way to examine negative drought effects would be to perform a LULC change analysis. LULC maps are often derived from remote sensing (Chaves et al., 2020; Talukdar et al., 2020). They inform on landscape structure and function (E. D. Chaves et al., 2020), and can be applied to map ecosystem degradation (Aghsaei et al., 2020; Yonaba et al., 2021). However, they are a static representation of ecosystems that are variable by nature, while remote sensing data is continuous, which could be exploited further to enhance the interpretation value of static LULC maps (Coops & Wulder, 2019). Metrics based on multitemporal satellite remote sensing data such as the Dynamic Habitat Index (DHI), which captures information related to productivity, seasonality and minimum vegetation cover, have successfully been applied in biodiversity studies (Coops & Wulder, 2019). The DHI can be computed based on the Normalized Difference Vegetation Index (NDVI) (Coops & Wulder, 2019). An NDVI data product at global level with high temporal resolution is available from the Copernicus Global Land Service (Copernicus, 2022). As the DHI is supposed to represent the natural variability of ecosystems with subsequent effects on biodiversity (Coops et al., 2008; Razenkova et al., 2020), it brings up the question how disturbances such as severe droughts affect these metrics. The benefit of multitemporal, continuously recorded satellite data is that it also allows retrospective analysis. For example, it could be examined if damaged and healthy coniferous forests shared the same DHI profiles before the drought, or if DHI metrics differed even before the strong disturbance event. Further, it could be tested how LULC types in general responded to the severe drought event, i.e. if they could recover and reach pre-drought levels, and if their environmental characteristics

related to water cycling such as usable field capacity influenced their DHI metrics before and after the drought.

1.1.4 Temperate agroforestry systems

In central European agricultural landscapes, small woody features (SWFs) and (mainly silvopastoral) agroforestry systems such as traditional orchards (“Streuobstwiesen”) contribute to a wide range of ecosystem services related to biodiversity, carbon cycling and reduction of erosion (Decocq et al., 2016; Kraft et al., 2021; Rubio-Delgado et al., 2024). Therefore, ecosystem degradation can be attributed to the loss of these features. To examine the spatio-temporal dimension of this type of ecosystem degradation or, on the contrary, to suggest measures to improve the provision of certain ecosystem services, baseline data is required such as the spatial distribution and dynamics of these landscape features (Nerlich et al., 2013; Santiago-Freijanes et al., 2018) or quantitative estimates of carbon sequestration. For example, maps of SWFs derived from satellite remote sensing are available at pan-European level (Faucqueur et al., 2019), and national agencies, e.g., the Federal Agency for Cartography and Geodesy (BKG) in Germany, produce high-resolution LULC maps (BKG, 2024), which inform on the spatial distribution of agricultural areas. These geospatial data sets could be intersected to give insights on the occurrence of SWFs in agricultural landscapes at broad spatial extents. Further, novel coefficients on the potential of SWFs to sequester soil organic carbon have recently been published (Cardinael et al., 2018), which in combination with the aforementioned remote sensing-based data sets could be applied to compute the contribution of SWFs on agricultural lands to national carbon budgets. This contribution can be relevant in times when other LULC types such as forests in Germany are turning from carbon sinks to carbon sources (BMEL, 2024).

Apart from semi-automatized satellite data analysis, inventories of small landscape features in Germany such as traditional orchards, that are protected by national law and at federal state level, are produced based on aerial imagery provided by state agencies (Henle et al., 2024). However, few comprehensive datasets covering larger areas exist, and official cadastral data often is inaccurate (Henle et al., 2024), so baseline data is missing to quantify their current spatial coverage, to examine their characteristics and to investigate temporal dynamics. In the Federal State of Hesse, where beyond their ecological importance traditional orchards are an integral part of the cultural landscape (Geske, 2018), spatial maps have been produced for the whole state based on manual aerial image interpretation for the years 2008-2010 (HLNUG,

2017). In addition, historical areal imagery covering the years 1952-1967 are available in georeferenced format (HVBG, 2024). These historical images have not been exploited to map traditional orchards at statewide level, yet. However, this would provide valuable data to perform spatio-temporal analysis of orchard decline and to compute loss rates not only at local or regional (Plieninger et al., 2015), but at state level. Further, these kind of data would enable comparisons of historical and recent traditional orchards regarding ecologically important parameters such as size and shape, or, if analysed together with ancillary geospatial data, exposition and soil conditions. Once orchard losses are identified in a spatially explicit way, joint analysis with recent LULC maps (BKG, 2024), could give insights into drivers of orchard decline, which might differ locally and regionally.

1.1.5 High Andean tropical grasslands

In certain ecosystems, the use optical remote sensing to map ecosystem degradation, e.g., LULC changes, is limited due to a very high cloud cover or intensive precipitation regimes. In this case, the use of active sensor technology such as synthetic aperture radar (SAR) is highly advantageous as data acquisitions is robust against dense cloud cover or difficult weather conditions in general (Tsokas et al., 2022). SAR data can be used to retrieve parameters related to ecosystem structure (Valbuena et al., 2020) and soil moisture (Babaeian et al., 2019) in a spatially explicit way, which can be used in classification models to map LULC changes (Tsokas et al., 2022). One example of an ecosystem that provides a wide range of ecosystem services, but which is difficult to map using optical satellite data, are Andean *paramós*. These high-mountain neotropical grasslands (Díaz-Granados Ortiz et al., 2005; Rangel, 2005) are vitally important for water regulation as well as carbon sequestration (Hofstede, 2003). At the same time, they are threatened by LULC changes in terms of intensification of agriculture (Brück et al., 2023) possible driven by an increasing demand from urban areas (Rodríguez, 2011). The mapping of LULC of *paramos* ecosystem in Colombia at broad spatial extents is so far limited to visual interpretation of optical imagery (Instituto Alexander von Humboldt, 2018), which means that creating and updating these maps to spot LULC changes related to degradation is challenging in terms of labour and timely updates. In this context, the use of spaceborne SAR data holds great potential. Particularly the use of multitemporal SAR data for LULC mapping remains understudied. In addition to traditional backscatter metrics based on different polarisations, metrics based on coherence that parametrise the phase stability between two images (Zhang et al., 2011)

can be derived from multitemporal SAR data as acquired by the Sentinel 1 mission (Plank, 2014). Such metrics have successfully been integrated with traditional backscatter metrics to increase the accuracy of LULC maps in wetlands, mountains, and flooded areas (Jacob et al., 2020; Vicente-Guijalba et al., 2018). It has to be tested, if these advantages also apply to Colombian *paramós* ecosystems, e.g., to map agricultural activities or to map natural grasslands. Using such kind of earth observation data will inevitably lead to large data volumes, which requires adequate capabilities for data processing and modelling such as cloud based solutions (Amani et al., 2020; Melo et al., 2022).

1.1.6 Dryland rangelands

Drylands, which constitute ca. 45% of terrestrial ecosystems, provide a wide range of ecosystem services (Berdugo et al., 2020). Their degradation affects at least 3.2 billion people at global level (IPBES, 2018). Typical dryland ecosystems in Iran are rangelands (Mazloun et al., 2021). A basic approach to map degradation of ecosystems is the use of LULC maps (Aghsaei et al., 2020; Yonaba et al., 2021) derived from remote sensing (Chaves et al., 2020), which inform on landscape structure, function and, if multitemporal data sets are available, dynamics (Crowley & Cardille, 2020). Indeed, rangelands in Iran are negatively affected by LULC changes (Mazloun et al., 2021). Such LULC maps can be interpreted further by using advanced remote sensing indices and landscape metrics related to ecosystem functioning (Bastin et al., 2002; Tanser & Palmer, 1999) to evaluate ecosystem health in drylands (Berdugo et al., 2020; Estevez et al., 2017; Retallack et al., 2023). Overgrazing and poor land management have been assessed using the Moving Standard Deviation Index (MSDI) that is related to environmental heterogeneity (Jafari et al., 2008; Tanser & Palmer, 1999), while the Leakiness Index (LI) is related to resource leakage at watershed-level and has been used to map degradation in arid and semi-arid ecosystems (Ludwig et al., 2007). However, challenges apply when linking remotely sensed metrics to ecological processes (Bastin et al., 2002; Lausch et al., 2016; Wu & Hobbs, 2002) and upscaling fine scale field to broad extent remote sensing data (Cavender-Bares et al., 2022). At field level, rangeland health is traditionally assessed using the Interpreting Indicators of Rangeland Health (IIRH) (Pyke et al., 2002). This approach has spatio-temporal limitations, so it would be worthwhile to investigate if these field-based, qualitative metrics using expert knowledge can be linked to remotely sensed information (Herrick et al., 2019; Toevs et al., 2011) to overcome these limitations. Methods to compare multivariate, ecological

data sets at field and remote sensing level exist (Feilhauer et al., 2010; Große-Stoltenberg et al., 2018; Magiera et al., 2013), and satellite archives (Wulder et al., 2016) could be exploited to examine the historical condition of rangelands where field data is lacking (Herrick et al., 2019). Therefore, integrative approaches based on both field and earth observation data could contribute to a science-based and data-driven approach to monitoring rangeland health using remote sensing (Herrick et al., 2006, 2019).

In summary, challenges of ecosystem degradation are manifold (IPBES, 2019). At the same time, a broad set of remote sensing tools exists and are developed further to map ecosystem conditions and degradation across scales (Li et al., 2014). However, challenges of scaling spatial data from fine to broad levels still apply (Cavender-Bares et al., 2022; Wu & Hobbs, 2002). Therefore, in situ and earth observation data on ecosystem conditions need to be integrated with care (Cavender-Bares et al., 2022) to leverage the full potential of remote sensing for ecological applications such as mapping and modelling condition and degradation of ecosystems.

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Chapter 2

2 Scope and objectives of the habilitation thesis

2.1 Scope

The main scope of this habilitation thesis is to present a broad range of approaches on how remote sensing and geospatial modelling can be applied to map condition and degradation of different types of ecosystems. Bearing in mind that there is no one-size-fits-all solution in remote sensing and geospatial modelling for every ecological application, I used different kinds of sensor types from passive to active sensors, different modelling approaches from classification, ordination to spatial modelling including mixed modelling approaches, different temporal resolutions from single shot to time series data and different spatial scales from site to landscape to federal state level including addressing questions of upscaling. Using plant invasions as an example, I give an outlook of the state-of-the-art of remote sensing and geospatial technologies in mapping changes of ecosystem conditions and lay out a perspective on how in the future research could advance using sensor based solutions. Therefore, my cumulative thesis comprises the following ten peer reviewed-articles as well as one invited book chapter published since 2020, and one manuscript that is currently under review:

- Martínez W, Lizarazo I, **Große-Stoltenberg A** (under review) Integration of InSAR coherence and SAR backscatter increases accuracy of LULC mapping in tropical high-mountain ecosystems. *Geocarto International*.
- **Große-Stoltenberg A**, Werner C, Hellmann C, Oldeland J, Thiele J (2025) Quantifying the spatial impact of an invasive *Acacia* on ecosystem functioning

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 - Cărlan I, Bogdan-Andrei M, Nistor C, **Große-Stoltenberg A** (2020) Identifying urban vegetation stress factors based on open access remote sensing imagery

and field observations. *Ecological Informatics* 55: 101032. doi: 10.1016/j.ecoinf.2019.101032

- Cărlan I, Haase D, **Große-Stoltenberg A**, Sandric I (2020) Mapping heat and traffic stress of urban park vegetation based on satellite imagery - A comparison of Bucharest, Romania and Leipzig, Germany. *Urban Ecosystems* 23: 363-377. doi: 10.1007/s11252-019-00916-z

2.2 Objectives

The objectives of my habilitation thesis follow the logic of my core scientific output regarding remote sensing and geospatial modelling of ecosystem condition and functioning since 2020. I address main drivers of ecosystem degradation such as LULC changes, climate change and invasive alien species, and I examine different types of ecosystems such as urban areas, temperate forests, Central European agricultural landscapes, tropical high-mountain grassland and dryland rangelands. The specific objectives are as follows:

- Summarising the state of the art and potential of remote sensing (RS) from UAVs to satellites in plant invasion science and management
- Reviewing the current state of the art and identifying advances in remote sensing assessments of globally invasive wattles
- Developing a spatio-temporal framework to map plant invasion impacts on ecosystem functioning considering environmental heterogeneity by integrating recent advances in invasion ecology, sensor-based technologies, and modelling approaches
- Mapping the context-dependant spatial impact of an invasive tree on ecosystem functioning by combining airborne hyperspectral and LiDAR data with spatial modelling approaches
- Identification of stress factors and their combined interaction on tree status in urban parks in a heterogeneous urban environment using satellite data
- Mapping status of urban green infrastructure along an urban-rural gradient and assessing the impact of the closeness to roads and satellite-derived land surface temperature on vegetation health using satellite data
- Identifying effects of soil properties and climatic factors on multitemporal metrics derived from satellite data across LULC types in Hesse in the light of the severe drought in 2018

- Assessing the health status of coniferous forests in Hesse before and after the severe drought of 2018 using multitemporal metrics derived from satellite data
- Quantifying long-term dynamics and characteristic of traditional orchards in a central European landscape using recent and historical aerial imagery, and identifying key drivers of orchard loss and LULC conversion
- Quantifying carbon stocks of small woody features in agricultural landscapes in Germany using remote sensing-based, European wide data products, and create future LULC scenarios to investigate the potential for increasing agroforestry cover to offset agricultural greenhouse gas emissions
- Exploring the potential of inSAR coherence and SAR backscatter to map LULC changes in Colombian high-altitude wetlands
- Mapping degradation of rangeland health at watershed level after 28-year LULC change in a dryland ecosystem by linking field-based assessments to remotely-sensed information

Chapter 3

3 Structure of the habilitation thesis

The thesis includes ten peer-reviewed manuscripts that are either accepted for publication or are already published as well as one invited and peer-reviewed book chapter. One manuscript is still under review, and has been resubmitted after the first round of revision. The overall theme of all studies is to investigate the condition of ecosystems using remote sensing, auxiliary geospatial data and geospatial modelling. The studies are either classical research papers or conceptual and review papers. In Chapters 4-7, the many facets of remote sensing in mapping ecosystem condition are explored using the example of plant invasion as a main driver of ecosystem degradation. In Chapter 4, an overview of the state-of-the-art of ecological applications of remote sensing in the field of plant invasion science and management in general is presented. The main focus was identifying the main fields of applications highlighting the increasing availability of remote sensing data that could be integrated to support analysis across spatio-temporal scales. Identifying the main applications enable at the same time identification of research topics that have been neglected so far and could be future research topics. In Chapter 5, ecological applications of remote sensing are summarized focussing on invasive Australian *Acacia* species. This genus comprises species that are invasive at global level, and, thus, can be considered ideal test cases for global comparative studies. In this chapter, *Acacia* species that were studied using remote sensing were identified and further characterized regarding study location and habitat, study objective, type of remote sensing data used, and analytical approach. By doing so, research gaps were identified for future comparative studies at global and the benefits of using invasive *Acacia* species as model species and test cases were examined. In Chapter 6, a conceptual framework is presented on how the impact of invasive plant

species on ecosystem functioning can be assessed in a spatio-temporal way using novel analysis techniques and sensor-based solutions, and how context-dependency of impact could be included in such analysis. It is explored how fine-scale heterogeneity of the environmental context can be mapped, how structure and function of the invaded system can be assessed in a spatially explicit way, how functional changes after invasion can be examined using functional tracers, and finally how all these pieces of information can be integrated in spatio-temporal modelling approaches. An example of this analytical approach joining LiDAR data with spatial data of functional tracers to map invader impact is given including a 3D-visualisation of the resulting impact map. In Chapter 7, a proof-of-concept is presented on how to integrate airborne hyperspectral with LiDAR data to model spatial impacts of an invasive tree species on ecosystem functioning across stages of invasion. It is explored how spatial impacts based on hyperspectral vegetation indices compare to impacts at invasive stand level, what effect the environment heterogeneity has on the spatial impact, and how to map the functional homogenization as induced by the invader.

Chapters 8 and 9 focus on the health of urban vegetation. The health of urban trees is essential for the provision of many urban ecosystem services. In Chapter 8, the health of park trees in the City of Bucharest, Romania, was assessed using freely available, multispectral satellite data. The Urban Heat Island (UHI) effect and air pollution likely affect the health status of the park vegetation in a negative way. Therefore, Sentinel 2 was used to compute vegetation indices related to chlorophyll, senescence, greenness and water stress, and Landsat 8 was used to compute land surface temperature. The parks were further characterised in terms of potential stress (e.g., distance to roads derived from Open Street Map, distance to construction sites) and mitigating (e.g., distance to fountains, level of shade) factors. These factors were used as predictors in linear mixed-models with parks as a random effect to include the heterogeneity of the parks in the models. In Chapter 9, the health of urban park vegetation is examined based on freely available, multispectral satellite data along urban-rural gradients comparing the cities of Bucharest, Romania, and Leipzig, Germany. In addition to the remote sensing and geodata used in Chapter 8, further publicly available, pan-European geospatial datasets from the Copernicus Land Monitoring Service, i.e. the imperviousness layer, and LULC data from the Urban Atlas, were used to identify similarities and differences of park tree health between Bucharest and Leipzig.

Chapters 10 and 11 deal with effect of the severe drought of 2018 in Central Europe on the condition across LULC types (Chapter 10) with the focus on coniferous forests

(Chapter 11) in Hesse. It was explored how NDVI-based, composite vegetation indices such as the Dynamic Habitat Index (DHI) changed due to the drought, and if the DHI profiles of the LULC types, which were computed for 2017 until 2020, returned to pre-drought conditions. In Chapter 10, the relationship between DHI profiles and soil properties as well as climatic conditions across Hesse were examined using freely available data from Copernicus Land Monitoring Service, the CORINE Land Cover product, the German Climate Data centre and the Hessian State Agency for Nature Conservation, Environment and Geology. In Chapter 11, it was explored if the coniferous forest in Hesse that died off after the severe drought of 2018 differed from coniferous forest that overcame the drought regarding their DHI profiles. It was further tested which parameters, the DHI components or other environmental parameters related to temperature, precipitation and elevation, were most important to distinguish the two coniferous forest type classes.

Chapters 12 and 13 address the role of small woody features and traditional agroforestry systems in a Central European landscape. In Chapter 12, long-term dynamics of traditional orchards (“Streuobstwiesen”) in Hesse were quantified between 1952-1967 and 2010. While for 2010 a state-wide geospatial data set already existed, a map for 1952-1967 was generated via aerial image interpretation using publicly available historical imagery. These two data sets were analysed to quantify, identify and characterize areas of loss, gain, and remaining orchards. Further, it was tested if these parameters differ at regional level. Loss rates were calculated at state-wide level, and drivers were orchard loss were identified by intersection lost orchards with public cadastral data. In Chapter 13, pan-european geospatial data sets such as the novel Copernicus Small Woody Features layer and the CORINE Land Cover provided by the Federal Agency for Cartography and Geodesy (BKG) were used to quantify the coverage of small landscape woody landscape features on agricultural land in Germany at national level. Based on this first analysis step, the contribution of small woody features to carbon sequestration in agricultural landscapes were computed using updated IPCC coefficients, and carbon sequestration potential after increase of small woody features or agroforestry systems using scenarios of LULC conversion were modelled.

In Chapter 14, LULC in tropical, high-mountain wetlands was mapped using multitemporal, spaceborne SAR data to examine the integrity of *páramos* ecosystems in Colombia. *Páramos* ecosystems are biodiversity hotspots and provide a wide range of ecosystem services, e.g., related to carbon sequestration and provision of drinking water, but they are threatened by LULC changes such as intensification of agriculture.

SAR data were employed as dense cloud cover limits the use of optical data in this region, and interferometric SAR (InSAR) metrics related to coherence were computed in addition to traditional backscatter metrics to leverage the availability of high temporal resolution data. The resulting large data volumes were processed in a cloud-based solution.

In Chapter 15, LULC changes over a time span of 28 years in rangelands in Central Iran were mapped using Landsat satellite data. Remote sensing metrics regarding ecosystem health such as landscape metrics, the Moving Standard Deviation Index and the Leakiness Index were computed at watershed level as proxies for ecosystem condition and degradation. They were compared for the most recent LULC map to a standardized field protocol to assess rangeland health, which addresses biotic integrity, soil and site stability as well as hydrological function. As a result, every watershed was assigned with a health class based on the field assessment, and was characterized by remote sensing metrics. Field and satellite-based assessments were then compared using multivariate and cluster analysis techniques to map and validate ecosystem health across different scales. The study was published in the special issue “Toward a Science of Scaling in Landscape Ecology” in the journal *Landscape Ecology*.

Chapter 4

Pattern to process, research to practice: remote sensing of plant invasions

Jana Müllerová^{1,}, Giuseppe Brundu^{2,3}, André Große-Stoltenberg^{4,5}, Teja Kattenborn^{6,7}, David M. Richardson^{8,9}*

¹Faculty of Environment, Jan Evangelista Purkyně University in Ústí nad Labem, Ústí nad Labem, Czech Republic

²Department of Agricultural Sciences, University of Sassari, Sassari, Italy

³National Biodiversity Future Center (NBFC), Palermo, Italy

⁴Division of Landscape Ecology and Landscape Planning, IFZ Research Centre for Biosystems, Land Use and Nutrition, Institute of Landscape Ecology and Resource Management, Justus Liebig University Giessen, Giessen, Germany

⁵Center for International Development and Environmental Research (ZEU), Justus Liebig University Giessen, Giessen, Germany

⁶Remote Sensing Centre for Earth System Research (RSC4Earth), Leipzig University, Leipzig, Germany

⁷German Centre for Integrative Biodiversity Research (iDiv), Halle-Jena-Leipzig, Leipzig, Germany

⁸Department of Botany & Zoology, Centre for Invasion Biology, Stellenbosch University, Stellenbosch, South Africa

⁹Department of Invasion Ecology, Institute of Botany, Czech Academy of Sciences, Průhonice, Czech Republic

*Corresponding author

Biological Invasions 25:3651-3676 (2023), doi: 10.1007/s10530-023-03150-z

Supplementary Information: The online version contains supplementary material available at <https://doi.org/10.1007/s10530-023-03150-z>.

Abstract

Processes that drive plant invasions play out across multiple spatial and temporal scales. Understanding individual steps along the introduction-naturalization-invasion continuum and its drivers is crucial for management. This review, targeting the broad audience of invasion scientists, field ecologists and land managers, summarizes the state-of-the-art and potential of remote sensing (RS) in plant invasion science and management. It identifies challenges and research gaps, discusses the discrepancies between technology, science and practice, and suggests ways of addressing some of these issues. Mapping, modelling and predicting invasion processes across scales is a major challenge since they are dynamic and highly complex. Integration of RS data collected at different spatial and temporal scales (“rocking” across scales) has the potential to elucidate the dynamics of invasions and to reveal its drivers, thereby improving the efficiency of control measures. Increasing spatial/temporal resolution of imagery from satellites and drones has much potential to (i) precisely identify even less conspicuous invasive species; (ii) map invasion dynamics; and (iii) provide information on environmental variables and landscape structure at scales fine enough to capture underlying ecological processes. Until now, RS research has focussed primarily on spatio-temporal patterns of plant invasions. Other more challenging topics, such as early monitoring, and revealing the invasion mechanisms and impacts have received less attention. Despite the power of RS technology and recent developments, large discrepancies remain between possibilities and actual implications in research and practical management of invasions. Although recent technological advances, such as powerful algorithms, cloud solutions, and data streams from citizen science, might overcome some limitations, the mutual dialog among field ecologists, managers, invasion scientists and RS specialists remains crucial; our review contributes to such communication.

Keywords

Invasion ecology · Invasion science · Monitoring schemes · Remote sensing · Spatio-temporal dynamics

Introduction

Biological invasions are a major threat to biodiversity and cause economic damage worth billions of dollars every year (Diagne et al. 2021; Zenni et al. 2021). Processes that drive plant invasions involve multiple steps, from introduction, establishment, survival, persistence, dispersal and landscape-scale invasion (Theoharides & Dukes 2007). Prevention and effective management of invasions demands an understanding of the dynamics at different scales that drive progression along the introduction-naturalization-invasion continuum (Hulme 2006; Richardson & Pyšek 2012; Haccou and Serra 2021). Invasions show spatio-temporal patterns that depend on both the invader and the invaded habitat (Pyšek and Hulme 2005). The perception of these patterns and processes can also change with the scale of observation (Richardson 2011).

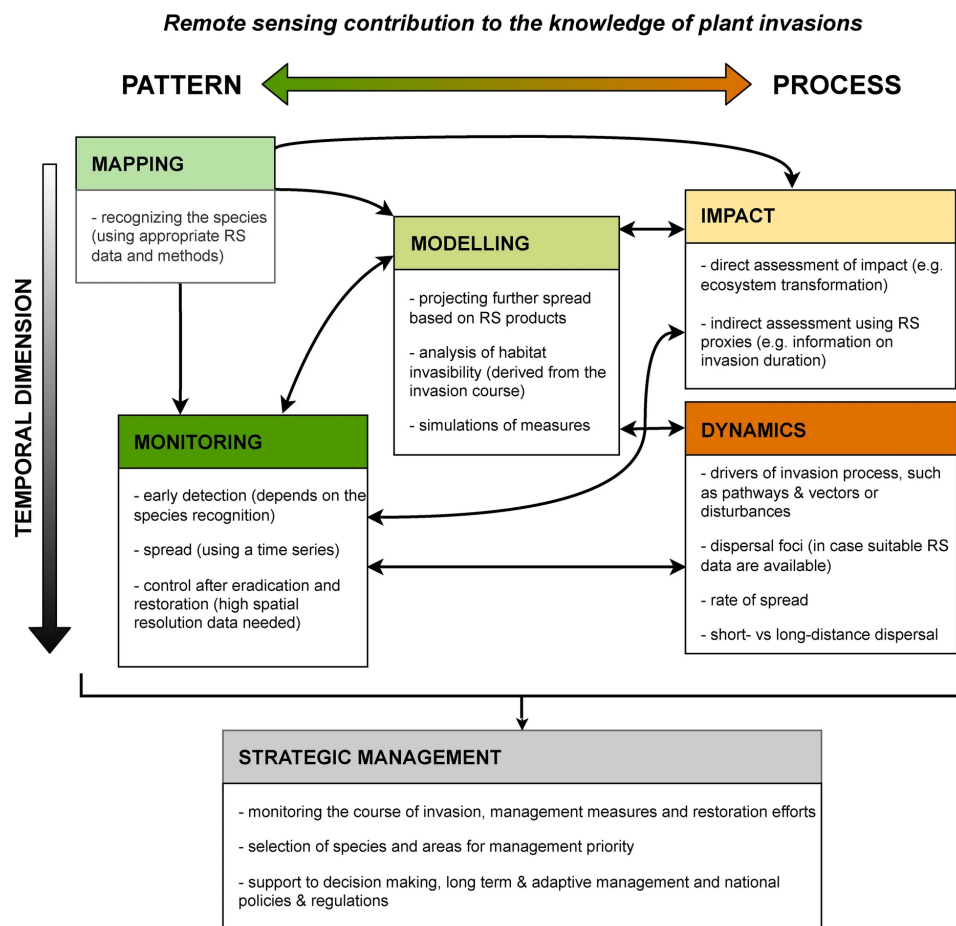


Figure 1: A conceptualization of the contribution of remote sensing to the knowledge of plant invasions (for examples see Table 1)

Remote sensing (RS) is an important data source for spatio-temporal information about plant invasions that has the potential to reveal new insights on invasion dynamics. Applications of RS in the domain of plant invasions range from mapping and monitoring

invasion patterns (including retrospective analyses) to the provision of information on the landscape and environmental characteristics for studies on invasion processes, such as dynamics, mechanisms, drivers and impacts, and from invasion science to the practical management of invasions at different spatial and temporal scales (Fig. 1, Table 1).

Table 1 Examples of the contribution of remote sensing to the study and management of plant invasions (related to the conceptual diagram at Fig. 1)

Topic	Objective	References (examples)
Mapping	Recognizing the species	Andrew & Ustin (2008); Carter et al. (2009); Dai et al. (2020); Evangelista et al. (2009); Gholizadeh et al. (2022); Große-Stoltenberg et al. (2016); He et al. (2011); Huang & Asner (2009); Huang & Geiger (2008); Lopatin et al. (2019); Müllerová et al. (2017a, 2017b); Niphadkar & Nagendra (2016); Pu et al. (2008); Ramsey et al. (2005); Resasco et al. 2007; Sandino et al. (2018); Shouse et al. (2013); Silván-Cárdenas & Wang (2010); Singh et al. (2015); Skowronek et al. (2018); Vaz et al. (2018, 2019); West et al. (2016); Wilfong et al. (2009)
Monitoring	Early detection	Asner & Vitousek (2005); Dash et al. (2019); Glenn et al. (2005); Lass et al. (2005); Slingsby et al. (2020)
	Spread	Bazzichetto et al. (2018); Gavier-Pizarro et al. (2012); Müllerová et al. (2005, 2013); Ren et al. (2021)
	Control after eradication and restoration	Lishawa et al. (2017); Meng et al. (2012); de Sá et al. (2018); Sankey et al. (2016)
Dynamics	Drivers of invasion process	Bazzichetto et al. (2018); Cunliffe et al. (2016); Hastings et al. (2005); Hellmann et al. (2017); Hobi & Ginzler (2012); Lefsky et al. (2002); Pyšek et al. (2008)
	Dispersal foci	Civille et al. (2005); Müllerová et al. (2013)
	Rate of spread	Andrews & Ustin (2010); Müllerová et al. (2005); Pyšek et al. (2008)
	Short- and long-distance dispersal	Andrews & Ustin (2010); Pergl et al. (2011)
Modelling	Projecting further spread	Ahmed et al. (2020); Barona & Mena (2014); Huang et al. (2008); Nehrbass et al. (2007)
	Analysis of habitat invasibility	Andrews and Ustin (2010); Bazzichetto et al. (2018); Mouta et al. (2021); West et al. (2016); Zimmermann et al. (2011)
Impact	Direct assessment	Asner et al. (2008); Ewald et al. (2018); Horn et al. (2017); Ren et al. (2021); Rosso et al. (2006)

Topic	Objective	References (examples)
	Indirect assessment using RS proxies	Asner & Vitousek (2005); Barbosa et al. (2017); van Cleemput et al. (2020); Dostál et al. (2013); Große-Stoltenberg et al. (2018); Hellmann et al. (2017); Helsen et al. (2020); Hughes et al. (2014); Jandová et al. (2014); Ren et al. (2021); Shiferaw et al. (2021)
Transfer to management	Monitoring the course of invasion, management Measures and restoration efforts	Bedford et al. (2018); Dahal et al. (2022); Doody et al. (2014); Lishawa et al. (2017); Rebelo et al. (2021); Rodgers et al. (2018)
	Selection of species and areas for management priority	Morisette et al. (2006); Mouta et al. (2021)
	Support to decision making, long term & adaptive management, national policies & regulations	Andrews & Usting (2010); Dahal et al. (2022)

The level of utility of RS in practical management of plant invasions is determined by the characteristics of the plant and the stage of the invasion. To benefit fully from the technology we need to define appropriate spatial and temporal scales to adequately address different phenomena related to plant invasions, and specify possible contributions of RS during individual invasion phases that can be separated into prevention, early detection and rapid eradication, and restoration (Regulation (EU) no. 1143/2014 on invasive alien species) (Fig. 2).

Recent research on RS and mapping of plant invasions has benefited greatly from the rapid development of technology and data availability. Key innovations have included increased spatial and temporal resolution, coverage, availability and accessibility of RS data, platforms, sensors, software and enhanced computational power. These advances open opportunities to develop new approaches to (i) precisely detect even the first onset of invasion and/or small and fairly inconspicuous invasive species; (ii) map invasion dynamics from multi-temporal series of RS data; (iii) help to assess and quantify invasion impacts; (iv) support risk assessment and the development of predictive models; and (v) improve our understanding of invasion mechanisms by providing spatially continuous information on the invaded environment (environmental variables and landscape structure) at scales fine enough to capture underlying ecological processes. This paper, targeted to the broad audience of both invasion ecologists and

land managers, outlines the potential and challenges of RS, discusses the discrepancies between science and practice, and proposes solutions on how current technological developments could alleviate some of these issues.

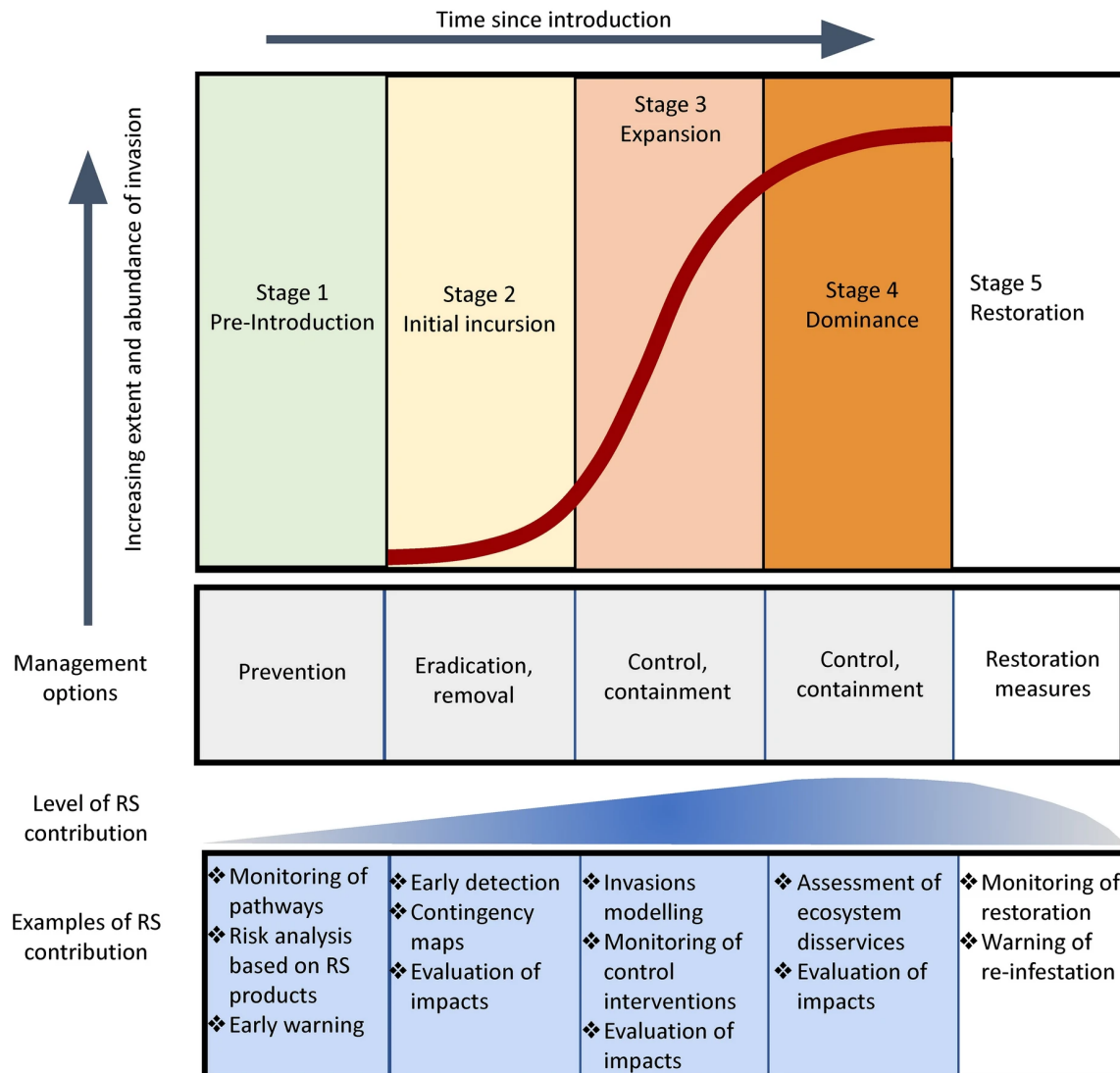


Figure 2: Potential contribution of remote sensing to different management options during the course of plant invasion. The red line in the top section indicates the extent and abundance of invasion. The background diagram (invasion curve) was inspired by van Wilgen et al. (2014)

From patterns to processes-rocking across scales

Ecological systems are characterized by cross-scale interactions in time and space (Peters et al. 2007), and describing and understanding these interactions has always been crucial in ecological research (Turner et al. 1989). Neglecting the fact that ecological patterns and their underlying processes are scale-dependent might lead to conclusions with limited interpretation value (Chase 2014; Chase et al. 2018). Likewise,

plant invasions are characterized by processes with clear spatio-temporal aspects and dimensions (Latombe et al. 2021). Therefore, some processes may be only discernible at certain scales (Bailey 1985), and a thorough understanding of ecosystem properties at one level may be insufficient to understand the whole phenomenon (Odum and Barrett 1971). Remote sensing has huge potential to bridge spatio-temporal scales in ecological studies (Kerr and Ostrovsky 2003), and to contribute to a better understanding of invasion processes and dynamics by improving the sampling and observation of important parameters related to occurrence, spread and impact of invasive plants at multiple scales (c.f. Latombe et al. 2017). Ideally, such approaches facilitate the assessment of the start of invasions at fine scales (individual plants) as well as patterns and processes at broader spatial scales, while also allowing for assessment over time. The idea of exploiting multiple scales or zoom-levels is neither new nor limited to the field of biological invasions. According to Richardson (2011), bird watchers frequently zoom in and out with binoculars (they use the term “rocking”) to identify key features of bird species that are difficult to identify. The same principle of rocking, i.e. moving back and forth across scales, can be applied in RS by using multi-temporal data or data at different spatial scales that are becoming increasingly accessible to bring new insights to our understanding of the invasion process.

Remote sensing observations provide the means for moving across space and time (rocking) by scaling up and down in space between site- and landscape scales by making use of drones (unmanned aerial systems, UAS, unmanned aerial vehicles, UAV, or remotely piloted aerial systems, RPAS), aerial and satellite imagery, and back and forth in time, utilizing the growing archives of analysis ready data (Giuliani et al. 2019) from, for example, the Landsat Archive (Dwyer et al. 2018), fused Landsat and Sentinel data (Frantz 2019; Lucas et al. 2019), the Brazilian CBERS data cube (Picoli et al. 2020), national archives (Dhu et al. 2019) historical datasets such as the SPOT World Heritage Programme (Nosavan et al. 2020) and up-to-date, high-resolution data from nano satellites (Boshuizen et al. 2014; Kopacz et al. 2020). Such repeated data acquisition over broad scales at appropriate intervals, e.g. across seasons, can facilitate capturing wall-to-wall key phenological phases of invasive species across heterogeneous landscapes (Andrews and Ustin 2010; Royimani et al. 2019). Combining RS data with different spectral, spatial and temporal resolution can be challenging (but see e. g. Harmonized Landsat Sentinel-2 data product, Pastick et al. 2020). Such combinations nonetheless allow for tweaking the focus on different spatio-temporal aspects of plant

invasions (rocking) to achieve a more complete picture of the invasion dynamics (Fig. 3).

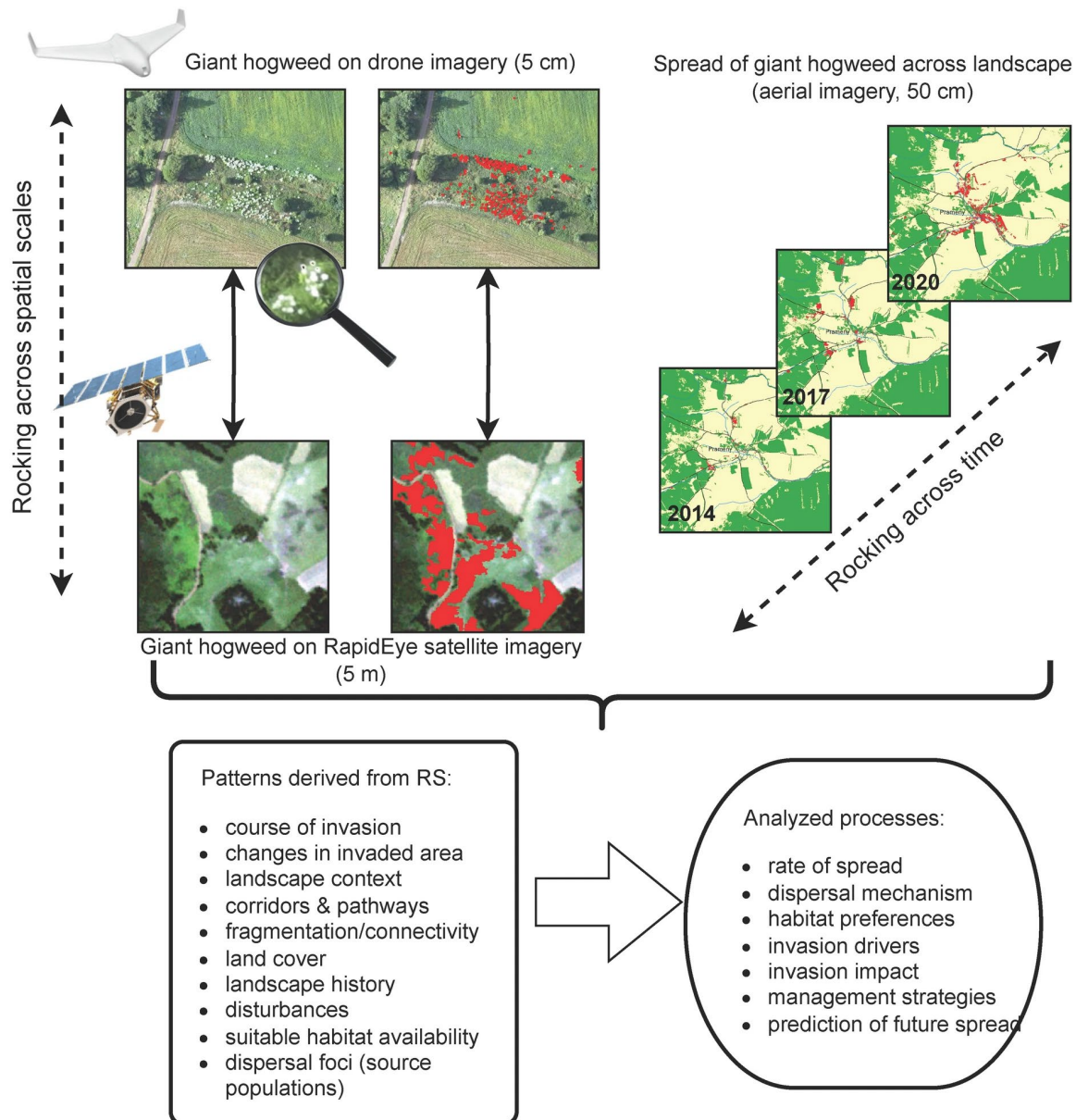


Figure 3: An example from an invasion of giant hogweed (*Heracleum mantegazzianum*) illustrates how rocking across space and time can help to better understand invasion dynamics. Rocking from the finer to coarser and from the current to archival imagery enabled the reconstruction of the invasion process at the landscape scale, and deriving multiple invasion patterns that later served to analyse invasion processes (based on works of Müllerová et al. 2005, 2013, 2017b; Nehrbass et al. 2007; Pyšek et al. 2008; Pergl et al. 2011; Dostál et al. 2013). Areas shaded in red indicate giant hogweed presence classified using drone and satellite imagery.

By moving (rocking) across spatial and temporal scales, RS can widen the perception, enabling not only mapping of plant distributions more precisely (Kattenborn et al. 2019a), but also opening opportunities for exploring invasion processes, monitoring invasion dynamics and studying impacts at different levels and scales (Große-Stoltenberg et al. 2018). Such changes in perspective can provide the context required

to fully understand the driving forces behind aspects such as the site history in terms of temporal scales, or the links between the behaviour of invasion (meta) populations at the site level with landscape features, such as disturbed sites or corridors that serve as pathways. There is a need for more RS-based studies on plant invasions across multiple scales and for studies that go beyond simple description of the invasion state towards understanding of the invasion processes, such as the impact of invasion (Vaz et al. 2018). Hence, land managers will need to adapt their skills to benefit fully from a multiple-scale approach by utilizing, in new ways, spatially and temporally rich datasets. Improved coverage of RS data over space and time is increasing the power of rocking. Such increased power is opening many new opportunities to explore the roles of diverse biotic and abiotic variables in launching and sustaining plant invasions. These advances offer new insights into invasion patterns and processes, but are also creating options for testing ecological concepts, and paradigms and for developing new management tools.

From research to practice

Remote sensing contribution to the invasion framework

Following the typical invasion curve (Fig. 2), expansion and dominance stages are the phases most commonly addressed using RS, employing a variety of sensors, platforms and algorithms at different spatial and temporal scales with the choice depending mainly on the size and conspicuousness of the invader (e. g. Bolch et al. 2020; Huang and Asner 2009). On the other hand, initial stages of invasion, measures of prevention and early warning/early detection of invasion onset, evaluation of invader impact and inspecting the efficiency of control, eradication and restoration measures are rather difficult to address using RS (see Sect. “New solutions”). However, with growing availability of ultra-high spatial resolution data from drones, coupled with high temporal frequency of data acquisition, miniaturized powerful platforms and sensors (hyperspectral and Light Detection and Ranging, LiDAR; Dash et al. 2019), sophisticated algorithms, such as deep learning (see Sect. 5.1), and automation of drones (autonomous flights, real time monitoring), the possibilities for detecting even small patches of invasive plants are increasing. Nonetheless, the limited coverage of these kinds of data means that they are not particularly suitable for operational monitoring; they are more useful for targeted screening (e.g. of vulnerable habitats or sites of high nature conservation value). This means that the efficient use of drones for early detection requires coupling with modelling tools, such as habitat suitability and

predictive modelling to identify target areas for detailed drone screening. Another possibility of early warning is via change detection, where rather rapid change in the spectral signature of a pixel or structural variables such as biomass increase may indicate invasion that is often pronounced by rapid growth (Asner and Vitousek 2005; Slingsby et al. 2020). Such a method is rather imprecise; the derived information therefore only provides a trigger for field surveyors and land managers to conduct more targeted surveys. On the other hand, it can be used rapidly and relatively easily without the need for expert knowledge of the situation. It is also applicable almost irrespective of the invasive species if the revisitation time of the satellite or other RS platforms is frequent enough. For inspecting the efficiency of eradication, control, and restoration measures, similar tools as for early detection could be applied, although this facet of RS application remains underrepresented [but see examples of tamarisk (Meng et al. 2012; Sankey et al. 2016; Bedford et al. 2018) and *Acacia longifolia* biocontrol (de Sá et al. 2018)].

The contribution of RS to plant invasion science spans a variety of life forms/domains, and applications along the introduction-naturalization-invasion continuum (Fig. 2), offering insights on both invasion patterns and processes, ranging from single dimension to spatially and temporally multi-scaled approaches and from scientific knowledge of invasion processes to the practical management of plant invasions (Fig. 1 and Table 1). Adoption of a particular RS approach is driven by the characteristic of the species or the phenomenon to be explored, as well as the overall aims of the study (for details see decision trees in Müllerová et al. 2021). Table S1 in Supplementary Material provides illustrative examples of RS application for different species, life forms and purposes, including technical details.

The core of RS applications lies in mapping and monitoring the invasion progress to inform management. Remote sensing technology can both provide information on invasions and assess aspects of invasion dynamics. The occurrence of the target species can be directly mapped from RS data from a single or multiple dates (Bolch et al. 2020; Evangelista et al. 2009; He et al. 2011; Huang and Asner 2009; Müllerová et al. 2013; Niphadkar and Nagendra 2016; Vaz et al. 2018, 2019). Plant invasions can also be detected indirectly; for example the rapid growth of invasive plants can be monitored as an increase in vegetation greenness by using vegetation indices (Pu et al. 2008).

Spatial heterogeneity of landscapes greatly affects the spatial spread of invasive species (Hastings et al. 2005), and the landscape parameters and dynamics derived from RS data can help to disentangle and describe the invasion. Important parameters pertaining to

spatial heterogeneity can, for example, be derived from airborne LiDAR data (Bazzichetto et al. 2018; Lefsky et al. 2002; Hellmann et al 2017; Potgieter et al. 2019), using photogrammetric methods based on drones (Cunliffe et al. 2016), or aerial (Price et al. 2020) and satellite stereo imagery (Hobi and Ginzler 2012).

Both direct and indirect approaches are subject to types of uncertainty. Direct recognition of particular invasive species/or lower taxa depends largely on its similarity to the surrounding vegetation driven by the species' characteristics and local context (Andrew and Ustin 2008) and depending largely on the spatial, spectral and temporal resolution of the RS data. Consequently, both direct recognition and similarity are rather specific to the site, case and data used, and may vary widely even for a single species. The approach of indirect mapping is more robust to the individual characteristics of particular invaders but can also bring confusion due to the fact that a sudden increase in vegetation greenness can be attributed to many processes including uncommonly high precipitation or local fertilization. Such problems make it hard to formulate generally applicable recommendations on how to use RS for invasive plant species mapping.

In cases where the invader is distinct enough and archival data are available, RS can be used in retrospective analyses using the rocking approach detailed above (Gavier-Pizarro et al. 2012; Müllerová et al. 2005). To reconstruct the course of invasion, archival remote sensing data can be combined with oral histories, museum records, and a variety of publications (scientific journals, newspapers and popular magazines) (Civille et al. 2005). Such information can be used to identify spread dynamics and develop hypotheses concerning dispersal mechanisms and drivers (Pyšek et al. 2008). RS can also support invasion science, conservation practice and management decisions indirectly by providing input data for various types of models for simulating current and future distribution, management measures, risk assessment, or invasion dynamics (Nehrbass et al. 2007; Zimmermann et al. 2011; Rocchini et al. 2015; West et al. 2016; Mouta et al. 2021; Große-Stoltenberg et al. 2023). One popular approach for modelling the spread dynamics between the individual time steps involves the use of cellular automata. Cellular automata are simple spatio-temporal models in which cells (pixels) change their state over time according to some user-defined rules (Hui and Richardson 2017). Such rules can be optimized using multiple reference time-points where the states are known. Successful applications of cellular automata in combination with RS-based maps are provided by Huang et al. (2008) and Barona and Mena (2014).

Unlike detection and monitoring, the impact of invasive species on ecosystem functioning or services is difficult to assess, measure or monitor using RS. Impacts are scale-dependent and can vary greatly across space and time (Ricciardi et al. 2013) depending on invader abundance (Latzka et al. 2016), cover (Barney et al. 2013), spatial extent (Barney et al. 2013), spatial heterogeneity of the landscape (Thiele et al. 2010; Hellmann et al. 2017; Ren et al. 2021) and complex interactions between features of the invader and the provision of ecosystem services (Potgieter et al. 2019; McInerney et al. 2021). Although methods have been developed for spatial upscaling of invader impacts on ecosystem functioning using RS data (e.g. Hellmann et al. 2017), the temporal dimension is often addressed by studying gradients of invasions (Hellmann et al. 2017) and relating cover to impact (Große-Stoltenberg et al. 2018; Shiferaw et al. 2021). In ecology, the common challenge of acquiring sufficient data with appropriate temporal resolution and quality is often addressed by using space-for-time substitution (SFTS) (Pickett 1989). However, this approach has been criticised, as inferring ecological processes from snapshot data might lead to inaccurate conclusions. New approaches are required that combine time-series with spatial data in causal ecological models (Damgaard 2019). Rocking in space and time using RS data can provide an appropriate framework for unravelling ecological impacts of invasive species on ecosystem functioning. RS-based information on the spatial patterns of the invader could potentially be used, for example, to assess resource competition between native and invasive species (c.f. Gioria and Osborne 2014) or to test models and theories of biological invasions (c.f. Shigesada and Kawasaki 1997) to gain insights into invasion success (Theoharides and Dukes 2007). This requires a multiscale approach (rocking) as interpretation might differ between scales (Knight and Reich 2005). RS-derived spatially explicit information on the course of invasion can be used to assess the dynamics of invader impact in time, such as changes in plant-soil feedback during the invasion progress (Dostál et al. 2013). However, while methods are available for assessing the spatial impact on ecosystem functioning, the temporal dimension of invader impacts, essential for management, remains a challenge. For example, the spatial impact of the N-fixing invader *Acacia longifolia* on N-cycling, mapped at plot level, can be upscaled to the landscape level and across invasion gradients using a combination of RS-assisted information on invader distribution (Große-Stoltenberg et al. 2018), LiDAR-derived vegetation cover and topographical metrics as predictors and stable isotope composition ($\delta^{15}\text{N}$) as a response variable in a mixed effect modelling approach (Hellmann et al. 2017). The use of stable isotopes allows us to understand invader-ecosystem

interactions (see also Hellmann et al. 2016). Thus, invader impact can be assessed along an invasion gradient, making the interpretation of the temporal dimension of the impact possible by substituting space for time. In line with the limits of the SFTS approach, mapping stable isotope ratios allows us to better understand the ecological process behind static spatial datasets. Further, the most important predictors in Hellmann et al. (2017), namely invader cover, native vegetation cover and topographical metrics, can all be captured using novel RS technologies at various scales. This means that RS-based rocking could fill important data gaps that reduce the utility of the SFTS approach (see Damgaard 2019); by doing so it could be the basis for confirming important predictors, identifying confounding variables, and assessing the scale- and context-dependency of invader impacts. We suggest that RS-based rocking is an appropriate framework to address the challenges of the SFTS approach (see Damgaard 2019) in the context of plant invasions and their impacts on ecosystem functioning.

Clearly, the utility of rocking is not limited to assessing the impacts of invasive species on nitrogen cycling. Invasive species are known to affect many key ecosystem functions (Asner and Vitousek 2005; Barbosa et al. 2017; Hellmann et al. 2016; Rascher et al. 2011b) with the potential to cause regime shifts (Gaertner et al. 2014). Using RS, the related impacts of invasive species on productivity, water-use strategies, water management and carbon storage (e.g. Rascher et al. 2011b; Nagler et al. 2012; Doody et al. 2014; Hellmann et al. 2016; Dzikiti et al. 2016; Le Maitre et al. 2020) can potentially be linked to key traits of ecosystem functioning derived from RS at various spatio-temporal scales like the Leaf Area Index (LAI), aboveground biomass, canopy height and foliar nitrogen content (Hughes et al. 2014; Barbosa et al. 2017; Migliavacca et al. 2021). The findings can then be integrated into monitoring schemes (Nagler et al. 2009). For example, the fast-growing invasive tree *Acacia longifolia* (e.g. Rascher et al. 2011b) can cause an increase in LAI (Rascher et al. 2011a), while at the same time LAI can be used to map the invader using satellite data (Mouta et al. 2021). Concerning canopy-height and above-ground biomass, integrating terrestrial LiDAR-derived height information with drone-borne hyperspectral data allowed for assessing the effects of the invasive *Lupinus polyphyllus* on biomass in extensively managed temperate grasslands (Schulze-Brüninghoff et al. 2021). In the case of *Spartina alterniflora* invasion, the above-ground biomass of the invader can be mapped by combining data from satellites and drones (Zhou et al. 2018), and the invader effects on soil properties can be assessed using a time-series of spaceborne radar data (Yang et al. 2019). The invasive *Prosopis glandulosa* can be mapped across spatial scales (Mirik and Ansley

2012), and approaches exist for estimating its biomass combining aerial imagery with LiDAR data (Ku and Pupescu 2019). Multitemporal and multiresolution aerial photographs and satellite data were integrated with field measurements to estimate the effect of invasive *Tamarix ramosissima* on the water use of riparian and wetland vegetation (Nagler et al. 2009). While most studies are still based on single time data acquisitions (Große-Stoltenberg et al. 2023), and given the fact that there are numerous showcases that integrate multisource and multitemporal data, we see great potential for applying the principle of “rocking” in RS-based impact studies as technological progress will soon facilitate the acquisition of key vegetation properties across spatio-temporal dimensions (e.g. Houborg et al. 2015). Such advances will make it possible to achieve multilevel assessments of post-invasion changes of, for example, LAI, biomass, and canopy height. Additional approaches for capturing impacts of invasion using RS data include mapping effects on biogeochemical properties (Asner and Vitousek 2005; Ewald et al. 2018, 2020), gross primary production (GPP) (Barbosa et al. 2017; Große-Stoltenberg et al. 2018), ecosystem structure (Asner et al. 2008), and erosion and water drainage patterns (Rosso et al. 2006). Moreover, spectrally-derived functional traits have been applied to assess invader effects on aboveground biomass, litter stabilization and soil available phosphorus (van Cleemput et al. 2020) as well as litter composition (Helsen et al. 2020), and have been linked to the concept of trait dissimilarity and impact (Große-Stoltenberg et al. 2018).

In summary, the increasing availability of RS data is paving the way for multi-site studies and is opening new opportunities for exploring typical invasion patterns in much greater detail, for elucidating the context-dependencies of RS-based impact assessments, and for testing diverse ecological concepts and theories. Remote sensing proxies of invasion impact, based on a thorough understanding of the invasion mechanisms across levels and coupled with RS-based analysis of the spatial pattern of the invasion (c.f. Huang and Asner 2009), represent an important step forward towards defining impact thresholds (Bartz and Kowarik 2019) in a spatially-explicit and updatable way to guide monitoring and management.

Limitations of the RS technology

Accurate recognition/identification of plant invaders is not always possible, and there is often a mismatch between invaders that can be identified and those that are critical for the region. For example, mapping of invasive plant species in the forest understorey is challenging. In case of dense canopy cover, they can either be mapped during a

specific time window (e.g., before leaf emergence of overstorey tree species or after the senescence for broadleaved forests) (Resasco et al. 2007; Wilfong et al. 2009; Shouse et al. 2013; Müllerová et al. 2017b), or indirectly by detecting, for example, changes in structure (Singh et al. 2015), or a fraction of shades and green vegetation (Lopatin et al. 2019; Dai et al. 2020). In some cases, only supra-species level recognition is achievable, e.g. *Fallopia* taxa (*Fallopia japonica*, *F. sachalinensis* and *F. × bohemica*; Müllerová et al. 2017b). Using different spatial or temporal scales (or a combination of both) can help to increase recognition success, such as where *Lepidium latifolium* mapping accuracies of ~ 90% were achieved by zooming into one specific area (Andrew and Ustin 2008). However, when choosing a wide-angle view and comparing different sites, the accuracy decreased due to lower phenological separability and possibly higher site complexity. Another possibility for increasing the recognition success is to use advanced sensors, such as those that analyse a wide spectrum of light instead of just assigning primary colours (i.e. hyperspectral; e.g., Gholizadeh et al 2022), or by combining several different sensors, such as fusion of Sentinel-2 and Landsat 8 multispectral with Synthetic Aperture Radar Sentinel-1 data to detect *Rubus cuneifolius* (Rajan et al. 2018). Photogrammetric digital surface models, created as a by-product of drone imagery processing, are an interesting option for improving detection accuracy (Müllerová et al. 2017a; Kattenborn et al. 2020).

Spatial resolution can be a severe limiting factor for detecting smaller species, and specifically for small patches or even individual invasive plants during the early stage of invasion. In some cases these limitations can be overcome by sub-pixel mapping and spectral unmixing (Ramsey et al. 2005; Silván-Cárdenas and Wang 2010). However, the often reported moderate accuracies of this approach may not suffice for operational applications (e.g., Padalia et al. 2013; Somers and Asner 2013). On the other hand, ultra-high spatial resolution may also create challenges and is not necessarily optimal for mapping a given target species. For example, Müllerová et al. (2017b) showed that in centimetre-resolution drone data, the compound inflorescences of giant hogweed (*Heracleum mantegazzianum*) were separated into individual umbels, which hampered the counting of flowering individuals and decreased the accuracy of mapping. However, such high-resolution drone data can help to identify non-flowering individuals by detecting specific leaf shapes, thereby extending the time window for species mapping. Very recently, new algorithms from the field of deep learning have greatly advanced opportunities for harnessing the fine details of high-resolution spatial data (see Sect. 5.1). Nonetheless, substantial challenges remain in maintaining long-time series of such

high spatial resolution data. One of the options to address this problem are PhenoCams (digital cameras that capture timelapse images of foliage) which can systematically monitor the site over a long period but only cover very small areas (Gill et al. 2021). PhenoCams can be combined with other types of RS data to allow a multi-scale approach, such as in Nagler et al. (2012) for testing the effects of beetles on invasive *Tamarix* evapotranspiration and leaf phenology.

Despite repeatability of RS analyses and available time series of RS data, the temporal aspects of invasion have received less attention in RS research. This is because variability in spectral reflectance of invasive plants can hamper the transportability of trained algorithms in space and time, making it challenging to add retrospective dimensions (long-term or phenological dynamics)(Dudley et al. 2015). Furthermore, it is usually only feasible for species that can be easily separated from their surroundings and where sufficient time series are available (Müllerová et al. 2005). The spatial resolution of long-term satellite missions, such as Landsat, AVHRR or MODIS, is often too coarse. However in some cases, temporal richness of the data can alleviate the deficiency in spatial resolution, such as when the phenology of the invader differs sufficiently from that of native species (Huang and Geiger 2008).

RS-derived data are often used to support modelling of plant invasions (Rocchini et al. 2015). From a modelling point of view, care should be taken to consider the real potential of RS as well as common sources of uncertainty such as the spatial mismatch between the detail of field data and the resolution of remote sensing data (e.g., Carter et al. 2009). Predictions of invasions are limited by the fact that, contrary to when native species distribution is modelled, invading species are not always at an equilibrium and the actual occurrence is often limited by time lags, disturbances or management actions rather than by bioclimatic factors (Bradley 2013; Ahmed et al. 2020).

Certain impacts of invasive species on ecosystem functioning are easy to identify, such as the transformation of a grassland ecosystem to a shrubland or productivity-related impacts. Others are difficult to decipher (Jarić et al. 2019), such as changing interactions among native species (Myczko et al. 2017), or those that have yet to reach a particular threshold (Bartz and Kowarik 2019). In such cases, more sophisticated sensors such as hyperspectral or LIDAR might be necessary (Asner and Vitousek 2005; Ewald et al. 2018). Alternatively, the RS-based information should be interpreted as only a proxy (Große-Stoltenberg et al. 2018) or for deriving information on invasion duration (Jandová et al. 2014). The ability of optical traits such as vegetation indices related to productivity such as the Normalized Difference Vegetation Index (NDVI) to

capture typical invasion patterns or syndromes (Kueffer et al. 2013) varies in time and space according to conditions that are not yet fully understood (c.f. Große-Stoltenberg et al. 2018; Horn and Clair 2017).

Transfer to practice

Technology transfer is a core principle in large parts of environmental law and international conventions, from Convention on Biological Diversity (CBD) to Sustainable Development Goals (SDGs), and it has been very clearly reaffirmed in Goal D of the Kunming-Montreal Global biodiversity framework (CBD/ COP/15/L.25, December 18th 2022). It is not a simple nor a single step process (Ryerson and Haack 2016). As demonstrated above, RS can be useful for understanding the invasion process and for guiding prevention and management strategies by providing accurate, timely and site-specific data for decision support systems and land planning (Lass et al. 2005; Lishawa et al. 2017; Rebelo et al. 2021; Shaw 2005; Zimmermann et al. 2011). Conceptual frameworks on how to integrate RS in species monitoring have been suggested (Jetz et al. 2019), and requirements of data infrastructures suitable for invasive species monitoring have been identified (Hardisty et al. 2019). Yet, despite the large amount of available data and tools (Kwok 2018; Martinez et al. 2020), many well-documented case studies on the application of RS in plant invasion topic (at least 97 papers in 2022 alone; Fig. 4), and well-studied species groups such as invasive *Acacia* species (Große-Stoltenberg et al. 2023), applications of the technology remain focussed at the experimental level, and evidence of effective implementation (operationalization) in invasion monitoring schemes and policy-making process is very scarce (Bell et al. 2023). However, following the recent technological progress towards freely available RS data of high spatial and temporal resolution, we can expect improvements in implementation of RS technology in invasion management.

Most RS research tools and workflows have not been tested in real-world conditions nor successfully transferred to practice. Among the rare success stories of operationalization of RS approach in management of plant invasions are the National Invasive Species Forecasting System in the USA that is based on habitat suitability models, realized for tamarisk (Morissette et al. 2006), or a regional-scale eradication project on giant hogweed in the Czech Republic from 2013 to 2016 (CZ.1.02/6.2.00/12.17406) that used aerial photography and satellite interpretation to support management actions (Müllerová et al. 2013). Long-term studies in the riparian corridor of the Colorado River delta using satellite time-series data revealed that the

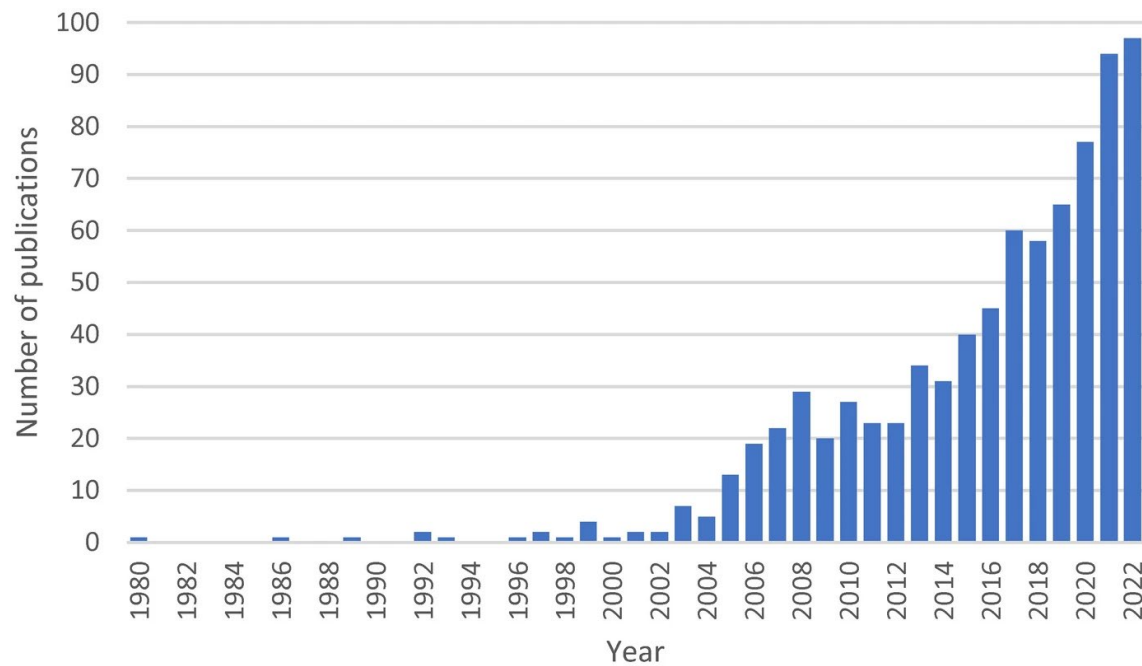


Figure 4: Number of papers published each year between 1980 and 2022 on the topic of remote sensing of plant invasions. Accessed from the SCOPUS database using the search string: (TITLE- ABS-KEY (remote AND sensing) AND TITLE-ABS-KEY (invasive OR invasion*) AND TITLE-ABS-KEY (plant OR vegetation) AND (LIMIT-TO (DOCTYPE,"ar")))

effect of the invasive tamarisk on water use is less than initially expected, and a monitoring scheme based on these data was developed to map the effect of a biocontrol agent, the tamarisk beetle, that causes defoliation in the frame of restoration measures (Nagler et al. 2020). Rodgers et al. (2018) described a multiscale invasive plant monitoring program in Everglades NP (USA) that combined visual observation during the flight and digital aerial sketch mapping. In the Framework of the Habitats Directive (which includes provision on alien species), the French Ministry of the Environment have launched the CarHAB program which aims to map terrestrial natural habitats including invasive species using Earth Observation imagery. Among other examples of successful technology transfer are works of Canada Centre for Remote Sensing (Heslop and Fadaie 2002), German GFZ working group, and the Danish Technological Institute (DTI), such as a drone-based solution coupled with artificial intelligence capable to automatically identify and spray herbicide on hogweed individuals (<https://www.dti.dk/services/drones-as-tools-flying-weed-control-can-provide-environmental-and-bottom-line-savings/42361>). The Earth Resources Observation and Science (EROS) Center of the United States Geological Survey (USGS) uses Harmonized Landsat and Sentinel-2 data products with a vast data set of 17,536 field plot observations from the Bureau of Land Management Assessment, Inventory, and Monitoring program to create fractional cover estimates of non-native annual grass species in Western US rangelands between 2016

and 2020 based on a deep learning framework (Dahal et al. 2022). Their work contributes directly to the USGS Rangeland Exotic Plant Monitoring System, and the maps are publicly available (Dahal et al. 2022).

Table 2 Barriers of broad application of remote sensing in plant invasions management, and proposed solutions

Barriers		Possible solutions	
Communication and engagement	Failure to communicate both potential and limitations of RS with invasion managers	Building trust in RS applications to plant invasions	Review lists of possible stakeholders Foster communication Promote networking among invasion managers and public-private partnerships Collaborate on decisions Identify key invasion process and management priorities Engage end users from the very beginning Shape the workflow according to their needs Promote pilot and demonstration projects for key invasive species and invaded habitats
	Failure to anticipate and support management needs		
	Mistrust of the community of invasion practitioners and field ecologists		Popularize RS among land managers and invasion ecologists Provide transparent assessments Report uncertainties related to RS of invasions Collaborate more with other disciplines and public Engage citizen scientists, promote hackathons

Barriers		Possible solutions	
	Failure to incorporate RS into policy and strategic documents on biological invasions		Integrate RS explicitly into policies and national or regional strategies on biological invasions, pest risk analysis, protected areas and biodiversity
Complexity, technical issues constraining operationalization	High complexity of tools, methods and data	Delivering timely and precise products and knowledge transfer	Simplify and automate the workflows, and train dedicated personnel to use complex methods
			Foster availability of reproducible and well-documented workflows
	Lack of standardization		Standardize the workflows
			Establish gold standards and examples of best practices, e.g. following FAIR Principles (https://www.go-fair.org/fair-principles/)
	Uncertainties and imprecision of both invasion detection and model performance		Take advantage of new sensors and platforms (e. g. high-resolution satellites and drones)
	Low ability to transfer the established RS workflows to other sites, time, RS data or invasive alien plant species		Support research and application of new powerful algorithms (machine and deep learning)
			Facilitate and promote data sharing to enhance the training of transferable models
			Employ crowdsourcing and citizen science
	Delay in delivering RS products, such as invasion risk maps		Establish real-time monitoring protocols
			Deploy high-resolution satellites and drones
			Capitalize on cloud solutions

Barriers	Possible solutions
Costs	Promote policies for both open data and free and open-source software (FOSS)
	Provide tutorials to reduce costs of training for dedicated personnel

The problems of transferring the RS technology to practice are neither new nor are they reserved to the invasion field. Three decades ago, Bruce and Ryerson (1993) identified the main sources of failure to make the RS technology operational; although technology has evolved tremendously since then, their findings remain valid. In particular, they identified problems in linking technology development, applications and management needs. In general, there is a gap between invasion scientists and practitioners/site managers in all aspects of invasion science (Shaw et al. 2010; Funk et al. 2020), and RS is no exception. It is apparently challenging to transfer the results and potentialities into practice, and this problem needs to be solved quickly to assure that the potential of RS methods is realized. This discrepancy between the potential and practical use is partly due to technical limitations of the technology and data that is caused by complexity and variety of both the invasive species and the RS data, pronounced e. g. in a mismatch between spatial/ temporal resolution of the data and the species to be studied, or in imprecision of RS products. However, the problem can be largely attributed to the failure to provide timely data products at the appropriate spatio-temporal scales and at sufficient accuracy to the respective stakeholders, and last but not least to difficulties in communication between land managers, field ecologists and RS experts (Pettorelli et al. 2014) (Table 2).

The limited number of practical applications of RS by public authorities and land managers belies the significant number of legal endorsements of the importance of both invasive species surveillance and RS. In fact, several policy and technical documents highlight the relationships between the CBD and RS, with special concern to those strategies, targets, indicators where RS can make an important contribution, e.g., for tracking progress, including the case of invasive alien species (e.g., Secades et al. 2014). More recently, the CBD/SBSTTA/24/10 document (July 10th 2020) states that “States are encouraged [...] to monitor the spread and impact of high-ranking sleeper species, particularly in sites or regions where biodiversity and ecosystem services are likely to

deteriorate rapidly under climate change. Best-practice approaches using, for example, RS or sensor networks are suggested to be undertaken”. According to European Union Regulation no. 1143/2014, Member States shall establish a dynamic surveillance system of invasive alien species of Union concern. Although the Regulation does not explicitly mention RS, it is clear that such a surveillance system would greatly benefit from RS and GIS technologies. However, European Alien Species Information Network (EASIN), appointed to facilitate implementation of the mentioned EU Regulation by providing technical and scientific support and gathering, analysing and modelling information on alien species, shows very limited use of RS data so far. On the other hand, precision agriculture is becoming an important component of landscape management practice, including (and largely based on) the use of novel RS technologies for native and alien weed mapping and control and a consequent reduction in the use of plant protection products and many other associated benefits. On top of that, the European Commission expects to publish a Communication on the long-term vision for rural areas with a prominent role of digitalization and RS in the future of rural areas and great implications for management of invasions.

For effective RS transfer, the competences of scientific method development must be combined with sustainable software development and aspects of business development, and end-users (practitioners) must be involved from the very first phase. It is crucial to bring RS technology to practice. This can be done especially by clearly communicating the results to the invasion managers and nature conservation practitioners, and making the outputs operational and useful for the managers. It is also important to provide clear and well documented workflows to make the analyses reproducible (West et al. 2016). Underestimating the challenges related to awareness and confidence of practitioners, mentioned by Bruce and Ryerson (1993), is still common. The attitude of the invasion community and practitioners to RS technology often suffers either from unrealistic expectations or scepticism. One reason could be that most RS research focuses on mapping that is traditionally done in the field, and application of RS for this task mostly mirrors the field research rather than searching for new research strategies that would leverage the full potential of RS. The potential of RS technology in addressing other aspects such as impact is less frequently addressed (Große-Stoltenberg et al. 2023). Among the serious technical limitations that hamper the practical use of RS in this field are: problematic species identification, defining optimal timing and spatial/spectral resolution of the data (Müllerová, 2019), within-species spectral variability (Große-Stoltenberg et al. 2016), early detection of individual plants or very

small populations serving as invasion onsets (Glenn et al. 2005), context-dependency of both detection (Andrew and Ustin 2008) and distribution models (Skowronek et al. 2018), delays between data acquisition, processing and delivery of resulting maps to the managers (Zhu et al. 2019; Bolch et al. 2020), and especially limited and rarely tested transferability of the models across species, time, RS acquisitions and sites (but see Skowronek et al. 2018). The resulting products need to be precise enough and informative. The data uncertainties and limitations of the methods and the predictive power of the models must be explained so that they are accepted and understood by various stakeholders ranging from land managers and nature conservation practitioners, invasion ecologists and the general public. This is not only to implement RS tools into monitoring schemes, but also to build overall trust in RS methods, and make the approach as accessible and easy to implement as possible.

New solutions

Rapid advances in RS technology in recent years offer potential solutions to some of the mentioned challenges, specifically those related to sensor and computing hardware/software. Such advances include the use of photogrammetric height information derived from optical drone imagery as a predictor in detection models (Wijesingha et al. 2020; Martin et al. 2018), protocols for the analysis of multitemporal data to account for phenology (Dudley et al. 2015; Somers and Asner 2012; Masemola et al. 2019; Tarantino et al. 2019; Liu et al. 2020), real-time monitoring using autonomous drones that would enable studying invader occurrence, drivers and impact with high-resolution data across temporal and spatial scales. Increasing spatial and spectral resolution and coverage of a new generation of space-borne systems providing very high resolution imagery on a daily basis, such as the hyperspectral missions EnMAP, PRISMA, CHIME (Seeley and Asner 2021), or microsatellites such as PlanetScope (Mudereri et al. 2019), opens new possibilities for precise mapping and especially for monitoring plant invasions. Low-cost drone technology could bridge spatio-temporal scale gaps (Tmušić et al. 2020) and coupled with advanced algorithms assure transferability of the models across sites (Sandino et al. 2018). In terms of image processing, methodologies to artificially increase the spatial resolution of a satellite image for improved object detection based on deep learning (“super-resolution”) (Shermeyer and Van Etten 2019) are very promising for mapping invasive plant species even at early stages of invasion (Chen et al. 2020). We can expect new powerful tools for image acquisition and processing to strengthen and reduce the time needed for

analyses. Standardization and generalization of methods and protocols (gold standards) for new technologies such as drones (as proposed by Müllerová et al. 2021) would help to fully utilize the ultra-high spatial resolution and flexibility of the technology, and hopefully to increase practical use of RS technology in invasion management. Virtual platforms and cloud solutions, such as Google Earth Engine or OpenEO, provide access to larger amounts of data and allow for running processes that are highly computationally demanding without the need for sophisticated local hardware (Visser et al. 2014; Vanthof and Kelly 2017; Elkind et al. 2019; Xu et al. 2020; Schramm et al. 2021). Such advances are expected to rapidly increase the range and operability of RS applications, allowing for more complex tasks such as early warning, assessing impacts of invasions on ecosystem services and especially practical use in invasion management. Such advances will also help to improve the transferability of models across taxonomic groups and geographical ranges, and in scaling up applications from site- to landscape- and regional scales (Kattenborn et al. 2019a).

Powerful algorithms

An urgent prerequisite for the increased operational use of RS is effective methods to identify the species of interest in the data. In this regard, computer vision methods based on deep learning are currently in the spotlight of RS-related research. Like machine learning in general, deep learning aims to automatically identify relevant patterns in data (e.g. canopy structures of an invasive species) through autonomously learned transformations of the input data. The basic property of deep learning is the immense number of such transformations (deep), enabling it to extract (learn) potentially more information than shallower machine learning approaches (for more details see Brodrick et al. 2019; Kattenborn et al. 2021). From an applied RS perspective, this has two major advantages over previous regression and classification methods: Firstly, the target can be mapped with unprecedented accuracy (Liu and Abd-Elrahman 2018; Kattenborn et al. 2019b; Qian et al. 2020). Secondly, the huge number of data transformations renders feature engineering obsolete: Whereas former RS-analysis approaches relied heavily on extracting relevant image features (e.g. band-combinations, vegetation indices, texture metrics), the intense number of transformations in deep neural networks allows the network to autonomously extract the features relevant for the problem at hand.

A frequently applied deep learning method to harness spatial patterns in RS imagery are Convolutional Neural Networks (CNNs). CNNs are composed of consecutive filter

operations that extract spatial information, e.g., characteristic canopy textures and structures of invasive and native species. CNNs were even shown to be very effective for detecting invasive species when used with low-cost drone-based RGB imagery (examples reviewed in Kattenborn et al. 2021). Such data does not contain much spectral information, but usually have very crisp spatial details, such as branching patterns or leaf forms that can be characteristic of an invasive species. This has great potential for the operationalization of RS for invasive species mapping, since such sensors are affordable, usually require little expert knowledge and do not require sophisticated pre-processing or calibration steps (Guirado et al. 2017; Qian et al. 2020; Liu and Abd-Elrahman 2018; Kattenborn, 2019b, 2020).

Despite its great potential, the use of this method is only promising if the invasive species is indeed clearly distinct (visible) from the surrounding vegetation. In addition to spatial patterns, deep learning methods have also great potential for analysing spectral and temporal patterns (Tian et al. 2020; Chen et al. 2020). While CNNs can also be used to extract patterns in spectral information (e.g. the spectral signature of an invasive plant), Recurrent Neural Networks (RNNs) or related methods like Long short-term memory (LSTM) are the current means of choice for time-series analysis. Briefly, such networks are designed to recognize the sequential characteristics in time series data, enabling to automatically extract temporal features, such as phenological characteristics of an invasive plant (Larson and Tuor 2021).

Open and FAIR data-citizen science and cloud solutions

Ample reference data are critical for developing, validating and comparing map products or spreading models, and also for assessing how transferable the models are in new, unseen domains, such as data from new sensors, new geographic areas or collected at different phenological stages. Understanding the model performance is crucial when it comes to operational monitoring. For instance, accuracy of invasive species detection is very context dependent and might differ largely due to differences in surrounding species, topography or illumination conditions. Particularly deep learning but also other statistical RS approaches benefit greatly from large amounts of reference data for model calibration and validation, i.e., RS data together with cover or abundance information of invasive species. However, the acquisition of truly representative reference data is costly, especially estimating the cover or even just the absence or presence of an invasive plant, and, thus, represent a major obstacle for individual stakeholders. The most obvious and sustainable solution is to synthesize the joint effort by involving

multiple stakeholders by curating the data in databases, including available RS data and models paired with observations of invasive species. This accounts particularly for drone data which are collected by many parties but for which sharing protocols are lacking. Platforms exist where users can upload and share drone imagery (geonadir.com; opendrop.com; openaerialmap.com) but they do not readily provide the option to share reference data along with the imagery as an integrated dataset. Such data would ideally be open and follow the *FAIR* principles (Findable, Accessible, Interoperable, Reusable; Wilkinson et al., 2016). In other disciplines, such initiatives have already been successfully implemented (BigEarthNet, National Ecological Observatory Network by NSF, PlantClef, etc.) (Sumbul et al. 2019). However, specifically for invasive species, such a data treasure chest remains a dream, due to missing data standards, limited capacity for data storage and limited long-term funding opportunities.

In this regard, citizen science data is increasingly contributing to the monitoring of invasive species (Johnson et al. 2020; Mesaglio and Callaghan 2021; Wallace et al. 2021). For instance, iNaturalist has already motivated more than 2 million users to contribute more than 20 million observations of vascular plants across all continents, while the project is still rapidly growing (Di Cecco et al. 2021). Many projects on invasive species already exist in iNaturalist (Howard et al. 2022). The deep learning-assisted mobile application, such as iNaturalist or Pl@ntNet, can be used to automatically identify photographed species. These plant image collections are hosted by the Global Biodiversity Information Facility (GBIF) as a survey-grade dataset, integrating photographs, geolocation and species annotations under creative commons licence. For many invasive species several thousand such observations exist (e.g., GBIF holds 117,428 georeferenced records of *Ailanthus altissima* as of 7 February 2023), which may contribute to monitoring invasive species in multiple ways. First, occurrence observations of invasive plants may be used to train or evaluate large-scale RS-based species distribution models and target monitoring actions. Secondly, photographs and connected taxonomic information may be used to train deep learning methods (cf. CNNs introduced above) for the identification of invasive plant species in photographs (Takaya et al. 2022). Models trained on photographs can even be used to identify the spatial distribution of such species in high-resolution RS imagery (Fig. 5, Soltani et al. 2022) even though idiosyncratic behaviour of citizen-science observers often differs largely from the “bird’s eye” perspective of RS. Nonetheless, exploiting the somewhat fuzzy, but ever increasing and freely available crowdsourced records of invasive species distribution and merging this with RS is clearly worth pursuing (Soltani et al. 2022). This

is especially true if we are able to rock between individual observers records from experimental site mapping via drone up to large-scale wall-to-wall mapping and operational monitoring using satellites (such as Planet Labs or Sentinel satellite constellations).

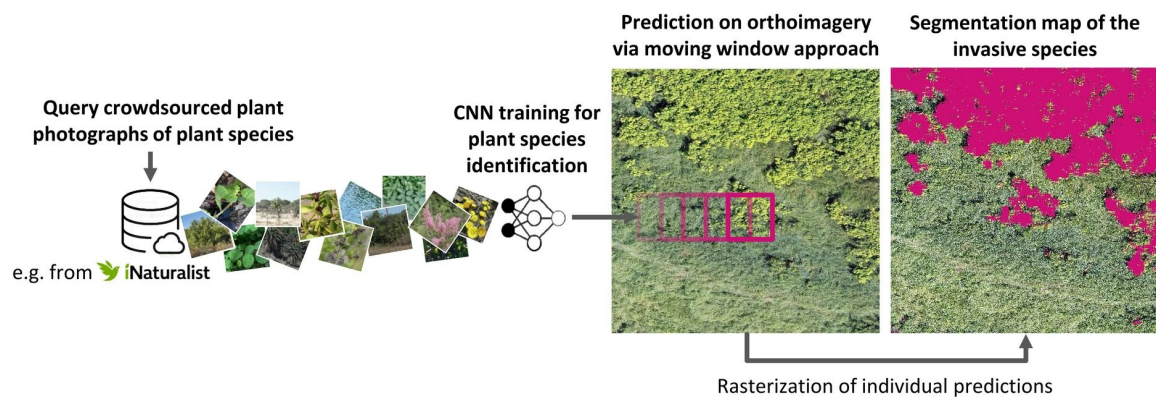


Figure 5: Conceptual scheme illustrating the integration of crowd sourced data in the training of deep learning models (Convolutional Neural Networks, CNN) to alleviate training data scarcity in the context of mapping invasive species (here, *Fallopia japonica*; see Soltani et al. 2022)

The increasing availability of RS data, including open and analysis-ready data together with the progress in Free and Open Source Software (FOSS) (Dwyer et al. 2018), supports skill building and sharing regarding data analysis (Rocchini et al. 2017). Other promising options are cloud solutions such as openEO (Schramm et al. 2021) and Google assisted tools, including Google Earth (Visser et al. 2014), Google Earth Engine (Dong et al. 2020) and Google Street View (Pardo-Primoy and Fagúndez 2019). Google Street View has proven to be quite efficient along roads which often serve as corridors for plant invasion (e. g. Deus et al. 2016; Barone et al. 2021; Kotowska et al. 2021). The tremendous power of Google Earth Engine can also be combined with deep learning algorithms (Tian et al. 2020).

Conclusions

Remote sensing has taken its place, along with other new technologies such as advanced modelling methods, geographic information systems, molecular ecology, and stable isotope analysis as an essential tool in invasion science that is helping to improve our understanding of invasion processes. It is changing the ways we perceive and can monitor invasion dynamics and impacts at different scales, and potentially improves our ability to manage invasions. Yet, examples of RS applications in practical management of plant invasions are rare. Among the main reasons for the mismatch between the potential of RS and the degree of uptake in practice is the discrepancy between the needs of invasion ecologists and managers and the current availability of RS products.

RS procedures are rarely transferable from experimental sites to other areas/species and/or coarser scales, and their accuracy is generally inadequate. There is a need for standardization of RS workflows for invasive plant species monitoring and assessment, including the use of new technologies such as drones. Besides such technical challenges, there are also problems in communication between RS specialists, ecologists and managers. We hope that this review will improve the dialog among RS specialists, invasion scientists, field ecologists and land managers. RS methods are still not consistently integrated into policy documents. Given its massive potential RS needs to form a fundamental part of policy and management of biological invasions. Most technical barriers are likely to be overcome soon. Fast development in the field and the potential of new powerful tools such as drones and deep learning algorithms, coupled with open data, citizen science and cloud solutions including user-friendly interfaces, will reduce these mismatches and pave the way for improved applicability of RS tools in invasion science and practice, including the transfer of RS-assisted approach towards field ecologists and managers. The task of building trust in RS methods among field ecologists, managers and policy makers should be neither overlooked nor underestimated. Remote sensing methods can never (nor should they aspire to) replace field campaigns but improved synergy is urgently needed.

Acknowledgements

We thank Fabian Fassnacht for valuable comments on an early draft of the manuscript. JM and AGS were supported under the joint German Academic Exchange Service (DAAD) and Czech Academy of Sciences (CAS) project "Alien species in a changing world: detection, monitoring and prediction" (DAAD-21-08, grant no. 57560648). AGS was supported by the Hessian Agency for Nature Conservation, Environment and Geology (HLNUG) under the project "Monitoring von naturschutzrelevanten Arten und Renaturierungsmaßnahmen per Fernerkundung (MonA)". DMR acknowledges support from the DSI-NRF Centre of Excellence in Invasion Biology, Mobility 2020 project no. CZ.02.2.69/0.0/0.0/18_0 53/0017850 (Ministry of Education, Youth and Sports of the Czech Republic) and long-term research development project RVO 67985939 (Czech Academy of Sciences). TK was supported by the German Research Foundation (DFG) under the project "BigPlantSens" (DFG grant no. 444524904) and "PANOPS" (DFG grant no. 504978936). GB was funded under the National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.4—Call for tender No. 3138 of 16 December 2021, rectified by Decree n. 3175 of 18 December 2021 of Italian Ministry of University and

Research funded by the European Union—NextGenerationEU, Project code CN_00000033, Concession Decree No. 1034 of 17 June 2022 adopted by the Italian Ministry of University and Research, Project title “National Biodiversity Future Center-NBFC”.

Author contributions

All authors participated in the formulation of the concepts and the paper outline and contributed to writing. JM conceived and co-ordinated the writing. All authors read and approved the final manuscript.

Declarations

Conflict of interest: The authors have no relevant financial or non-financial interests to disclose.

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Chapter 5

Remote sensing of invasive Australian *Acacia* species: state of the art and future perspectives

André Große-Stoltenberg^{1,2,}, Ivan Lizarazo³, Giuseppe Brundu⁴, Vinicius Paiva Gonçalves⁵, Lucas Prado Osco⁶, Cecilia Masemola⁷, Jana Müllerová^{8,9}, Christiane Werner¹⁰, Ian Kotze¹¹ and Jens Oldeland¹²*

¹Institute of Landscape Ecology and Resource Management, Research Centre for Biosystems, Land Use and Nutrition (iFZ), JLU Giessen, Giessen, Germany

²Center for International Development and Environmental Research (ZEU), JLU Giessen, Giessen, Germany

³Facultad de Ciencias Agrarias, Universidad Nacional de Colombia, Bogotá, Colombia

⁴Department of Agricultural Sciences, University of Sassari, Sassari, Italy

⁵National Historic and Artistic Heritage Institute (IPHAN), Florianópolis, Santa Catarina, Brazil

⁶Faculty of Engineering and Architecture and Urbanism, University of Western São Paulo (UNOESTE), Presidente Prudente, São Paulo, Brazil

⁷Precision Agriculture Unit, Advanced Food, Agriculture and Health Cluster, Council for Scientific and Industrial Research (CSIR), Pretoria, South Africa

⁸Department of GIS and Remote Sensing, Institute of Botany, Czech Academy of Sciences, Průhonice, Czech Republic

⁹Faculty of Environment, Jan Evangelista Purkyně University in Ústí n. Labem, Ústí n. L., Czech Republic

¹⁰Ecosystem Physiology, Institute of Geo- and Environmental Sciences, University of Freiburg, Freiburg, Germany

¹¹Department of Forest and Wood Science, Stellenbosch University, Stellenbosch, South Africa

¹²Institute for Globally Distributed Open Research and Education (IGDORE), Hamburg, Germany

*Corresponding author

Wattles - Australian *Acacia* species around the world. Richardson D, Le Roux JJ, Marchante E (Eds.). CABI, Wallingford, pp. 474-496, doi: 10.1079/9781800622197.00

This chapter contains supplementary material, which is available in open access at [https:// doi.org/10.5281/zenodo.8038826](https://doi.org/10.5281/zenodo.8038826)

Abstract

Remote sensing is a rapidly advancing technology with a wide range of applications in ecosystem management. This chapter presents a literature review focusing on ecological applications of remote sensing in the context of invasions of Australian *Acacia* species ('wattles') at the global level. Of ten studied species worldwide, only half, namely *A. cyclops*, *A. dealbata*, *A. longifolia*, *A. mearnsii* and *A. saligna*, were studied more than once. Research hotspots are South Africa and Portugal, while large gaps exist elsewhere. The most common study objective is mapping the distribution of invasive wattles using machine learning. Novel approaches using deep learning and citizen science are still largely untapped resources, and comparative approaches to test the transferability of these novel techniques are rare. Coastal dunes and forests are frequently studied, while agroforestry systems, for example, are neglected despite a high interest in using wattles in these habitats. Beyond mapping, remote sensing is used for impact assessments, for example to map effects on nitrogen cycling and water balance, and suggestions have been made on how to include environmental heterogeneity in impact models. However, research in this field is scarce, and further studies as well as conceptual work are required. Other applications include monitoring of invasion after (bio)control, analysing the importance of land use/land cover in the invasion process and modelling invasion dynamics. Phenological information has high potential for mapping wattles, but this possibility needs to be explored further, particularly in combination with environmental impact assessments. The global nature of wattle invasions and recent technological advancements in remote sensing analyses enable both local-scale studies as well as worldwide comparisons to assess context dependency from both a (technical) remote sensing angle and an ecological perspective. We envision that the increased popularity of remote sensing studies on invasive wattles can be projected into the future to fill these research gaps and to inspire remote sensing-based monitoring systems as the backbone of invasion management.

Setting the Scene: Remote Sensing of Invasive Plant Species

Remote sensing is a powerful tool for assessing vegetation properties and the condition of ecosystems (Ustin and Middleton, 2021). Remote sensing applications in ecology range from biodiversity assessments (Wang and Gamon, 2019), mapping of ecosystem functions across spatiotemporal scales (Gonzalez et al., 2020), to studying ecological processes (Ustin and Middleton, 2021). In addition, remote sensing tools have become popular in supporting ecosystem management. Rapid technological progress and increasing availability of remote sensing data at various scales, from unoccupied aerial vehicles (UAVs) to satellites, are paralleled by fast-developing processing capacities (Wang and Gamon, 2019; Ustin and Middleton, 2021). Machine learning and deep learning approaches for species distribution mapping (Osco et al., 2021; Gonçalves et al., 2022) and change detection (Khelifi and Mignotte, 2020) can be implemented on cloud computing platforms to make mapping large areas computationally feasible, since they allow access to supercomputers and dispense with hardware investment (Gomes et al., 2020; Arasumani et al., 2021; Osco et al., 2021).

Methods of remote sensing are regularly used in the field of biological invasions (Vitousek et al., 2011; Vaz et al., 2018, 2019; Bolch et al., 2020), where they are a key tool to support management and decision making (van Rees et al., 2022). Global monitoring approaches (Latombe et al., 2017) and reproducible workflows for global monitoring of invasive alien species, including Australian *Acacia* species ('wattles'), have been suggested (Hardisty et al., 2019). However, mapping invasive alien species using remote sensing can be challenging and might be constrained by the environmental context, e.g. by differences in site complexity or phenology (Andrew and Ustin, 2008). Thus, a wide array of remote sensing-based workflows for biodiversity monitoring is necessary to accommodate diverse stakeholders' capacities and needs, and to enable worldwide cooperation (Cavender-Bares et al., 2022).

Biological invasions, including those involving wattles, are outstanding natural experiments in biogeography (Richardson et al., 2011). The genus *Acacia* contains several species which are considered global invaders (Richardson et al., 2015; Souza-Alonso et al., 2017; Richardson, 2018; Chapter 1, this volume). Their impacts on ecosystems are manifold and include, for example, a decrease in biodiversity and changes in ecosystem structure and functioning (Marchante et al., 2008; Rascher et al., 2011a,b; López-Núñez et al., 2017; Souza-Alonso et al., 2017; Chapters 22 and 23, this volume). Accordingly, some studies have generalized findings of the impacts of invasive

wattles and restoration of invaded sites (Le Maitre et al., 2011; Chapter 22, this volume) to identify drivers and traits that could indicate the invasiveness of Australian wattles (Richardson et al., 2011, 2015), or have focused on management practices at a global level (Wilson et al., 2011). In terms of remote sensing, there are several single studies on invasive wattles, for example on mapping invasions (Pellikka et al., 2009; Masemola et al., 2020a), upscaling from local to the regional level (Kattenborn et al., 2019), impact assessment (Hellmann et al., 2017; Sibanda et al., 2019) and management (de Sá et al., 2017). Being global invaders (Richardson, 2018), wattles might serve as model species (see also Kueffer et al., 2013; Chapter 31, this volume) to comprehensively assess ecological applications of remote sensing. However, a concise overview of ecological applications of remote sensing approaches in the context of wattle invasion is still lacking.

This chapter summarizes the current state of the art and identifies advances in remote sensing assessments of wattle invasions. We also identify research gaps in remote sensing of wattle invasion.

Methodological Approach: Structured Literature Search

We conducted a structured literature review using the Web of Science (WoS) Core Collection database (Clarivate Analytics, 2022) on 21 January 2022 through institutional access at the Justus-Liebig University Gießen, Germany (see Gusenbauer and Haddaway, 2020 for a review on academic search systems) with no specification of the time range. We used the terms ‘*Acacia*’ and ‘wattle’ to specify the plant genus, the terms ‘alien’, ‘exotic’, ‘invasive’ and ‘non-native’ to select studies in invaded ranges, and various terms related to ‘earth observation’ and ‘remote sensing’ to cover different approaches and scales from field spectroscopy to UAVs, aircraft and satellite imaging systems. The structure of the final query including terms and blocks can be found in Supplementary file 29.S1 in the Supplementary Material.

We initially found 83 publications. We screened the full-text articles for eligibility, and 41 articles fitted the scope of this chapter (excluding, e.g., pure field research, or the genera *Vachellia* and *Senegalia* that were part of the genus *Acacia* until 2009; see Chapter 2, this volume). While this type of structured literature search is rigorous and reproducible, and choosing the WoS database guarantees a certain quality of the articles, some studies including those published in regional journals or written in other languages than English might have been missed. Six publications on the topic not found

by the WoS search were included. Different study areas were counted separately (in three publications), thus yielding 51 studies in total.

The majority of the data were extracted manually from the publications. Data directly related to the study site included information about study species, country of the study site, climate, habitat, size of the study area, protection status, study years and study objectives. Technical attributes included remote sensing platform, sensor type (e.g. multispectral or hyperspectral), cost (e.g. free/public data, low-cost UAV RGB (red-green-blue) imagery or high-cost hyperspectral data), temporal resolution of remote sensing data (e.g. single time or multitemporal), applied algorithms, type of predictors (e.g. vegetation indices, light detection and ranging (LiDAR) metrics), and information on the use of multiple spatial scales and on the use of multiple sensors. If the geographic coordinates were not reported, they were estimated based on the description of the study site. The keywords were extracted automatically via the WoS search except for the six articles that were added manually.

The metadata about each article included the journal title, category or focus of the journal (i.e. remote sensing, ecology, biological invasions, multidisciplinary), the digital object identifier (DOI) and the source of the article (via WoS or sent by an expert).

Studied Wattle Species, Regions and Ecosystems

All in all, research articles reporting remote sensing data were available for ten invasive wattle species (Table 29.1; Supplementary files 29.S2, 29.S3, 29.S4 and 29.S5 in the Supplementary Material), with the earliest study being from 2000 (Stow et al., 2000 in South Africa), but only six of the species were studied more than once. The most studied species were *Acacia mearnsii* (18 studies), *A. dealbata* (14), *A. longifolia* (nine), *A. saligna* (nine), *A. cyclops* (nine) and *A. melanoxylon* (two; Fig. 29.1). However, at least 28 wattles species are known to be invasive (Chapter 1, this volume), and 75 species naturalized (Chapter 9, this volume), so remote sensing-based approaches to assess wattle invasion remain underexplored. The same applies to the global distribution of the studies. The core study regions of research are South Africa and Portugal, followed by Israel, Kenya and Chile (Fig. 29.2), and only the five most studied wattles species were studied in more than one country (Fig. 29.2). Nevertheless, there are recent advances in the field, especially since the 2010s (Fig. 29.3).

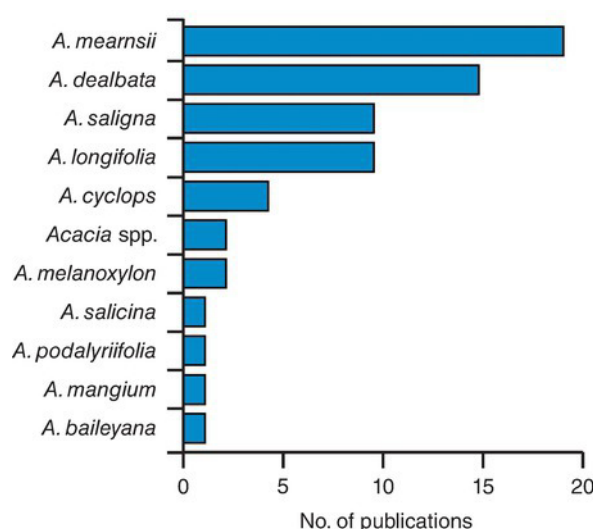


Figure 29. 1: Number of publications about remote sensing of invasive wattles per studied wattle species, retrieved from a structured literature search using the Web of Science Core Collection database. The most studied wattle species that could be used in comparative studies were *Acacia mearnsii*, *A. dealbata*, *A. longifolia*, *A. saligna* and *A. cyclops*. The base data can be found in Supplementary file 29.S2, and the query string together with the query link can be found in Supplementary file 29.S1, in the Supplementary Material.

We found few studies conducted in South America, none in North America, and only one in Asia. This is in contrast to the increase of wattle invasions, especially in South America (Chapter 13, this volume) and South-East Asia, with regard to their use for (agro)forestry (Richardson et al., 2015; Chapter 25, this volume). There is a high chance that wattles planted for forestry become invasive if no management is applied (Richardson et al., 2015). Wattles are frequently used in agroforestry systems to improve soil conditions and for climate mitigation measures (Richardson et al., 2004; Koutika and Richardson, 2019; Chapter 15, this volume), although they can have

negative effects on carbon gain (Rascher et al., 2011a) and water balance (Rascher et al., 2011a; Sibanda et al., 2019). Even though the most common land-cover and land-use types based on our keyword analysis were coastal dunes and, indeed, agroforestry systems (Fig. 29.4), the most common habitats manually extracted from the manuscripts were forests, grasslands, dunes, shrubland and agricultural (Supplementary file 29.S2 in the Supplementary Material). Indeed, remote sensing has been conducted in coastal ecosystems (e.g. Bar et al., 2004; Calvino-Cancela et al., 2014; Große-Stoltenberg et al., 2018a; Marzioletti et al., 2021; Kozhoridze et al., 2022), but we found only two studies linked to agroforestry systems (Palmer et al., 2017; Piironen et al., 2017). Regions with high potential carbon sequestration in agroforestry systems include South America and South-East Asia (Zomer et al., 2022). At the same time, these are regions where large-scale wattle invasions are to be expected and monitoring is recommended (Richardson et al., 2015; Koutika and Richardson, 2019), but so far remote sensing-based monitoring studies are lacking or might have been missed by our query. For example, *A. mangium* is often used in restoring degraded habitats in South America (Koutika and Richardson, 2019), but we found only one local UAV-based study in Brazil (Lehmann et al., 2017). This species has a large invasion potential and might hamper

habitat restoration under current climate change scenarios (Heringer et al., 2019), which emphasizes an increasing need for efficient monitoring and management. Thus, while many remote sensing approaches exist to map invasive wattles in coastal areas, more broadscale studies are needed, especially for mapping wattles in other ecosystems (e.g. Scorer et al., 2019; Vundla et al., 2020; Rebelo et al., 2021 in South Africa) such as agroforestry schemes, especially if future land-use and climate change scenarios indicate large invasion potential.

Table 29. 1: Overview of the remote sensing studies on invasive Acacia species including study country, platform, sensor and citation. Studies are listed in chronological order. The information was retrieved from a structured literature search using the Web of Science Core Collection database. The base data can be found in Supplementary file 29.S2, and the query string together with the query link can be found in Supplementary file 29.S1, in the Supplementary Material. Abbreviations: BW = black and white; CIR = colour infrared; FSpec = field spectroscopy; Hyper = hyperspectral; LiDAR = light detection and ranging; Multi = multispectral; Panchr. = panchromatic; RGB = red-green-blue; UAV = unoccupied aerial vehicle.

<i>Acacia</i> species	Country	Platform	Sensor	Citation
<i>A. cyclops</i> , <i>A. saligna</i>	S. Africa	Aircraft	CIR	Stow et al. (2000)
<i>A. cyclops</i>	S. Africa	Aircraft	Not specified	Higgins et al. (2001)
<i>A. cyclops</i> , <i>A. mearnsii</i> , <i>A. saligna</i>	S. Africa	Satellite	Multispectral	Rouget et al. (2003)
<i>A. cyclops</i> , <i>A. mearnsii</i> , <i>A. saligna</i>	S. Africa	Satellite	Multi	Theron et al. (2004)
<i>A. saligna</i>	Israel	Aircraft	RGB	Bar et al. (2004)
<i>A. dealbata</i> , <i>A. mearnsii</i>	S. Africa	Aircraft	BW	de Neergaard et al. (2005)
<i>A. mearnsii</i>	Kenya	Aircraft	BW, RGB	Pellikka et al. (2009)
<i>A. dealbata</i>	Chile	Aircraft, Satellite	RGB, Multi	Visser et al. (2014)
<i>A. mearnsii</i>	S. Africa	Aircraft	Hyper	Peerbhay et al. (2013)
<i>A. longifolia</i> , <i>A. melanoxylon</i>	Spain	UAV	Hyper	Calvino-Cancela et al. (2014)
<i>A. dealbata</i>	Portugal	Aircraft	RGB	Vazquez-de-la-Cueva (2014)
<i>A. longifolia</i>	Portugal	FSpec	Hyper	Große-Stoltenberg et al. (2016)
<i>A. dealbata</i>	Portugal	Satellite	Multi	Martins et al. (2016)
<i>A. longifolia</i>	Portugal	Aircraft	LiDAR	Hellmann et al. (2017)
<i>Acacia</i> spp.	S. Africa	Satellite	Multi	Mararakanye et al. (2017)
<i>A. longifolia</i>	Portugal	Satellite	Multi	de Sá et al. (2017)
<i>A. mearnsii</i>	Kenya	Aircraft	Hyper, LiDAR	Piironen et al. (2017)
<i>A. mangium</i>	Brazil	UAV	RGB, CIR	Lehmann et al. (2017)

<i>Acacia</i> species	Country	Platform	Sensor	Citation
<i>A. podalyriifolia</i>	S. Africa	Satellite	Multi	Adam <i>et al.</i> (2017)
<i>A. dealbata</i>	Portugal	Satellite	Multi	Monteiro <i>et al.</i> (2017)
<i>A. dealbata</i> , <i>A. mearnsii</i>	S. Africa	Satellite	Multi	Palmer <i>et al.</i> (2017)
<i>A. longifolia</i>	Portugal	Aircraft	Hyper, LiDAR, RGB, BW	Große-Stoltenberg <i>et al.</i> (2018a)
<i>A. longifolia</i> , <i>A. saligna</i>	Portugal	FSpec	Hyper	Große-Stoltenberg <i>et al.</i> (2018b)
<i>Acacia</i> spp.	S. Africa	Satellite	Multi	Sibanda <i>et al.</i> (2019)
<i>A. mearnsii</i>	Kenya	Aircraft	Hyper, LiDAR	Piironen <i>et al.</i> (2018)
<i>A. longifolia</i>	Portugal	UAV	RGB, CIR	de Sá <i>et al.</i> (2018)
<i>A. mearnsii</i>	S. Africa	Aircraft	BW, RGB	Scorer <i>et al.</i> (2019)
<i>A. dealbata</i>	S. Africa	Aircraft	RGB	Gouws and Shackleton (2019)
<i>A. salicina</i> , <i>A. saligna</i>	Israel	Satellite, Aircraft	Multi, Hyper	Paz-Kagan <i>et al.</i> (2019)
<i>A. mearnsii</i>	S. Africa	FSpec	Hyper	Masemola <i>et al.</i> (2019)
<i>A. dealbata</i>	Chile	UAV, Satellite	RGB, Multi, Hyper	Kattenborn <i>et al.</i> (2019)
<i>A. dealbata</i>	Chile	UAV	RGB, Hyper	Lopatin <i>et al.</i> (2019)
<i>A. dealbata</i> , <i>A. mearnsii</i>	S. Africa	FSpec, Satellite	Hyper, Multi	Masemola <i>et al.</i> (2020b)
<i>A. baileyana</i> , <i>A. dealbata</i> , <i>A. mearnsii</i>	S. Africa	Satellite	Multi	Vundla <i>et al.</i> (2020)
<i>A. mearnsii</i>	Algeria	Satellite, Aircraft	Multi, Panchr., RGB	Chekchaki <i>et al.</i> (2020)
<i>A. longifolia</i>	S. Africa	Satellite	Multi	Shoko <i>et al.</i> (2020)
<i>A. dealbata</i> , <i>A. mearnsii</i>	S. Africa	Satellite	Multi	Masemola <i>et al.</i> (2020a)
<i>A. dealbata</i>	Portugal	Satellite	RGB	Nunes <i>et al.</i> (2021)
<i>A. longifolia</i>	Portugal	Satellite	Multi	Mouta <i>et al.</i> (2021)
<i>A. mearnsii</i>	India	Satellite	Hyper, Multi, Radar	Arasumani <i>et al.</i> (2021)
<i>A. saligna</i>	Italy	UAV	RGB, Multi	Marzialesetti <i>et al.</i> (2021)
<i>A. mearnsii</i>	S. Africa	Satellite	Multi, Radar	Rebello <i>et al.</i> (2021)
<i>A. dealbata</i> , <i>A. melanoxylon</i>	Portugal	Aircraft	Multi	Lourenço <i>et al.</i> (2021)
<i>A. mearnsii</i>	Kenya	Aircraft	Hyper, LiDAR	Zhao <i>et al.</i> (2022)
<i>A. saligna</i>	Israel	Satellite	Multi	Kozhoridze <i>et al.</i> (2022)
<i>A. mearnsii</i>	S. Africa	Satellite	Multi	Brewer <i>et al.</i> (2022)

<i>Acacia</i> species	Country	Platform	Sensor	Citation
<i>A. saligna</i>	Italy	UAV, Satellite	Multi	Marzialetti <i>et al.</i> (2022)

Several wattle species, notably *A. cyclops*, *A. longifolia* and *A. saligna*, have also become invasive outside their native ranges within Australia (Manea *et al.*, 2019). While there are remote sensing approaches for mapping of native wattles (e.g. van Dongen *et al.*, 2019), there is a lack of monitoring of those which have become invasive (J. Kinloch, Department of Biodiversity, Conservation and Attractions, Western Australia and S. Firby, Commonwealth Scientific and Industrial Research Organisation (CSIRO), Western Australia, March 2022, personal communication). However, mapping approaches might differ, since growth strategies (Leishman *et al.*, 2014), phenology (Morais and Freitas, 2015), functional traits (Heberling *et al.*, 2016), habitat (Hejda *et al.*, 2015) and the effects on community composition (Helsen *et al.*, 2021) of invasive plant species might differ between native and non-native ranges. All these factors can affect spectral properties or separability, e.g. regarding the phenological signature (Ma *et al.*, 2022; see also Section 29.6), and remote sensing studies comparing native and invaded ranges are rare (see, e.g., Helsen *et al.*, 2021 for a trait-based approach). In addition, trait shifts of invasive wattles are region- and trait-specific (Leishman *et al.*, 2014), while phenology might differ also within the invaded range (Morais and Freitas, 2015). Hence, comparing mapping approaches of wattles in native and non-native ranges could be an interesting future avenue of research for using remote sensing to better understand the invasion ecology of wattles.

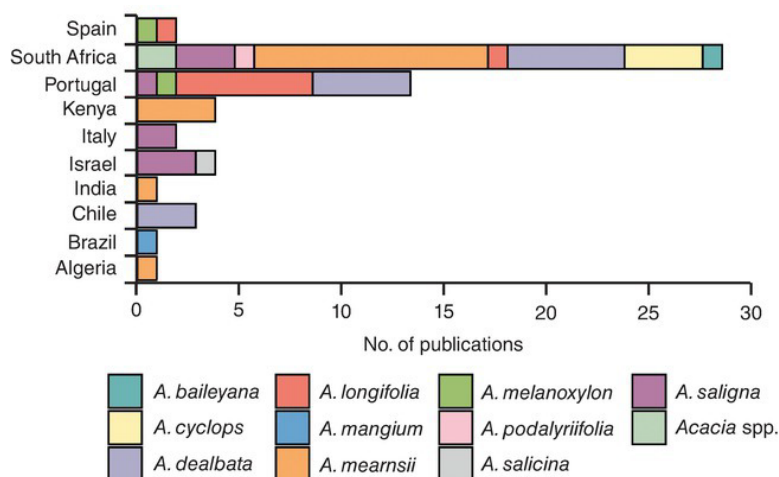


Figure 29. 2: Number of publications about remote sensing of invasive wattles for each studied country and wattle species, retrieved from a structured literature search using the Web of Science Core Collection database. The most studied countries that could be used in comparative studies were South Africa, Portugal, Kenya, Israel and Chile. The base data can be found in Supplementary file 29.S2, and the query string together with the query link can be found in Supplementary file 29.S1, in the Supplementary Material.

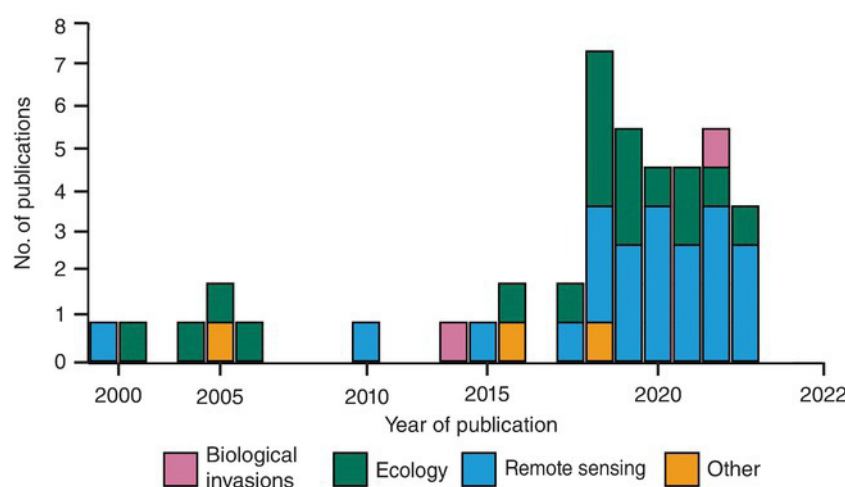


Figure 29. 3: Number of publications about remote sensing of invasive wattles across time and according to the type of scientific journal where the study was published. The information was retrieved from a structured literature search using the Web of Science Core Collection database. The base data can be found in Supplementary file 29.S2, and the query string together with the query link can be found in Supplementary file 29.S1, in the Supplementary Material.

We identified five invasive wattle species (Fig. 29.1) and five focal study areas (Fig. 29.2) that were most abundant. These species and areas could be test cases where it would be worthwhile to investigate the potential to consolidate knowledge on remote sensing of wattle invasions in comparative studies, for example to identify invasion syndromes (also see Chapter 31, this volume, for the description of a wattle-specific syndrome). However, more than half of the invasive wattle species have yet to be assessed by remote sensing, with large research gaps in South America, Asia, and within the native Australian range. Even in the regions with more remote sensing studies, only a few wattle species have been studied. In Africa, for example, there is clear paucity of studies outside South Africa and Kenya, where there is considerable evidence of wattles being widespread problematic invaders in many other countries (Richardson et al., 2022; Chapter 12, this volume). In addition, the ability of remote sensing to distinguish between similar wattle species has been rarely assessed (see, e.g., Große-Stoltenberg et al., 2016; Masemola et al., 2020a,b). Moreover, different wattle species may also co-invade the same habitats, e.g. *A. cyclops* and *A. saligna* in South Africa's fynbos vegetation (Stow et al., 2000) or *A. longifolia* and *A. saligna* in Portuguese dune ecosystems (Große-Stoltenberg et al., 2018b). So, more research is required towards an operational use of remote sensing for monitoring wattle invasions. A good example is the satellite-based monitoring of cheatgrass (*Bromus tectorum* L.) invasion in the rangelands in the western USA (Maestas et al., 2020). Comparative studies on the same wattle species in different countries could generate new knowledge on the generalizability of approaches. Further, both climate and land-use change have to be considered, as well as potentially neglected land-use types such as agroforestry systems. We envision that the increased popularity of remote sensing studies on invasive

wattles from the mid-2010s can be projected to the future to fill these research gaps and broaden comparative approaches focusing on knowledge transfer and synthesis to inspire remote sensing-based monitoring systems supported by invasion theory.

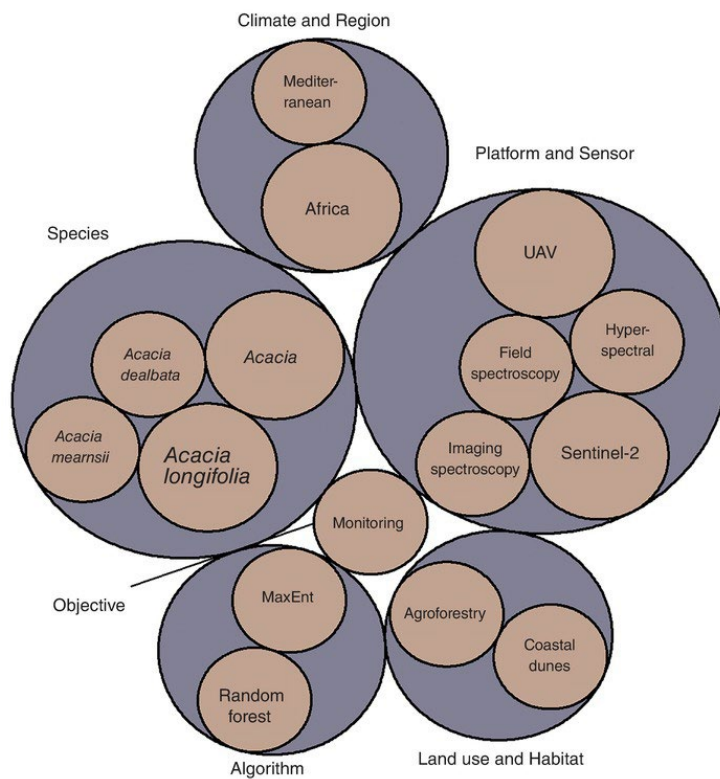


Figure 29. 4: Bubble plot and network analysis of keywords from the publications. The keywords were retrieved automatically, and the groups were assigned manually to add a hierarchical level for better interpretability. The size of both the bubbles and the font is relative to the number of keywords mentioned. Keywords that were only mentioned once were not considered. MaxEnt = maximum entropy; UAV = unoccupied aerial vehicle. The plot was created using the package ‘igraph’ version 1.3.1 (Csardi and Nepusz, 2006) in R statistical software (R Core Team, 2022). The information was retrieved from a structured literature search using the Web of Science Core Collection database. The base data can be found in Supplementary file 29.S2, and the query string together with the query link can be found in Supplementary file 29.S1, in the Supplementary Material.

Platforms and Sensors

A wide range of sensors, from RGB cameras to hyperspectral imagers, and platforms, from UAVs to satellites, have been applied around the globe to assess wattle invasions, reflecting the increasing use of remote sensing tools in ecology (Wang and Gamon, 2019; Ustin and Middleton, 2021; Cavender-Bares et al., 2022) and invasion science (Vaz et al., 2018, 2019). However, their application differed markedly between regions (Fig. 29.5). For South Africa, the majority of the studies have been conducted using airborne and spaceborne data (Fig. 29.5). Despite the increasing use of UAVs to map invasive

wattles species (e.g. Lehmann et al., 2017; Lopatin et al., 2019; Marzioletti et al., 2021, 2022) or invasive alien plants in general (Bolch et al., 2020), we found no UAV-based study in South Africa. For Portugal, the second research hotspot, remote sensing studies on wattles were mainly based on satellite, aircraft and UAV data. Despite being a research hotspot we found no studies using a mixed platform approach, for example to test the spatial scalability and limitations of the respective approach (Fig. 29.5).

Most methods were based on optical data - namely multispectral (25 studies), hyperspectral (14) or RGB (13) cameras - and used either spectral bands or vegetation indices for image analysis (Tables 29.1 and 29.2). The widespread use of optical data may be due to several reasons. First, there is the broad availability of aerial imagery that enables multi-year studies (Higgins et al., 2001; de Neergaard et al., 2005; Pellikka et al., 2009; Vazquez-de-la-Cueva, 2014; Große-Stoltenberg et al., 2018a; Scorer et al., 2019; Chekchaki et al., 2020). There is also free access to satellite data, for example from the Sentinel (e.g. Kattenborn et al., 2019; Masemola et al., 2020a; Shoko et al., 2020; Nunes et al., 2021), Landsat (e.g. Rouget et al., 2003; Theron et al., 2004; de Sá et al., 2017; van Dongen et al., 2019; Domingo et al., 2023) and ASTER programmes (e.g. Martins et al., 2016). The temporal frequency of spaceborne data also allows for time-series analysis (de Sá et al., 2017; Masemola et al., 2020a) and mapping combined with species distribution modelling (Mouta et al., 2021). Finally, there is the increasing use of low-cost UAV solutions for detailed mapping (Lehmann et al., 2017; de Sá et al., 2018; Marzioletti et al., 2021, 2022), which may potentially replace field data collection in areas with difficult access (e.g. Kattenborn et al., 2019). Approaches that use both active (like LiDAR or radar) and passive (like optical) sensors are still not very common (but see Große-Stoltenberg et al., 2018a; Piironen et al., 2018; Kattenborn et al., 2019; Potgieter et al., 2019; Arasumani et al., 2021). While the potential of sensor fusion to increase mapping accuracy may be case-specific (see references above), LiDAR data can be essential to quantify environmental heterogeneity in remote sensing-based impact assessments (Hellmann et al., 2017). At the same time, structure from motion (SfM) photogrammetry can be used to generate information about vegetation structure from optical data and facilitate mapping trees in open ecosystems (Oldeland et al., 2017), including invasive wattles (e.g. Kattenborn et al., 2019). Further, few studies exploited textural metrics (e.g. Bar et al., 2004; Kattenborn et al., 2019; Lopatin et al., 2019; Brewer et al., 2022). Thus, remote sensing approaches to map invasive wattles across platforms exist, but the choice of remote sensing metrics for modelling is still case- and context-specific. Models based on optical data seem to deliver satisfying results in many

cases (e.g. Stow et al., 2000; Calvino-Cancela et al., 2014; Masemola et al., 2020b; Lourenço et al., 2021; Mouta et al., 2021), but applications using active sensors such as LiDAR or radar can help improve mapping accuracy (e.g. Große-Stoltenberg et al., 2018a; Piironen et al., 2018; Kattenborn et al., 2019; Arasumani et al., 2021; Zhao et al., 2022).

Approaches combining data collected from multiple platforms are still relatively uncommon (Fig. 29.5), but examples exist in Algeria, Chile, Israel and South Africa (see Visser et al., 2014; Kattenborn et al., 2019; Paz-Kagan et al., 2019; Chekchaki et al., 2020; Masemola et al., 2020b). Field spectral devices were used in only two countries (Fig. 29.5): in Portugal to test species separability (Große-Stoltenberg et al., 2016) as well as to retrieve functional properties (Große-Stoltenberg et al., 2018b); and in South Africa to evaluate seasonal effects on separability (Masemola et al., 2019) and to assess the potential for mapping at satellite level (Masemola et al., 2020b).

Table 29. 2: Predictors used in remote sensing studies of invasive Acacia species. The total number of predictors used ('n') exceeds the total number of studies as several predictors could be used in the same study. The information was retrieved from a structured literature search using the Web of Science Core Collection database. The base data can be found in Supplementary file 29.S2, and the query string together with the query link can be found in Supplementary file 29.S1, in the Supplementary Material. Abbreviations: DSM = digital surface model; HIS = hue, intensity, saturation; LAI = leaf area index; LiDAR = light detection and ranging; MNF = minimum noise fraction; RTM = radiative transfer model.

Predictor	<i>n</i>
Spectral bands	39
Vegetation indices	17
Texture	4
DSM	3
LiDAR	3
MNF	3
HIS	2
Radar	2
Other (grouped, separated by a semicolon): LAI; RTM; None	1

Data Analysis and Modelling Approaches

For data classification, machine learning algorithms from random forest (Breiman, 2001) or support vector machine (Cortes and Vapnik, 1995) families usually yield high accuracies (Fernández-Delgado et al., 2014). Accordingly, along with traditional methods like visual interpretation, these machine learning algorithms as well as the maximum likelihood classifier (Tou and Gonzalez, 1974) were the most common approaches used to study wattle invasion (Table 29.3). Since these established machine learning approaches enable the mapping of invasive wattles, there is a clear potential

for remote sensing applications for practical application, e.g. to guide management schemes.

Table 29. 3: Algorithms used in remote sensing studies of invasive Acacia species. The total number of algorithms used ('n') exceeds the total number of studies as several algorithms could be used in the same study. The information was retrieved from a structured literature search using the Web of Science Core Collection database. The base data can be found in Supplementary file 29.S2, and the query string together with the query link can be found in Supplementary file 29.S1, in the Supplementary Material. Abbreviations: ANN = artificial neural network; CART = classification and regression tree; CNN = convolutional neural network; DA = discriminant analysis; FDA = Fisher's discriminant analysis; MaxEnt = maximum entropy; PLS = partial least squares regression.

Algorithm	n
Random forest (RF; including RF-DA)	13
Visual interpretation	10
Support vector machine	9
Maximum likelihood	6
(sparse) PLS, (sparse) PLS-DA	4
CART	3
ISODATA	3
MaxEnt	3
Generalized linear models	2
Linear DA	2
Neural networks (ANN, CNN)	2
Other (grouped, separated by a semicolon): box class; FDA; fusion ensemble; generalized additive mixed models; gradient boosting machine; high-dimensional DA; interval extended canonical variable analysis; iterative self-organizing data analysis; k-means clustering; minimum distance; nearest neighbour	1

Surprisingly, novel approaches based on deep learning, particularly convolutional neural networks, have been rarely applied (e.g. Zhao et al., 2022; Table 29.3) despite their potential for improving vegetation mapping (Kattenborn et al., 2021; Osco et al., 2021), for example by facilitating both upscaling and transferability (e.g. Kattenborn et al., 2021). In addition, deep learning is a powerful tool for automatic change-detection analysis, and novel methods such as reinforcement learning or weakly supervised learning only require a relatively small amount of labelled data (Khelifi and Mignotte, 2020). Similarly, geostatistical approaches such as generalized linear (mixed effect) models are scarce (Table 29.3), in spite of the fact that they can be used in combination with remote sensing data to assess changes in ecosystem functioning (White et al., 2020) and have been applied to assess the impacts of wattles on nutrient cycling (Hellmann et al., 2017). In addition, approaches that integrate citizen science with remote sensing, which have a large potential for biodiversity monitoring (Chandler et al., 2017), including invasive species (Soltani et al., 2022), were completely missing (also see Chapters 28 and 30, this volume). Hence, while proofs of concepts exist, there is a large untapped resource based on deep learning, citizen science and advanced geostatistics for mapping and impact assessments of invasive wattles.

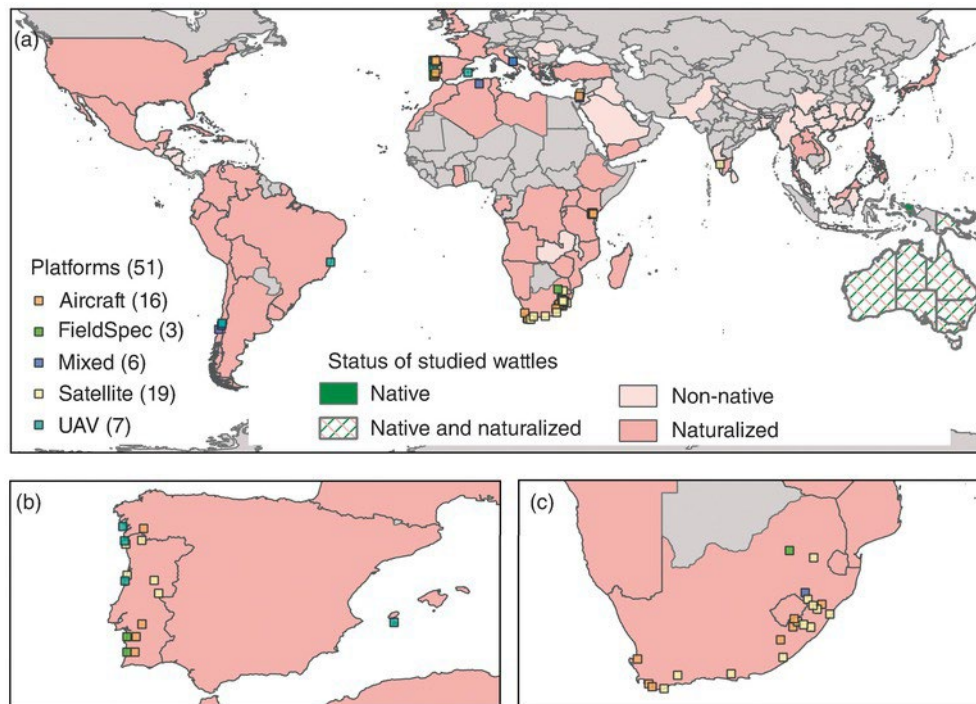


Figure 29. 5: Locations and platforms (number of studies using the platform in parentheses) used in remote sensing studies about invasive wattle species worldwide (a) and focused on the research hotspots of Portugal (including studies from the neighbouring country Spain; b) and South Africa (c). FieldSpec = field spectroscopy; UAV = unoccupied aerial vehicle. The status of the studied wattle species was mainly retrieved from WorldWideWattle (<http://worldwidewattle.com/>, accessed 1 July 2022): cultivated and introduced was coded 'non-native,' while the presence of one naturalized species in a country led to the category 'naturalized.' The 'naturalized' status was updated based on Botella et al. (Chapter 9, this volume). The basic data were retrieved from a structured literature search using the Web of Science Core Collection database. The base data can be found in Supplementary file 29.S3, spatial data on the invasion status in Supplementary file 29.S4, the code for wattle status in Supplementary file 29.S4_1 and species maps can be found in Supplementary file 29.S5, in the Supplementary Material.

Free access to remote sensing software and data is important to ensure establishment of remote sensing technology in the field of biological invasions (Vaz et al., 2018, 2019; Bolch et al., 2020) and, more generally, in landscape analyses (Crowley and Cardille, 2020). Freely available Sentinel-2 data have often been used for monitoring wattle invasions (Fig. 29.4). These recent developments probably promoted the increase of studies about remote sensing of invasive wattles (published especially in remote sensing journals; Fig. 29.3). Challenges for monitoring systems and policy development might emerge, as thematic maps based on machine learning require a thorough accuracy assessment, possibly at local or site level, to evaluate generalizability and transferability (see e.g. Meyer and Pebesma, 2022), and technical challenges of remote sensing change detection apply (see e.g. Tewkesbury et al., 2015). To assess the transferability of remote sensing approaches to study wattle invasion is challenging as almost half of the studies were conducted at one site only, and the extent of the study

sites ranged between 0.11 km² and 87,891.6 km² with a median extent of 53.5 km² (Supplementary file 29.S2 in the Supplementary Material). New computational tools (e.g. Simoes et al., 2021; FAO, 2022) that allow for analysis of large data sets are developing fast, which enables the creation of global-scale, near-real-time maps, for example of land use/land cover (LULC; Brown et al., 2022). Indeed, understanding LULC changes, as well as closely related wattle invasion dynamics, are key objectives in remote sensing research involving wattles (Fig. 29.6), and half of the studies we identified exploited multitemporal information to track and study wattle invasions (Supplementary file 29.S2). LULC data can be used, for example, to investigate landscape permeability (Heringer et al., 2019), to assess the effect of land abandonment (Scorer et al., 2019), to estimate future habitat transformation (Rouget et al., 2003), and to analyse the importance of landscape composition (Mouta et al., 2021) for wattle invasions or to reconstruct planting history (Pellikka et al., 2009). While the use of single, historical images is a well-established technique to study wattle invasions (Supplementary file 29.S2), the broad availability of remote sensing data together with improved processing and analysis infrastructure will facilitate the use of spatiotemporal data cubes to analyse landscape processes based on dense time series (Crowley and Cardille, 2020). However, even if global data and maps are available, local thematic accuracy assessments (Meyer and Pebesma, 2022), supported by local knowledge and context for interpretation (Wyborn and Evans, 2021), are essential. Even if transferring a machine learning-based model to a new site is technically possible, the resulting prediction might be inaccurate (Meyer and Pebesma, 2022). In the case of remote sensing of plant invasions, the use of high-fidelity hyperspectral data (Fig. 29.4) does not guarantee accurate maps across sites due to differing environmental complexity (Andrew and Ustin, 2008), which emphasizes the importance of comparative case studies (sensu Kueffer et al., 2013). This context dependency is a common problem in ecological studies (Catford et al., 2021) and for quantifying invasive species' impact on ecosystems (Kumschick et al., 2015; Catford et al., 2021; Chapters 22 and 23, this volume). The global nature of wattle invasion (Richardson et al., 2011; Chapters 1 and 8-14, this volume) and the recent technological advancements enable both local-scale case studies and global comparisons to assess context dependency from both a (technical) remote-sensing angle and an ecological perspective. This could lead to progress in the field of transferability and generalizability of remote sensing-based mapping approaches.

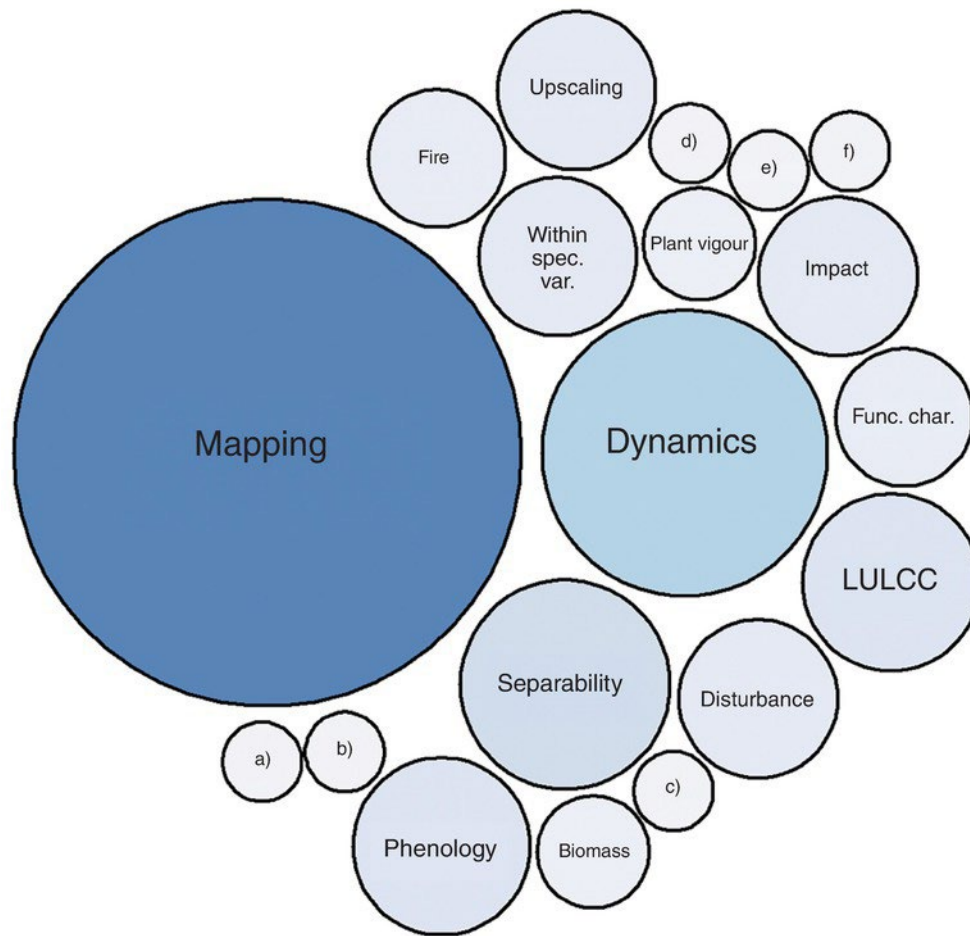


Figure 29. 6: Bubble plot of the manually assigned objectives of the remote sensing studies on invasive wattles. The size and the shading of the bubbles are relative to the number of publications with the respective objective ranging from one (e.g. invasion stage) to 41 (mapping). Objectives were abbreviated when the bubble size was too small: a) = invasion stage; b) = biocontrol; c) = management; d) = radiative transfer modelling; e) = invasion success; f) = annual growth. Func. char. = functional characteristics; LULCC = land use/land cover change; Within spec. var. = within-species variability. The plot was created using the package 'packcircles' version 0.3.4 (Bedward et al., 2020) in R statistical software (R Core Team, 2022). The information was retrieved from a structured literature search using the Web of Science Core Collection database. The base data can be found in Supplementary file 29.S2, and the query string together with the query link can be found in Supplementary file 29.S1, in the Supplementary Material.

Applications of Remote Sensing in Wattle Invasion Ecology and Management

The most common objective in remote sensing of wattles is mapping their invasion of native vegetation, but assessments of dynamics, species separability, phenology, and linking wattle invasion to disturbance (e.g. fire events, overgrazing) are also prevalent. Studies on, for example, wattle impact and upscaling were less common, and studies on invasion stage (using wattle cover as a proxy), biocontrol monitoring and

management were rare (Fig. 29.6). Indeed, the location of an invasive species is a key variable for its monitoring and the first pillar for a global monitoring scheme (Latombe et al., 2017). For mapping wattles, the use of remotely sensed phenological information on flowering (Martins et al., 2016; de Sá et al., 2018; Paz-Kagan et al., 2019; Marzialetti et al., 2021) and, more generally, on seasonality (Masemola et al., 2019, 2020a) is a successful approach, which deserves further attention. The investigation of mapping approaches based on temporal analysis of remotely sensed data and the subsequent derived phenological signatures of wattle species is now possible due to the much-improved temporal and spectral resolution of the freely available Landsat and Sentinel sensor databases that cover the globe (Ma et al., 2022). At the same time, there are recent advances in integrating phenological data across scales from different sources, such as remote sensing platforms, phenocam networks, citizen science observations (Ma et al., 2022; Chapters 28 and 30, this volume) or flux towers, at potentially very high spatiotemporal resolution (Moon et al., 2022). In addition, there are further applications of remote sensing to manage wattle invasions that would also benefit from high-resolution (phenological) space-time data cubes, such as monitoring of invasive populations after control (Adam et al., 2017), mapping the effects of biocontrol agents (de Sá et al., 2018), considering specific effects of LULC such as abandonment and overgrazing on wattle invasion (Scorer et al., 2019), and assessing the effect of infrastructure such as railways as dispersal pathways (Mararakanye et al., 2017).

Furthermore, spatial information on range expansion or spread provides insights into the status of an alien species, which is the second pillar of a global monitoring system (Latombe et al., 2017). In the case of wattle invasion (Chapter 30, this volume), for example, remotely sensed data are often used to parameterize spread models (Higgins et al., 2001), species distribution models (Monteiro et al., 2017; Mouta et al., 2021; Mtengwana et al., 2021), mechanistic models (Cheney et al., 2019) or cellular automata (Kozhoridze et al., 2022). In addition, remote sensing products are the basis to compute and model landscape susceptibility for wattle invasion (Heringer et al., 2020). All these models can be applied to quantify invasion success, estimate future invasion potential, or evaluate the effectiveness of management measures. While such models can be important for implementing legislative regulations (Lozano et al., 2020), remote sensing-based modelling approaches to assess invasion dynamics receive less attention compared to mapping approaches (Fig. 29.6).

The third essential variable for a global invasion monitoring system is impact (Latombe et al., 2017). There are numerous studies on impacts of invasive wattles (Le Maitre et

al., 2011; Chapters 22 and 23, this volume), but only a few studies have mapped the impact of invasive wattles (Fig. 29.6) on nitrogen cycling (Hellmann et al., 2017), ecosystem structure (Große-Stoltenberg et al., 2018a), canopy storage capacity (Sibanda et al., 2019) and plant biomass (Vundla et al., 2020), for example. Indeed, remote sensing can contribute to upscaling wattle impacts on nitrogen cycling from plot to landscape scale considering environmental heterogeneity when coupled with advanced geostatistics (Hellmann et al., 2017). Furthermore, application of field spectroscopy at fine scales enables assessing a broad range of functional traits at an individual level (Homolová et al., 2013), which can help to understand invasion processes and effects on ecosystem functions (Niphadkar and Nagendra, 2016). For example, the impact of nitrogen-fixing invaders such as wattles on ecosystem functioning is well documented both in South Africa (e.g. Yelenik et al., 2004, 2007) and in Portugal (Marchante et al., 2008, 2019; Hellmann et al., 2011, 2017; Rascher et al., 2012). However, the effect of nitrogen-fixing invaders on nitrogen cycling is constrained by leaf trait dissimilarity at community level (Lee et al., 2017), and wattles might affect nitrogen cycling differently compared to other native (Hellmann et al., 2011; Rascher et al., 2012) or invasive nitrogen-fixing species (Yelenik et al., 2007). For example, wattles might alter foliar nitrogen content and nitrogen stable isotope composition of surrounding vegetation (Hellmann et al., 2011; Rascher et al., 2012) as well as total soil nitrogen and organic matter with long-term effects possible due to different leaf properties linked to decomposition (Yelenik et al., 2007). Using field spectroscopy, it has been shown that *A. longifolia* and *A. saligna* differ from native species of the same growth type regarding leaf carbon, nitrogen and fibre content (Große-Stoltenberg et al., 2018b). Thus, besides species identity, which can be mapped using remote sensing, knowledge about key functional traits at the community level is essential to predict impacts and to guide management and restoration.

In addition to field spectroscopy, UAVs have the potential to make the bridge from fine scale to satellite level (Kattenborn et al., 2021; Marzioletti et al., 2022), and this technology is commonly used for remote sensing of wattles (Fig. 29.4). However, only two studies used UAV-based hyperspectral data (Calvino-Cancela et al., 2014; Lopatin et al., 2019). The objective of both studies was mapping, and not the retrieval of functional properties, which also applies to the six studies that were based on airborne hyperspectral data (Peerbhay et al., 2013; Piironen et al., 2017, 2018; Große-Stoltenberg et al., 2018a; Paz-Kagan et al., 2019; Zhao et al., 2022). Thus, hyperspectral remote sensing is a very promising tool for impact assessments, but

research using this tool is still scarce. However, limitations might apply as scaling from leaf to community is challenging, especially in ecosystems with low vegetation cover (Homolová et al., 2013), and spatial effects of invader impact need to be considered (Hellmann et al., 2017). The invasion of nitrogen-fixing wattles into nutrient-poor ecosystems might be a typical invasion pattern or syndrome (see Kueffer et al., 2013; Novoa et al., 2020; Chapter 31, this volume), which can be captured using remote sensing (Große-Stoltenberg et al., 2018a).

Another unexplored research line for multiscale approaches is the use of land surface phenology (see, e.g., Ma et al., 2022) in impact assessments based on remote sensing. Drivers of plant phenological variation, which can affect phenological signatures captured by sensors, include water and nutrient availability as well as species diversity and physiological parameters (Ma et al., 2022). For example, field experiments in tree-grass ecosystems based on multi-sensor and multi-scale approaches have shown that adding nitrogen to the ecosystem changed the phenological signature (senescence) captured by flux towers, phenocams and satellites due to increased soil water depletion during the dry-down period (Luo et al., 2020; Ma et al., 2022). Typical impacts of wattles include changes of nitrogen and water cycles as well as plant diversity (Marchante et al., 2008; Rascher et al., 2011a,b; López-Núñez et al., 2017; Souza-Alonso et al., 2017). Altered water fluxes after plant invasion can result in changed remotely sensed phenological signals (Prater and DeLucia, 2006), and wattles can show a clear, productivity-related and remotely sensed phenological response during the green-up phase in spring (Große-Stoltenberg et al., 2018a). Therefore, multi-scale, sensor-based phenology metrics have the potential to map these effects on ecosystem functioning, and thus give insights into invasion mechanisms. The global availability of remote sensing data, advances in data analysis tools (see, e.g., Crowley and Cardille, 2020) and the global nature of wattle invasions make them an ideal test case to identify recurring patterns or syndromes including phenological metrics across ecosystems and scales. Further conceptual work, and more case studies from low cost to high fidelity, are required to develop workflows for remote sensing-based ecological assessments, transfer them to practice and support management.

Priorities for Further Work and Research Gaps

A broad knowledge base to map invasive wattle species across platforms exists. As most of the wattle species that have been studied occur in regions where they are also regulated by law (e.g. in Europe and in South Africa; Chapters 10 and 12, this volume),

remote sensing can be used as a powerful tool to support national commitments to control and manage invasive wattles. In general, the analysed studies show that invasive wattles can be mapped with high accuracies using optical remote sensing data. Concerning image analysis, progress has been made from manual image interpretation to semi-automated mapping using established machine learning algorithms such as random forest. The increasing temporal resolution and flexible acquisition of remote sensing data facilitates the use of phenological information in mapping models. Although many other wattle species are also invasive, most remote sensing studies reviewed in this chapter focused on only five species (*A. cyclops*, *A. dealbata*, *A. longifolia*, *A. mearnsii* and *A. saligna*) and were conducted in only five countries (Chile, Israel, Kenya, Portugal and South Africa), and most were done at only one location in each country. Thus, for the most frequently studied species and countries, it would be interesting to develop comparative studies with common objectives and technological set-ups to test the transferability of classification approaches and to explore differences that hinder operational solutions. This could be done, for example, for mapping wattles using machine learning algorithms such as random forest based on UAV or satellite data. For all other species and regions, including the native range, new methods need to be developed and tested. Knowledge gaps exist regarding novel mapping and change detection approaches based on deep learning methods (e.g. reinforcement learning, weakly supervised learning) and studies focusing on invasion ecology (i.e. related to impact assessment, (bio)control, invasion dynamics, habitat restoration and management). Recent technological advances also allow for a deeper exploration of multitemporal, remotely sensed data on phenology, which has proven useful for mapping wattles, but has also a large potential to be used in impact assessments and to investigate invasion dynamics. In addition, virtual globes such as Google Earth (Visser et al., 2014), panoramic street view data (e.g. from the Google Street View program; Kotowska et al., 2021) or mobile mapping solutions (e.g. iNaturalist; Howard et al., 2022) are untapped resources and have future innovation potential for early detection and monitoring for invasive species, especially when combined with remote sensing data. As invasive wattles occur around the globe with manifold impacts and reoccurring invasion patterns, they could help to tackle the challenge of context dependency of invasive plant mapping and impact models from both remote sensing and biological invasion perspectives. Additionally, they could serve as a global test case to build a trustable and transferable remote sensing-based monitoring system for invasive plant species.

Acknowledgements

We thank Nuno César de Sá and Teja Kattenborn for contributing to the literature search, and Juliana Figueiredo da Silva for assisting to assemble the references. We also thank David M. Richardson, Elizabete Marchante, Jaco Le Roux and two anonymous reviewers for their thoughtful comments which helped us to improve the manuscript. A.G.-S. was supported by the Hessian Agency for Nature Conservation, Environment and Geology (HLNUG) under the project ‘Monitoring von naturschutzrelevanten Arten und Renaturierungsmaßnahmen per Fernerkundung (MonA)’ and, together with J.M., under the joint German Academic Exchange Service (DAAD) and Czech Academy of Sciences (CAS) project ‘Alien species in a changing world: detection, monitoring, and prediction’ (DAAD-21-08, grant no. 57560648). J.M. was also supported by RVO 67985939 (CAS). I.L. was supported by the German Academic Exchange Service (DAAD) from funds of the Federal Ministry for Economic Cooperation (BMZ), SDGnexus Network (grant no. 57526248), programme ‘exceed-Hochschulexzellenz in der Entwicklungszusammenarbeit’.

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Chapter 6

An integrative framework to assess the spatio-temporal impact of plant invasion on ecosystem functioning

Christiane Werner^{1,}, Christine Hellmann¹, André Große-Stoltenberg^{2,3}*

¹Ecosystem Physiology, Faculty of Environment and Natural Resources, University Freiburg, Georges-Köhler-Allee 53/54, Freiburg, Germany

²Institute of Landscape Ecology and Resource Management, IFZ Research Centre for Biosystems, Land Use and Nutrition, Justus Liebig University Giessen, Heinrich-Buff Ring 26-32, 35392 Giessen, Germany

³Center for International Development and Environmental Research (ZEU), Senckenbergstraße 3, 35390 Giessen, Germany

*Corresponding author

NeoBiota 94: 225-242 (2024), doi: 10.3897/neobiota.94.126714

Supplementary Information: The online version contains supplementary material available at <https://doi.org/10.3897/neobiota.94.126714>.

Abstract

Invasive species can alter the structure and functioning of the invaded ecosystem, but predictions of the impact of invasive species on ecosystem functioning are weak. Invasion is determined by the interplay of invasive species traits, the recipient community, and the environmental context. However, efficient approaches to assess the spatial dimension of functional changes in heterogeneous environments and altered plant-plant interactions are lacking. Based on recent technological progress, we posit a way forward to i) quantify the fine-scale heterogeneity of the environmental context, ii) map the structure and function of the invaded system, iii) trace changes induced by the invader with functional tracers, and iv) integrate the different spatio-temporal information from different scales using (artificial intelligence-based) modelling approaches to better predict invasion impacts. An animated 3-D model visualisation demonstrates how maps of functional tracers reveal spatio-temporal dynamics of invader impacts. Merging fine- to coarse-scale spatially explicit information of functional changes with remotely sensed metrics will open new avenues for detecting invader impacts on ecosystem functioning.

Keywords

community structure, environmental context, functional tracer, invader-ecosystem interaction, remote sensing, spatio-temporal heterogeneity, spatio-temporal modelling

Introduction

Biological invasions of non-native species pose a large threat to biodiversity (IPBES 2019). Many invasive plant species significantly alter the biophysical and biochemical environment, thereby facilitating their own growth (Gaertner et al. 2014), with cascading effects on the structure and functioning of the invaded ecosystems. However, mechanisms of invader impact can be manifold (Ehrenfeld 2010; Sapsford et al. 2020), and challenges to quantify impact occur due to the multiplicity of invading species, context-dependencies, and interactions, as well as intraspecific trait variation (Sapsford et al. 2020). Predicting the effects of biological invasions on ecosystem functioning and services is of uttermost importance for prioritizing management and anticipating undesirable consequences of invasions (Simberloff et al. 2013; Jeschke et al. 2014; Brundu et al. 2020; Essl et al. 2020; Kumschick et al. 2020; Pyšek et al. 2020b; Ricciardi et al. 2021; Gallardo et al. 2024; Vilà et al. 2024). To date, multiple hypotheses and concepts have been developed that capture different aspects of invasion impact, habitat invasibility, and species' invasiveness (Hobbs and Humphries 1995; Alpert et al. 2000; Whitney and Gabler 2008; Enders et al. 2020; Novoa et al. 2020; Catford et al. 2021; Cavieres 2021; Hui et al. 2023), although data to thoroughly test these are often scarce (Gioria et al. 2023).

The ecological impact of invasive species depends on direct interactions between native and invasive plants, which in turn are influenced by native and invasive species' traits (Pyšek et al. 2012, 2020a; Sapsford et al. 2020), or trait differences between both groups (Castro-Díez et al. 2014; Lee et al. 2017; Kuebbing et al. 2018; Dyderski and Jagodziński 2019). Consequently, there is increasing awareness of the relevance of interactions and dynamics for invasion success, such as the interplay between invading species' traits and the recipient ecosystem (Kueffer et al. 2013; Kumschick et al. 2015; Sardans et al. 2017; Novoa et al. 2020). However, new approaches are needed to quantitatively assess these interactions (Gioria et al. 2023).

Species interactions as well as plant-soil feedbacks take place on a spatially confined scale within centimetres to metres in the neighbourhood of the invader (Mitchell et al. 2006), which is further referred to as fine-scale. While the temporal aspect of such feedbacks has been documented (Yelenik and D'Antonio 2013; Gioria and Osborne 2014), studies on impacts at plant-individual scale are clearly underrepresented (Crystal-Ornelas and Lockwood 2020). The spatial arrangement and distribution of native and invasive species is a decisive factor determining whether individuals interact

and, potentially, which type of interaction - i.e., competition or facilitation - dominates (Hellmann et al. 2016a, 2016b; Cavieres 2021).

In addition, there is growing recognition that the effect of the invasive species is influenced by the environmental conditions, such as microclimatic or local edaphic conditions (Sapsford et al. 2020; Catford et al. 2021). The environmental context, namely the fine-scale spatial heterogeneity of abiotic and biotic conditions, is an important but often neglected dimension (Jarić et al. 2019; Fenesi et al. 2023), and the spatio-temporal variation of a system is a major source of uncertainty of impact assessments (Probert et al. 2020). Local availability of resources, such as water, nutrients or light, can shift the competitive balance between invasive and native species (Werner et al. 2010; Soliveres et al. 2015; Alba et al. 2019; Haberstroh et al. 2021). Therefore, predicting ecological impacts of invasive species considering context-dependency is still a major challenge (Ricciardi et al. 2021).

We posit that spatio-temporal heterogeneity can represent an environmental property in itself, which can affect invasibility, or else be affected by invasion, and requires better inclusion in invasion ecology. In the past, progress was hampered by a lack of methodological approaches, but now significant progress, e.g. in remote sensing technology, allows capturing high-resolution information on environmental heterogeneity at fine scales where plant-plant interactions take place.

Hence, we advocate combining advances in various disciplines of ecophysiology, invasion ecology, remote sensing, mapping, and modelling. This will open new opportunities to characterize environmental heterogeneity and associated changes in invasive-native species interaction at high-spatiotemporal resolution to better predict invasion dynamics and impact, as outlined in the following.

Concept for integrating fine-scale environmental heterogeneity and functional changes into spatial models of invader-ecosystem interactions

Direct interactions between the invasive and native species, such as above- or below-ground facilitation or competition for e.g. resources, spaces, or pollinators will determine the invaders' successful establishment and growth (Fig. 1). These direct interactions are embedded in the environmental context, which is likewise shaping the competitive balance if conditions favour either native or invasive substitute by species. The competitive balance may even shift between competition and facilitation under changing environmental conditions or extreme climatic events (Werner et al. 2010; Grossiord 2020; Cavieres 2021; Haberstroh and Werner 2022). Inversely, some invaders can change environmental properties through positive or negative feedback loops,

thereby often promoting their own invasion success, which can ultimately result in regime shifts (Gaertner et al. 2014) and potentially magnify the impact beyond direct competition through cascading effects (Carboni et al. 2021).

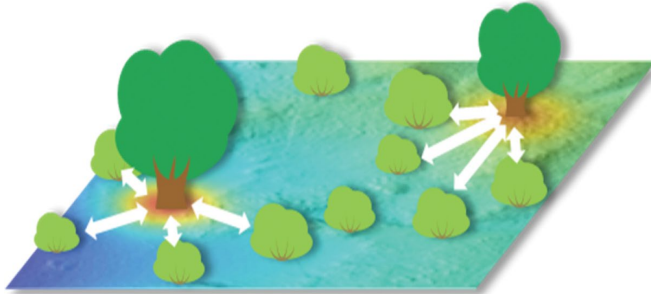


Figure 1: Invasive species directly interact with native species by competition or facilitation e.g. for above and belowground resources, thereby changing the biotic and abiotic environment locally.

Currently, there exists a robust theoretical framework addressing the success of invasiveness as a result of direct and indirect interactions and the interplay between species traits, as well as on the recipient community structure and functioning and the environmental context (Gaertner et al. 2014; Novoa et al. 2020; Pyšek et al. 2020a; Hui et al. 2023; summarized in Fig. 2).

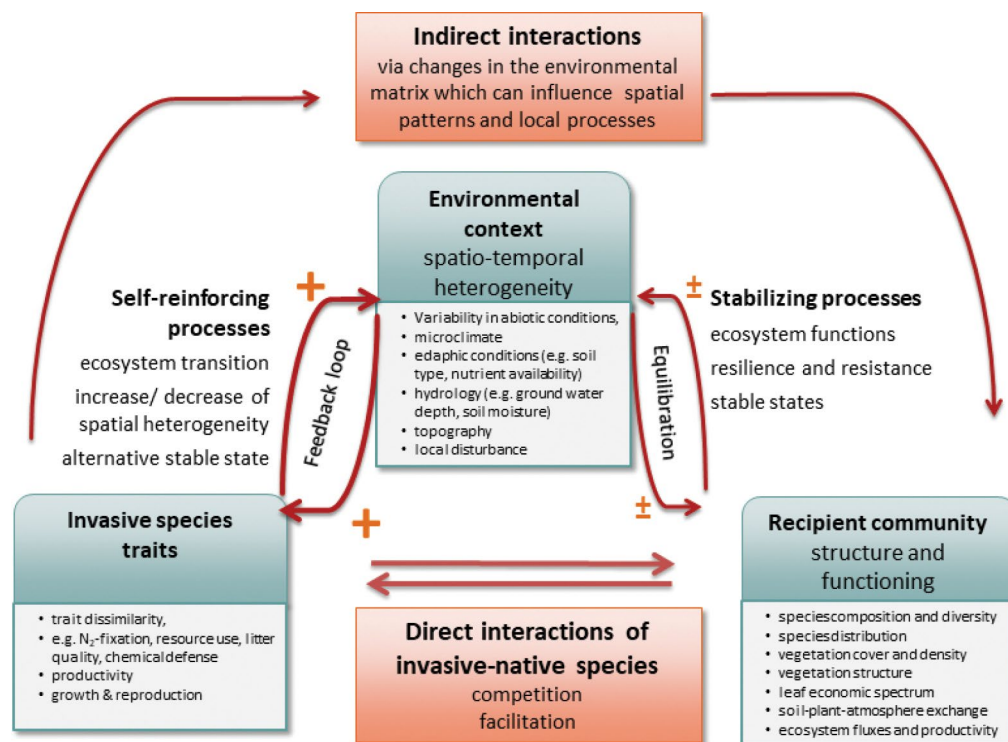


Figure 2: Mechanisms determine plant invasion impact. Plant invasion impact results from direct and indirect interactions between invasive and native species based on the interplay between invasive species traits, structure and function of the recipient community, and spatio-temporal heterogeneity of the environment. Direct interactions between invasive and native species result from competition or facilitation, e.g. for resources, whereas indirect interactions are mediated via subsequent changes in the biotic and abiotic environment, which may favour self-reinforcing processes of the invader or stabilizing processes of the community. Examples of important factors for each category are given in the boxes.

However, detecting and tracing the impacts of invasive species in natural environments have been hindered in the past due to a lack of suitable measurements and integration methods to explicitly quantify the spatio-temporal dimensions involved. This would require not only mapping the invasive species and its spread in natural systems, but also quantifying local changes in different abiotic and biotic processes that are altered by the invader (i.e. quantifying the local impact of the invader). As the latter is a function of both the environmental conditions and the structure and functioning of the native community, both need to be quantified at high spatio-temporal resolution. For each of these aspects, the required tools are at hand, but new integrative analyses are required. Hence, we posit a way forward (Fig. 3) on how to i) quantify the fine-scale heterogeneity of the environmental context, ii) map the structure and function of the invaded system, iii) trace changes induced by the invader with functional tracers, and iv) apply effective approaches for integration of spatio-temporal information from different scales, e.g. via different (artificial intelligence-based) modelling approaches, for better prediction of invasive species impact.

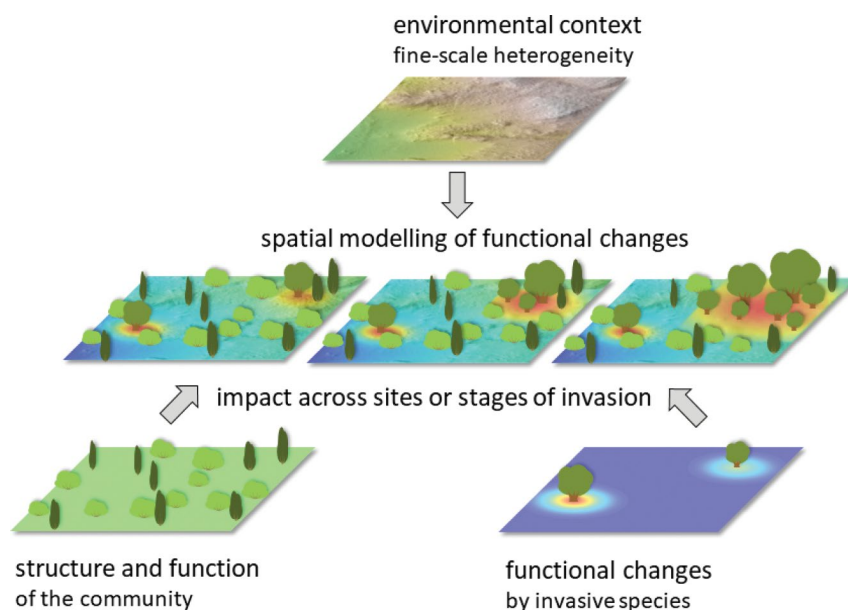


Figure 3: Framework for integrating fine-scale environmental heterogeneity and functional changes into spatial models of invader-ecosystem interactions. Maps of biochemical and biophysical heterogeneous environments can be directly incorporated into predictive models of impact measures across different sites or stages of invasion. Essential complementary spatial data include the location of the invasive species, maps of functional tracers that reflect local changes in key functions induced by the invader, and maps of the recipient community structure and function (e.g. Hellmann et al. (2017)). Technological advances in measurement techniques, sensor networks, and remote sensing will facilitate the collection of high-resolution data on the environmental context, the invasive species, and the recipient community, thereby improving the understanding of invasion dynamics and processes, particularly at the neighbourhood scale.

Environmental context

The environmental context is defined as the biogeochemical and physical matrix, which provides the background for both native and invasive species' biotic interactions (Fig. 3). This includes the fine-scale spatio-temporal heterogeneity in, e.g. abiotic conditions like hydrological and edaphic conditions or microclimate, as well as resource patches, e.g. after local disturbance. On the scale of centimetres to kilometres, variation in these conditions can influence plant performance and interactions, thereby creating a multi-layered mosaic of background conditions. An inherent challenge of geospatial analysis is that fine-scale or high resolution data are often collected over small areas, while for large areas only coarse-scale data are available (Millington 2021). However, research rapidly advances regarding the retrieval of two- and three-dimensional geospatial information on the environmental matrix using sensory networks (Allan et al. 2018; Lahoz-Monfort and Magrath 2021; Besson et al. 2022; Sethi et al. 2022) and remote sensing (Lausch et al. 2020; Lahoz-Monfort and Magrath 2021; Skidmore et al. 2021; Timmermans and Kissling 2023). Currently, a broad set of novel digital tools to describe the environmental context is emerging, including UAVs (Unmanned Aerial Vehicles), microsatellites (e.g. PlanetScope), active sensor systems based on LiDAR (Light Detection and Ranging) or SAR (Synthetic Aperture Radar) technology for vegetation structure analysis, and advanced versions of the established Landsat and Sentinel-2 satellites (Crowley and Cardille 2020).

Structure and function

The environmental context further shapes native species distribution patterns as well as structure and function of the community. Indeed, spatial complexity, in which invasive species interactions take place, can be a proxy for ecosystem structure and dynamics in itself (Parrott 2010). Similarly to assessing the environmental conditions, advances in remote sensing techniques allow for multiscale and multi-temporal mapping of species distribution, and landscape structure and function (Crowley and Cardille 2020), which are exceptionally valuable to describe both the environmental context and structure of the recipient community. LiDAR, SAR, and digital aerial photogrammetry hold great potential to describe ecosystem structural parameters such as vegetation height, cover, density, structural complexity, and population structure (Valbuena et al. 2020). Proofs-of-concept exist for high-resolution automated structural measurements

(Calders et al. 2023), while both active and passive sensor systems can be used to map ecosystem functions (Pettorelli et al. 2018).

Moreover, spatially explicit maps of the invader are required, as impact is related to abundance in various forms (Sofaer et al. 2018; Strayer 2020; O'Loughlin et al. 2021). Access to spatial data on invasive plant distribution is improving (Fusco et al. 2023), and distribution maps of the invader can be created and updated across scales using data from UAS (Uncrewed Aerial Systems), aircrafts, and satellites (Vaz et al. 2018; Timmermans and Kissling 2023). Freely available earth observation data are extremely useful to produce such distribution maps, particularly in data poor regions (Truong et al. 2017). Novel approaches to map invasive species and characterize the species composition of the recipient community include methods of Deep Learning (DL) and other methods of machine learning. In invasion ecology, the potential use of DL is manifold (Christin et al. 2019; Hirn et al. 2022; Perry et al. 2022), but its main application is probably species identification and mapping (Christin et al. 2019; Kattenborn et al. 2021; Borowiec et al. 2022; Müllerová et al. 2023).

Functional tracers of invader impact

Ultimately, the impact of the invader, i.e. its effect on the biophysical, biochemical, and biological environment, has to be assessed. One effective way to quantify invasive species impact is the use of functional tracers, which reflect local changes in key functions at fine spatio-temporal scales. The choice of suitable tracers will depend on both the invasive species under study and invaded community properties, and should capture the processes likely altered by the invasive species, for example nitrogen for N-fixing invaders in N-poor environments or water balance for water-spending invaders in water-limited systems (Fig. 2). Stable isotopes, for example, can provide such functional or ecophysiological tracers, as they reflect changes in interactions and altered functional processes at fine spatial resolution (Cheesman and Cernusak 2016), and provide great potential to unravel mechanisms of invasions (McCue et al. 2020). Applied in a spatially explicit manner (i.e. isoscapes (Rascher et al. 2012)), they can trace local changes in plant-plant interaction and in environmental conditions (Hellmann et al. 2017). Maps can be generated for isotopic measurements of the soil environment or leaves of different native species, thereby directly mapping the invader impact on these species (Hellmann et al. 2016a, 2016b; Nielsen et al. 2016; Sena-Souza et al. 2023). For example, atmospheric N₂-input by N-fixing invaders can be traced into the native vegetation by nitrogen isotopes ($\delta^{15}\text{N}$, example in Fig. 3). These changes can

lead to cascading effects on other ecosystem functions. Besides nutrient cycling, subsequent changes, e.g. in water and/or carbon cycles, may also be involved (Le Maitre et al. 2015; Dzikiti et al. 2017). Competition for water can affect the water-use-efficiency and hydraulic regulation of native species (Haberstroh et al. 2021), with cascading effects on ecosystem water balance (Rascher et al. 2010; Caldeira et al. 2015; Le Maitre et al. 2020). Changes in native species' carbon isotope ratio ($\delta^{13}\text{C}$) can resolve changes in water use efficiency in response to competitive or facilitative invader interactions (Hellmann et al. 2016a; Crous et al. 2019; Sena-Souza et al. 2023). Even shifts between facilitation and competition with increasing distance to the invader have been observed (Hellmann et al. 2016a). Different tracers can be combined (Funk et al. 2017), such as C, N, P concentrations or other biochemical properties that may be affected by the invasion (Drenovsky et al. 2012; Hellmann et al. 2016a; Helsen et al. 2020; Sena-Souza et al. 2023) or which might reveal functional differences (Große-Stoltenberg et al. 2018b; Meira-Neto et al. 2023) along environmental gradients (Crous et al. 2019). Thereby, differences in the spatial dimension of impact can be revealed both between native and invasive species, depending on their susceptibility to these changes, and with respect to different processes involved.

Remote sensing techniques have also proven invaluable in examining functional properties of invasive species (Helsen et al. 2020; Andrew et al. 2014; Dzikiti et al. 2016; Große-Stoltenberg et al. 2018a, 2018b; Ewald et al. 2018; Hacker and Coops 2022; Große-Stoltenberg et al. 2023) as well as plant-plant interactions (Chen et al. 2022). Further, first studies show that mycorrhizal traits (Chaudhary et al. 2022), which may constrain invasion success (Pringle et al. 2009) and/or be altered after invasion (Lekberg et al. 2013), can be inferred from hyperspectral data at leaf (Jantzen et al. 2023) and canopy level (Sousa et al. 2021). Where remote sensing methods reach their limits, novel field-portable instruments and sensor networks are very promising tools to measure ecophysiological information at the individual plant level with very high temporal resolution (Tognetti et al. 2022).

Additionally, advances in wireless, autonomous microsensors, such as leaf wearable sensors of ecophysiological processes (Frey et al. 2023; Reimer et al. 2021), may offer novel sampling strategies. Currently, novel autonomous sensor networks are being developed (e.g. ECOSENSE, Werner et al. 2024; Allan et al. 2018; Besson et al. 2022; Tognetti et al. 2022), enabling high spatial coverage of different functional properties in heterogeneous environments with distributed sensors continuously recording at high temporal resolution. Autonomous sensing is coupled to wireless data transmittance and

real-time data assimilation into large databases to streamline the information flow and enable real-time analysis. Though still in its infancy, these novel automated sensing networks may also provide valuable new insights in invasion ecology. Such standardized and automated networks of field sensors are required to validate proxies of ecosystem functioning derived from satellite data, particularly in heterogeneous ecosystems (Naethe et al. 2024). Clearly, challenges apply when sampling at such fine resolution regarding data volume, data heterogeneity, varying data quality, and timely data availability, which requires sophisticated data management and analysis (Farley et al. 2018), as well as appropriate sampling strategies. Despite all technological progress, trade-offs between resolution and extent of analysis will still apply. Nevertheless, these new technologies bear the potential to provide the high spatial coverage required in heterogeneous environments to quantify invader-ecosystem interactions and validate remote sensing data for model transfer and upscaling.

Integration: spatial modelling of functional changes and impact assessment across different stages of invasion

Integration of the information on functional changes by the invader, characteristics of the recipient community, and the environmental context from different sources and at different scales is needed to assess and predict the invader impact on ecosystem functioning along gradients of invasion in heterogeneous ecosystems (Figs 3, 4). Once the functional tracer of impact is identified, the spatio-temporal dimension of the impact is understood, and spatial layers of both ecosystem structure and invader distribution at appropriate scale are available, alterations of ecosystems in the neighbourhood of the invader can be mapped using spatial modelling approaches. Novel technologies clearly facilitate data sampling at multiple resolutions (see above). This enables explorative analysis of species-environment interactions at multiple scales, which is essential when spatio-temporal dimension of the effect is not known (see Holland and Yang 2016). Integrative approaches include mixed-effect models (Golicz et al. 2023), which have been applied to map invader-ecosystem interactions (Hellmann et al. 2017). To assess model transferability, area of applicability, variable selection, and methods of cross-validation need to be carefully evaluated (Ludwig et al. 2023). Recording data with high spatio-temporal resolution will inevitably lead to large data sets. Again, machine learning approaches, in particular DL, have recently gained popularity to analyze complex spatio-temporal datasets (Wikle and Zammit-Mangion 2023). Within the field of ecology, the versatility of DL is evident (Christin et al. 2019;

Hirn et al. 2022; Perry et al. 2022), with its primary utility likely lying in species identification and mapping (Christin et al. 2019; Kattenborn et al. 2021; Borowiec et al. 2022; Müllerová et al. 2023).

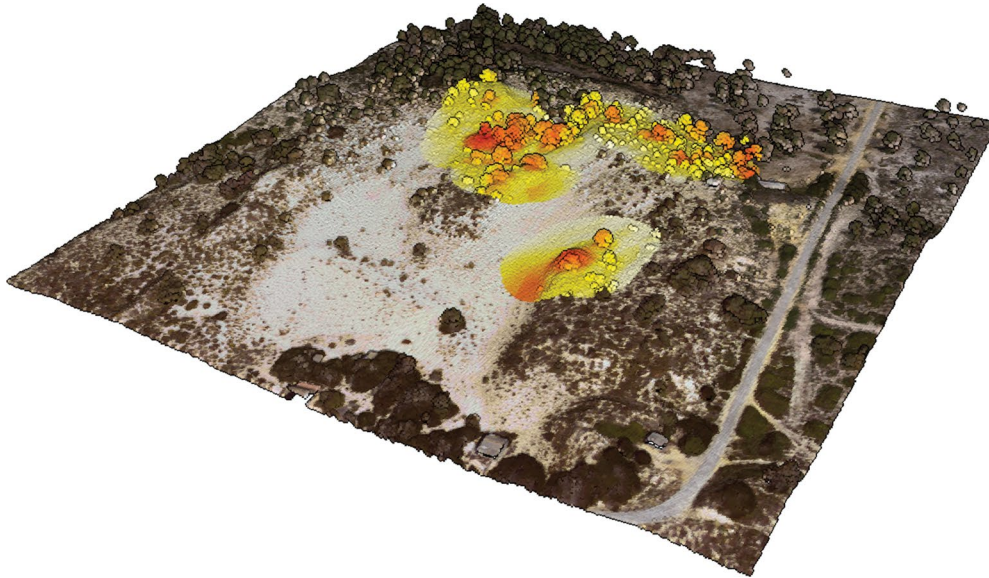


Figure 4: Model visualisation of spatio-temporal dynamics of invader impacts based on the suggested framework. Modelled isoscapes centred around a N_2 -fixing invasive plant species using the functional tracer $\delta^{15}N$ and information on the environmental matrix in a nutrient poor ecosystem based on Hellmann et al. (2017). Reddish colours indicate high-levels of atmospheric fixed nitrogen inputs (e.g. dense invader patches and flushes of N into native vegetation); yellow colours indicate lower levels of impact, while whitish colours indicate no impact and are representative for the original status before invasion. The local functional changes do not occur uniformly. Isoscapes are plotted onto high-resolution airborne LiDAR data fused with true colour imagery to illustrate the effect of LiDAR-derived vegetation structure of the recipient community and topography on invader impact in this heterogeneous ecosystem. The 3D map was created using QGIS version 3.30. An animated 3D-video of the model can be found at <https://tinyurl.com/4hs23b8p>.

Further, methods of DL enable multi-trait retrieval across vegetation types even when data are scarce (Cherif et al. 2023). Recent progress also includes the retrieval of traits using hybrid models, which combine leaf-canopy-atmosphere radiative transfer modelling with Gaussian processes and enable upscaling of trait maps from the local to regional level, including uncertainty estimates (Estévez et al. 2022). Especially in earth system sciences, DL approaches have been used to model system states and analyze systems processes (Reichstein et al. 2019). Future progress regarding model interpretability and explainability is expected if data-driven approaches and physical models are combined (Reichstein et al. 2019), and concepts are developed for automated workflows and pipelines to study ecosystem dynamics (Besson et al. 2022). However, progress in automated data collections and analysis based on artificial intelligence is not a solution per se to answer questions in ecology. It also poses challenges, e.g. in terms of standards, protocols and workflows, data infrastructure and

data quality. Thus, defining scope and scale to study ecological phenomena will still be required (de Koning et al. 2023).

In the following, we will use an example to quantify the impact of a N-fixing invader in a N-poor Mediterranean ecosystem as one efficient but not exclusive way to integrate spatio-temporal information and functional tracers for invader impact assessment (Fig. 4).

We used field-based maps of both a N-fixing invasive species and a functional tracer ($\delta^{15}\text{N}$), which were joined with airborne LiDAR data on topography (environmental context) and vegetation structure (recipient community) to model functional changes across sites and stages of invasion (Hellmann et al. 2017). Plotting these maps onto fused airborne LiDAR and true colour image data allows visualizing and communicating context-dependent invader-ecosystem interactions at the molecular level, which are otherwise undetectable. The nitrogen isoscapes in Fig. 4 are centred around a N-fixing invasive species and illustrate the effect of dynamic N enrichment by the invader (reddish colours) in a N-poor open dune ecosystem (indicated by the yellowish colours) in three-dimensional space. This N-fixing effect does not occur uniformly around the invader, but is shaped by vegetation structure and topography. This explains, for example, N-transfer from fixation into the non-N-fixing native vegetation (yellowish colours), and the flush of nitrogen into sparsely vegetated areas downhill from the invader, which will slowly be transformed into denser habitats.

Other integrative approaches include the combination of field-based and remotely sensed data on native and invasive species distributions, vegetation structure, Leaf Area Index, or evapotranspiration to, for example, estimate water consumption of an invader in riparian habitats (Nagler et al. 2009; Dzikiti et al. 2017). To transfer and validate approaches across landscapes, information on topography (environmental context) and species composition (recipient community) is deemed essential (Le Maitre et al. 2015). In summary, the importance of linking ecophysiology with remote sensing data to understand invasion processes has been outlined (Niphadkar and Nagendra 2016), and integrative approaches on mapping invader-ecosystem interactions are at hand (Nagler et al. 2009; Dzikiti et al. 2016; Hellmann et al. 2017). Due to technological progress, automated systems to study ecosystem dynamics at unprecedented scales are being developed and implemented (Allan et al. 2018; Besson et al. 2022; Tognetti et al. 2022), with potential to build digital twins (de Koning et al. 2023) of plant invasion impact, i.e. dynamic virtual representations or models used for simulations and analyses. We envision that these new approaches will also lead to advances in the field of biological

invasions, namely to better understand fine-scale invader-ecosystem interactions, test invasion theories, and provide robust validation data for interactions across spatio-temporal dimensions in heterogeneous ecosystems.

Concluding remarks

Spatio-temporal patterns and variation of plant-plant interactions in heterogeneous environments deserve better integration in invasion research. Here we advocate the use of functional tracers for integrating fine-scale interactions between the invasive species, the recipient community, and the environmental context into spatial models to assess context-dependency of invader impact, namely the interplay of direct and indirect invasive-native species interactions. We advocate drawing on the large toolbox of recent methods, which when combined, can open new doors for mapping and predicting changes in ecosystem functioning and for assessing and disentangling the influence of spatio-temporal heterogeneity on invader impacts. By explicitly emphasizing the spatio-temporal variation of plant-plant interactions in invasion ecology, we anticipate major advances for understanding of invasion history, patterns of spread, impact assessment, and prediction of future invasions.

Acknowledgements

Funding was provided by the DFG (WE 2681/8-1, WE 2681/10-1), EUFAR (DeInVader, EUFAR11-06), DAAD (AGS). We thank NERC's Airborne Research Facility and Data Analysis Node for conducting the airborne survey.

Additional information

Conflict of interest: The authors have declared that no competing interests exist.

Ethical statement: No ethical statement was reported.

Author contributions: All authors developed the framework. CH and CW wrote the first draft, which was revised by CW and AGS. AGS implemented the video animation.

Data availability: All of the data that support the findings of this study are available in the main text or Supplementary Information.

Supplementary material 1: Description of the animated video

Authors: Christiane Werner, Christine Hellmann, André Große-Stoltenberg

Data type: docx

Link: <https://doi.org/10.3897/neobiota.94.126714.suppl1>

Supplementary material 2

Animated video

Authors: Christiane Werner, Christine Hellmann, André Große-Stoltenberg

Data type: mp4

Link: <https://doi.org/10.3897/neobiota.94.126714.suppl2>

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Chapter 7

Quantifying the spatial impact of an invasive *Acacia* on ecosystem functioning using remote sensing

André Große-Stoltenberg^{1,2,}, Christiane Werner³, Christine Hellmann³, Jens Oldeland⁴, Jan Thiele⁵*

¹Division of Landscape Ecology and Landscape Planning, iFZ Research Centre for Biosystems, Land Use and Nutrition, Institute of Landscape Ecology and Resource Management, Justus Liebig University Giessen, Heinrich-Buff-Ring 26-32, 35392 Giessen, Germany

²Center for International Development and Environmental Research (ZEU), Justus Liebig University Giessen, Senckenbergstrasse 3, 35390 Giessen, Germany

³Ecosystem Physiology, University of Freiburg, Georges-Köhler-Allee 53/54, 79110 Freiburg, Germany

⁴Institute for Globally Distributed Open Research and Education (IGDORE), Burgunderweg 9d, 22453 Hamburg, Germany

⁵Thünen Institute of Biodiversity, Bundesallee 65, 38116 Braunschweig, Germany

*Corresponding author

Ecological Indicators 170: 112928 (2025), doi: 10.1016/j.ecolind.2024.112928

The version presented here is the final draft of the manuscript as accepted for publication.

Supplementary Information: The online version contains supplementary material that is be available at <https://doi.org/10.1016/j.ecolind.2024.112928>.

Highlights

- *Acacia* invasion in a pristine and diverse coastal dune ecosystem
- Synergistic use of airborne hyperspectral and LiDAR data to map impact after invasion
- Significant impact on ecosystem functions using spectral indices as proxy measures
- Including environmental heterogeneity and spatial effects improves impact assessment
- Spectrally derived functional diversity decreased due to invasion

Abstract

Remote sensing technology is increasingly applied to map the occurrence of invasive plant species, yet its use to map their ecological impact remains limited. Furthermore, invader-induced changes beyond the canopy, as well as the environmental context, are rarely considered. This study aimed to assess the impacts of an invasive tree on ecosystem functioning at the landscape scale using remote sensing, taking into account both spatial effects and environmental heterogeneity. Specifically, we investigated a coastal Mediterranean dune ecosystem invaded by the N-fixing tree *Acacia longifolia* (Andrews) Willd. ('*Acacia*'). Four vegetation indices were calculated as proxies of ecosystem functions, and these indices were used to compute functional diversity in terms of spectral Rao's Q for assessing impacts by *Acacia* based on airborne hyperspectral data. Vegetation cover and topographic indices derived from airborne LiDAR (Light Detection and Ranging) were used to account for spatial heterogeneity. For seven sites, we employed Generalized Linear Mixed Models to model the effects of environmental variables and *Acacia*-related variables on proxies of ecosystem functions. Significant impact of the invader was found beyond the invaded area augmenting to 50% total impact on ecosystem functions. These spatial impacts are particularly prevalent at rather early stages of invasion (~20% invader cover at landscape level). Consequently, the impact of invaders is underestimated when spatial effects are ignored, but it is overestimated when environmental heterogeneity is neglected. Furthermore, functional diversity decreases due to invasion, though it reaches its maximum at the edges of invader stands, where Rao's Q index captures spectral effects of both the invader and the native vegetation. Thus, we highlight that both 2D and 3D remote sensing data complement each other in remote sensing-driven impact assessments. We envision that advancements in remote sensing of ecosystem structure and functioning in terms of increasing availability of high spectral, spatial and temporal data as well as enhanced methods for data analysis will facilitate tracing the context-dependent and function-specific spatial effects of invasive species especially at early stages of invasion to enable timely management.

Keywords

impact assessment, invasive alien species, ecosystem function, hyperspectral, LiDAR, environmental heterogeneity

Introduction

Impact assessments of biological invasions seek to quantify adverse effects of invasive alien species on ecological, economic or social goods at regional levels in order to identify high-impact invaders and to prioritize most harmful species for management (Brundu et al., 2020; Kumschick et al., 2015; Parker et al., 1999; Powell et al., 2013; Pyšek et al., 2020; Ricciardi et al., 2021; Thiele et al., 2010). In order to assess ecological impacts at larger scales, it is necessary to understand the local effects of invasive species (Blackburn et al., 2014; Hulme et al., 2013; Latombe et al., 2017). This can be done by empirical field studies or by experimental approaches that relate local presence or abundance of the invader to particular ecosystem functions or other goods (Barney et al., 2015; Bernard-Verdier and Hulme, 2019; Lee et al., 2018; Marchante et al., 2019; Sofaer et al., 2018; Vilà et al., 2024; Vitousek and Walker, 1989; Yokomizo et al., 2009). Regarding plant species, such studies are usually based on vegetation samples that are either located within invasive stands or in uninvaded and unaffected areas. Hence, effect estimates do rarely (e.g. Gómez-Aparicio and Canham (2008)) consider impacts of the alien species on the surroundings of invasive stands ('spatial impact'). However, disregard of spatial impacts might lead to underestimation of total impact, which may distort rankings of invasive species if they differ in strength and extent of influence on the surroundings.

Quantifying the effects of nitrogen-fixing invasive species on ecosystem processes has gained special attention in invasion ecology for decades (Ehrenfeld, 2010; Scherer-Lorenzen et al., 2007; Vitousek and Walker, 1989). Clear impacts on N cycling have been demonstrated particularly for invasive *Acacia* spp. (Marchante et al., 2019; Rodríguez-Echeverría et al., 2009; Yelenik et al., 2007), which can be regarded as global high impact invaders (Kumschick and Jansen, 2023; Le Maitre et al., 2011; Richardson et al., 2023). It is known that nitrogen fixation of *Acacia* spp. considerably affect nitrogen budgets of adjacent native species (Rascher et al., 2012) especially within a 5-8 m margin outside of their stands (Hellmann et al., 2017). These findings suggest that nitrogen-fixing invasive species may have a significant spatial impact on nitrogen cycling and, consequently, other ecosystem functions, such as photosynthesis and primary productivity, beyond their canopy edges.

In quantitative impact assessments, local effects are projected to the region where the alien species is invasive to provide a measure of total impact. Such impact measures can be calculated by multiplying the average local effect of the invader by the invaded

range, i.e. the area that is affected (Parker et al., 1999) although abundance-impact relationship are not necessarily linear (Sofaer et al., 2018; Strayer, 2020; Yokomizo et al., 2009). Clearly, if significant spatial impact is not taken into account, total impact might be underestimated. This might be extremely relevant in case of the invasion by an ecosystem engineer that can profoundly modify ecosystem functioning and, subsequently, cause regime shifts (Kumschick et al., 2015). Thus, it is important to consider areas that are adjacent to invasive stands and to include spatial components, e.g. distance from the invader, into effects models in order to quantify a total impact score of the invader at landscape scale.

Environmental heterogeneity is another important factor to consider when projecting impacts to landscape or regional scales because effects of invasive species are context-dependent and may vary with local conditions, such as topography, habitat type or vegetation structure (Bartz and Kowarik, 2019; Gioria et al., 2023; Hulme et al., 2013; Kumschick et al., 2015; Lee et al., 2018; Pyšek et al., 2012; Sofaer et al., 2018). Not taking into account environmental heterogeneity may lead to substantial bias in impact assessments (Thiele et al., 2011). Hence, environmental covariates should be used in effect models in addition to presence or abundance of the invader and, possibly, variables of invader proximity.

If spatial impacts are to be considered, the underlying data need to be spatially explicit, and scattered samples will not be sufficient. In fact, precise maps of invader occurrence, key environmental variables and state variables of ecosystem functioning that cover large areas are required (Latombe et al., 2017). Obviously, exhaustive field sampling of large areas is not feasible, in particular with regard to the increasing numbers of invasive species (McGeoch et al., 2023; Seebens et al., 2017), but new approaches are needed to support early-warning and surveillance systems to prevent high impacts (Müllerová et al., 2023; Tollington et al., 2017). Remote-sensing technologies, such as airborne hyperspectral imagery and Light Detection and Ranging (LiDAR), have the potential to deliver the required data at regional scale.

Finally, spatial impacts on ecosystem functioning by invasive ecosystem engineers can result in a change of habitat diversity and complexity (Crooks, 2002). However, this effect can be both positive or negative (Crooks, 2002), and subtle invader-induced functional changes might be difficult to decipher (Jarić et al., 2019). While in particular *Acacia* species are known to be invaders that simplify habitats (Le Maitre et al., 2011), very little is known on how to capture such impacts using remote sensing. Rocchini et al. (2017) developed a new method to map environmental heterogeneity by remote

sensing using a spectrally derived Rao's Q index based on information theory. The underlying concept of the spectral Rao's Q is the Spectral Variation Hypothesis (SVH), which was conceived by Palmer et al. (1999, 2002) and firstly tested by Gould (2000), as stated in the recent review by Torresani et al., (2024). According to the SVH, spectral variability relates to different facets of biodiversity (Torresani et al., 2024). It was firstly applied to study the biodiversity of plants (Gould 2000, Palmer et al., 2002), e.g., by relating the variability of the Normalized Difference Vegetation Index (NDVI) of a landscape as a proxy for its heterogeneity to plant species richness (Gould 2000). Since then, Torresani et al. (2024) found more than 130 studies using the SVH in remote sensing-based biodiversity assessment, with the majority of studies having been conducted in forest or grassland ecosystems, while coastal ecosystems have received less attention, and only accounted for 5% of the studies. Beyond assessment of plant species richness, the first studies to assess functional diversity using spectrally derived metrics emerged in 2017 (Torresani et al., 2024) coinciding with the development of the spectrally derived Rao's Q index (Rocchini et al., 2017). In remote sensing approaches, the pixel-based Rao's Q outperforms common biodiversity metrics such as Shannon's entropy H' (Rocchini et al., 2017), it relates to β -diversity as well as functional plant diversity (Rocchini et al., 2018) and it can be parameterized in multidimensional mode to account for both abundance and distance to describe the environmental heterogeneity of a site (Rocchini et al., 2021). However, its application in the context of biological invasions is underexplored. In the aforementioned review regarding the SVH, Torresani et al. (2024) found only one study that examined the potential of the spectral Rao's Q to assess effects of the invasive species on species diversity (Khare et al., 2019). In terms of effects on ecosystem functioning, Gholizadeh et al. (2024) recently demonstrated the positive and linear relationship between remotely-sensed functional diversity and invasive legume cover in a grassland ecosystem. This said, no studies have been found which were in a coastal ecosystem or which used the spectrally derived Rao's Q index to assess the spatial effects of an invasive ecosystem engineer on ecosystem functioning.

In this study, we modelled the impacts of the invasive *Acacia longifolia* on coastal Mediterranean ecosystems using remote sensing data. The aims of our study were:

1. to quantify the spatial impacts of the invader on ecosystem functions (e.g. primary productivity, photosynthesis);

2. to determine the influence of environmental heterogeneity on impact assessment;
3. to assess the effect of the invader on functional diversity.

Material and methods

Study area

The study area was located in Southwest Portugal and comprised a coastal strip of approximately 35 km length for which we chose a subset of seven sites of between 50 and 75 ha (Fig. 1): Fonte do Cortiço (FdCo), Monte Velho (MoVe), Melides (Meli), Pinheiro da Cruz (PdCr), Pinheirinho (Pinh), Aberta Nova (AlNo), Lagoa da Sancha (LdSa). At these sites, we studied the invasion of *Acacia longifolia* (Andrews) Willd. (in the following being referred to as *Acacia*) into coastal dunes, which are protected under the European NATURA2000 directive (ICNB, 2005) and partly by national legislation (Pinto, 2014). This pristine and diverse dune ecosystem comprises a variety of NATURA2000 habitat types such as “Atlantic decalcified fixed dunes” (2150*), “coastal dunes with *Juniperus* spp.” (2250*), “dune sclerophyllous scrubs” (2260) or “wooded dunes with *Pinus pinea* and/or *Pinus pinaster* (2270*)” (ICNB, 2005). Priority habitat types according to the NATURA2000 directive are marked with an asterisk (“*”) (ICNB, 2005). Native tall shrubs or trees that co-occur with *Acacia* at the site include *Phillyrea angustifolia* L., *Pinus pinaster* Ait., *Pistacia lentiscus* L., and *Juniperus phoenicea* L. . Examples for medium-size native shrub species are *Cistus salviifolius* L., *Halimium halimifolium* (L.) Willk., *Lavandula stoechas* L., and *Rosmarinus officinalis* L. . Typical dwarf shrubs include *Armeria pungens* (Link) Hoffmanns. & Link, *Santolina impressa* Hoffmanns. & Link, *Thymus camphoratus* Hoffmanns. & Link, and *Thymus carnosus* Boiss. (Große-Stoltenberg et al., 2018a). The climate of the study area is Mediterranean with Atlantic influence. For further details on study area and sites including descriptions and analyses of the vegetation see ICNB (2005), Rascher et al. (2011a,b, 2012), Hellmann et al. (2011, 2016a,b, 2017), Pinto (2014), Lehmann et al. (2015), Große-Stoltenberg et al. (2016, 2018a,b) and Ulm (2017a).

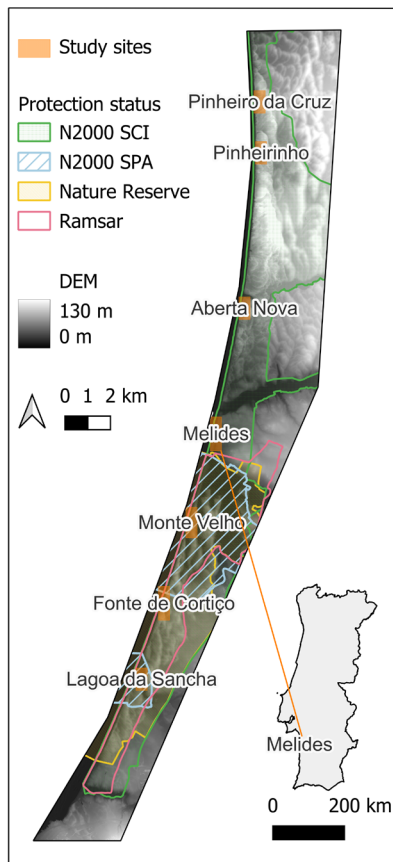


Figure 1: Map of the studied Mediterranean dune ecosystem in SW Portugal showing the seven study sites with a Digital Elevation Model (Große-Stoltenberg et al., 2018b) in the background. The coastal dunes are part of the Natura 2000 (N2000) network of protected areas in the European Union and are situated in the SCI (Site of Community Importance) 'Comport / Galé'. The southern part of the dune ecosystem is further protected by national legislation, the Ramsar wetland convention, and it included two N2000 Special Protection Areas (SPA).

Study species

Acacia has been introduced to Portugal at the beginning of the 20th century to fix sandy coastal soils (Marchante et al., 2023). In the study area, it gradually spread out into the herbaceous and scrubby dune vegetation as well as in pine plantations that are abundant at the inland side of the study area (e.g., Große-Stoltenberg et al., 2018b; Rascher et al., 2011a, 2011b).

The impacts of *Acacia* at the site include the decrease of plant diversity (Hellmann et al., 2011), changing vegetation (Rascher et al., 2011a) and plant community structure (Hellmann et al., 2011; Rascher et al., 2011a), modifying soil properties (Hellmann et al., 2011; Ulm et al., 2017b) and nutrient cycling (Rascher et al., 2012; Ulm et al., 2017a, 2017b) as well as alterations of water and carbon cycling (Rascher et al., 2011b). Spatial impacts of *Acacia* on ecosystem functioning in particular have been studied by analysing the spatial distribution of foliar isotopic signatures $\delta^{13}\text{C}$ and $\delta^{15}\text{N}$ of native plant species growing in vicinity to the invader (Hellmann et al., 2017, 2016a, 2016b; Rascher et al., 2012) to compute so-called "isoscapes" (West et al., 2008). *Acacia* has

a spatial effect on N-cycling ($\delta^{15}\text{N}$) (Hellmann et al., 2017, 2016a, 2016b; Rascher et al., 2012) as well as on water use efficiency ($\delta^{13}\text{C}$) of the surrounding vegetation (Hellmann et al., 2016a, 2016b). In the case of the $\delta^{15}\text{N}$ isoscapes, airborne LiDAR data, specifically proxies for topography and vegetation structure, have shown to be useful to account for the heterogeneity of the ecosystem and, thus, of the invaders' spatial impacts on N cycling (Hellmann et al., 2017).

Remote sensing data

We used airborne remote data on *Acacia* invasion (Große-Stoltenberg et al., 2018b). The hyperspectral (AISA Eagle and Hawk, Spectral Imaging Ltd., Oulu, Finland), LiDAR (Leica ALS50-II, Leica Geosystems AG, Heerbrugg, Switzerland), and true-colour image (Leica RCD105, Leica Geosystems AG, Heerbrugg, Switzerland, Switzerland) data were simultaneously collected on April 8th, 2011, ± 2 h around solar noon at an altitude of 1350 m. The raw data were processed (see Große-Stoltenberg et al. (2018b) for details), and the pixel size of the hyperspectral data was 2m x 2m with a spectral coverage of 400 - 970 nm and 970 - 2516 nm, 241 and 245 bands with Full-Width Half-Maximum (FWHM) of 2.20 - 2.45 nm and 6.3 - 6.31 nm for the Eagle and Hawk sensor, respectively. The LiDAR data had a point density of 4-5 points/m², and LiDAR-derived products (see below) were also gridded to 2m x 2m, so both data sets had the same pixel size. The true colour images with a spatial resolution of 0.2 m were not processed any further, and were used for visual interpretation and visualization.

Hyperspectral indices as proxies of ecosystem functions

We calculated four vegetation indices related to ecosystem functioning and potential impacts by *Acacia* based on the airborne hyperspectral data. The Near-Infrared Vegetation Index (NIR_V) (Badgley et al., 2017) is sensitive to canopy structure and has been used to scale up gross primary production (GPP) from local to large levels (Badgley et al., 2019). It is based on the Normalized Difference Vegetation Index (Tucker, 1979), and adds further information from the infrared part of the spectrum while having a strong physical basis (Badgley et al., 2017):

$$\text{NIR}_V = \text{NDVI} \times \text{NIR} \quad (1)$$

We calculated the NDVI as following, where R_x is the reflectance at the defined wavelength (nm):

$$NDVI = (R800 - R680) / (R800 + R680), \quad (2)$$

The Modified Chlorophyll Absorption in Reflectance Index (MCARI) is based on the depth of the chlorophyll absorption at 670 nm (Daughtry et al., 2000):

$$MCARI = ((R700 - R670) - 0.2 \times (R700 - R550)) \times (R700 / R670). \quad (3)$$

The MCARI is sensitive to both leaf chlorophyll concentrations and background reflectance (Daughtry et al., 2000).

As a proxy for nitrogen, we computed the Normalized Difference Nitrogen Index (Serrano et al., 2002):

$$[\log(1/R1510) - \log(1/R1680)] / [\log(1/R1510) + \log(1/R1680)] \quad (4)$$

The NDNI uses spectral information from the shortwave infrared part of the electromagnetic spectrum, and it has been developed for shrub vegetation using airborne hyperspectral data in a Mediterranean Ecosystem (Serrano et al., 2002).

To estimate the effect on the water content of vegetation canopies, we used the normalized difference water index (NDWI) (Gao, 1996):

$$(R860 - R1240) / (R860 + R1240) \quad (5)$$

The NDWI is similar to the NDVI, but instead of using information from the visible part of the spectrum, it uses a water absorption feature of vegetation canopies near 1240 nm (Gao, 1996). The NDWI has been used, for example, to identify drought effects on nutrient availability in Mediterranean grasslands (Cerasoli et al., 2018).

Spectrally derived Rao's Q index as a proxy for functional diversity

All vegetation indices were selected as input layers to calculate the spectrally derived Rao's Q index (Rocchini et al., 2017) to map the invader's impact on functional diversity. In vegetation science, Rao's quadratic entropy has originally been developed to assess functional diversity based on several traits (Botta-Dukát, 2005). The spectral Rao's Q

index has mainly been used together with the NDVI (Khare et al., 2019; Rocchini et al., 2018, 2017; Torresani et al., 2020) or tree height (Torresani et al., 2020) to map species diversity. Here, we assessed the effect of the invader on functional diversity by calculating the parametric spectral Rao's Q entropy (Rocchini et al., 2021) using the *paRao* function from the package *rasterdiv* 0.3-4 (Marcantonio et al., 2024) using R statistical software, version 4.3.3 (R Core Team, 2024). We computed the Rao's Q index in multidimensional mode for all four vegetation indices (NIRv, MCARI, NDNI, NDWI) using Euclidean distance with a spatial moving window of 3x3 pixels so spatial distances between the central pixel and neighbouring pixels in each window (see Rocchini et al., 2024) would be below the spatial range of impact in terms of ^{15}N -enrichment of up to 6-8 m to *Acacia* canopy as observed in earlier field studies (Hellmann et al., 2017), and the alpha parameter set to infinity to maximise pixel distances and, thus, discrimination potential of the Rao's Q (Rocchini et al., 2017). Within the *paRao* function, the values for each vegetation index were standardised, i.e. centred on the layer mean and divided by the standard deviation, to assure similar value ranges for the different vegetation indices, which is important for calculating distances using Euclidean geometry.

Data related to *Acacia* invasion

We derived a raster map of presence-absence of *Acacia* from the remote sensing-based detection model (Große-Stoltenberg et al., 2018b). Further, we calculated the horizontal distance and the elevational difference of each raster cell to the nearest stand of *Acacia* with SAGA GIS 8.1 (Conrad et al., 2015). We also allocated the size of the closest *Acacia* stand to each raster cell. For impact modelling, we reduced the dataset to those raster cells that overlapped with 25-m buffers around the *Acacia* stands because previous studies showed that the influence of this invader was virtually zero at this distance (Hellmann et al., 2017).

As distance from *Acacia* is negatively related to impact, we converted distances to proximities by subtraction from the respective maximum values. Regarding horizontal distance, we used 27 m so that the farthest raster cells (max. distance 26.9 m) received a proximity value of 0.1, while cells that were directly adjacent to *Acacia* stands received 25 (given the spatial resolution of 2 m). For cells where *Acacia* was present, we set proximities values to zero (instead of 27) in order to avoid confusion between the statistical effects of invader presence and proximity. To explore the detailed effects on functional diversity, we additionally differentiated between *Acacia* stands ("invasion", distance of zero), the edge of *Acacia* stands ("edge", cells bordering *Acacia*

canopy from in- and outside), and the area beyond the edge of *Acacia* canopy (“uninvaded”).

Likewise, we calculated elevational proximity values. For this purpose, we coded elevation proximity above and below *Acacia* stands as two separate variables in order to account for possible directional differences. In addition to the original values, we calculated log and square-root transformed elevational distances that we converted to proximities in the same fashion.

Environmental data

We used vegetation cover and topographic indices to account for spatial heterogeneity of the invaded ecosystems. Vegetation cover was estimated based on LiDAR data with a cut-off of zero, which means that all non-ground points were considered to represent vegetation. Using the airborne LiDAR-derived, smoothed bare-earth DEM (see 2.3 and Große-Stoltenberg et al. (2018b)), we calculated the Topographic Wetness Index (TWI). Further, we calculated a topographic position index (Weiss, 2000) that we used to classify the landform into ridges, slopes, drainages, valleys and plains according to Hellmann et al. (2017).

Impact modelling

For impact modelling, we discarded all cells that were located within 25 m from the borders of the sites in order to avoid edge effects due to *Acacia* stands at the outside. All subsequent statistical analyses were conducted in R statistical software, version 3.4.2 (R Core Team, 2017).

We modelled the effects of environmental variables and *Acacia*-related variables on proxies of ecosystem functions with Generalized Linear Mixed Models (GLMM) that contained site ID as random effects. Regarding the fixed effects, we calculated two variants of models: (i) full models that contained all predictors and (ii) basic models that contained only variables related to *Acacia*, but ignored environmental heterogeneity. Pre-analyses with correlograms and Moran's I showed significant spatial auto-correlation in the residuals of preliminary impact models that included all predictors. Thus, as spatial auto-correlation may affect significance tests and estimates of linear models, we included Gaussian spatial correlation structures in the final models (Dorman et al., 2007).

When model residuals did not deviate substantially from the normal distribution, we used *lme* from the package nlme 3.1-131 (Pinheiro et al., 2018). This was the case with

nitrogen (NDNI) and water (NDWI). The other three target variables, primary productivity (NIRv), indicator of photosynthesis (MCARI) and functional diversity (Rao's Q), followed a gamma distribution and were modelled with *glmmPQL* from the package MASS 7.3-60.2 (Venables and Ripley 2002). The appropriateness of the gamma distribution was tested with *simulateResiduals* from the package DHARMa 0.4.6 (Hartig 2022).

In all models, we used the identity link which proved to be most suitable. We tested linearity of the relationship between target and predictor variables using *cumres* from the package gof 0.9.1 (Holst 2015). As *cumres* does not work with GLMM, we calculated corresponding models using *lm* or *glm* that included 'site' as a fixed effect, for this purpose. Based on the linearity tests, we identified the best variants of the metric predictor variables (original, log or square root transformed).

The datasets used for modelling comprised between 181,483 and 194,613 raster cells and, thus, were by far too large for models that include spatial correlation structures. For that reason, we divided the datasets into folds of approximately 2000 rows that were stratified by site and *Acacia* presence. Then, we iteratively calculated the same model (regarding predictors and setup etc.) using all of the folds. Finally, we calculated weighted averages of the estimates and their standard errors over all models. Standard errors of the average estimates were calculated according to the following formula:

$$se_t = \frac{\sqrt{\sum_i^N n_i \times s_i^2}}{\sum_i^N n_i}, \quad (6)$$

where se_t is the standard error of the average estimate, N is the number of models, n_i is the sample size of model i and s_i is the standard deviation of the estimate in model i (NB: $s_i = se_i \times \sqrt{n_i}$). Based on the average estimates and their standard errors, we calculated t and p -values to assess the significance of predictors for the whole dataset. We used the average estimates to calculate expected values of the target variables for each raster cell of the dataset. First, we calculated the expected background values using only the estimates of environmental variables plus estimates of the random intercepts of sites (background model). Second, we calculated expected values using the background model plus the effect of presence of *Acacia* (*Acacia*-presence model). Finally, we used all predictors, including the spatial effects of *Acacia* (spatial model). As the values of the water proxy (NDWI) are in the range $[-1, 1]$, we scaled its predicted values to the interval $[0, 1]$ before summing up over the landscape.

We calculated the impact that occurred within the stands of *Acacia* ('stand impact') as the difference between the expected values of target variables as predicted by the

Acacia-presence model and the background model for each raster cell. Further, we calculated cell-level impact that occurred outside of the stands ('spatial impact') as the difference between the spatial model and the background model. In addition to these scores of absolute impact, we calculated impact percentages as the ratio of stand or spatial impact to the background value, multiplied by 100.

We measured the total impact of *Acacia* summing up the cell-level impact scores of both *Acacia* presence and of the spatial impact over the invaded range. Here, we defined the invaded range as those raster cells that overlapped with the 25-m buffers around invasive stands. We also summed up the background scores over the invaded range in order to calculate the percentage of increase due to *Acacia* presence and spatial impact. All sums of scores were standardized to 1 ha for comparability.

In order to assess the influence of invasion stage on the relative strength of stand and spatial impacts, we calculated the sums of impact scores and the number of raster cells occupied by the invader (invader cover) in moving windows of $26 \times 26 \text{ m}^2$ (13×13 cells) over all sites. Thereby, we used stand impact and total impact (spatial model minus background). For graphical presentation, we randomly sampled one hundredth of the moving-window dataset, stratified by site, using *sampleRandom* from the package raster 2.5-8 (Hijmans 2016).

Results

Impacts on ecosystem functions

Presence of *Acacia* significantly increased the values of all proxies of ecosystem functions (Fig. 2; for detailed model summaries see Appendix A1, Tables A1-A10). Proximity of *Acacia* also had significant positive effects on the proxies of ecosystem functions outside of the invasive stands. This was mainly due to horizontal proximity (i.e. inverted distance from *Acacia* stands; Fig. 2). Regarding nitrogen, elevation proximity had small negative effects (Tables A5, A6), which however did not diminish the overall positive effect of proximity of *Acacia*. With respect to water, elevational proximity and stand size had minor negative effects that were overridden by the positive effect of horizontal proximity.

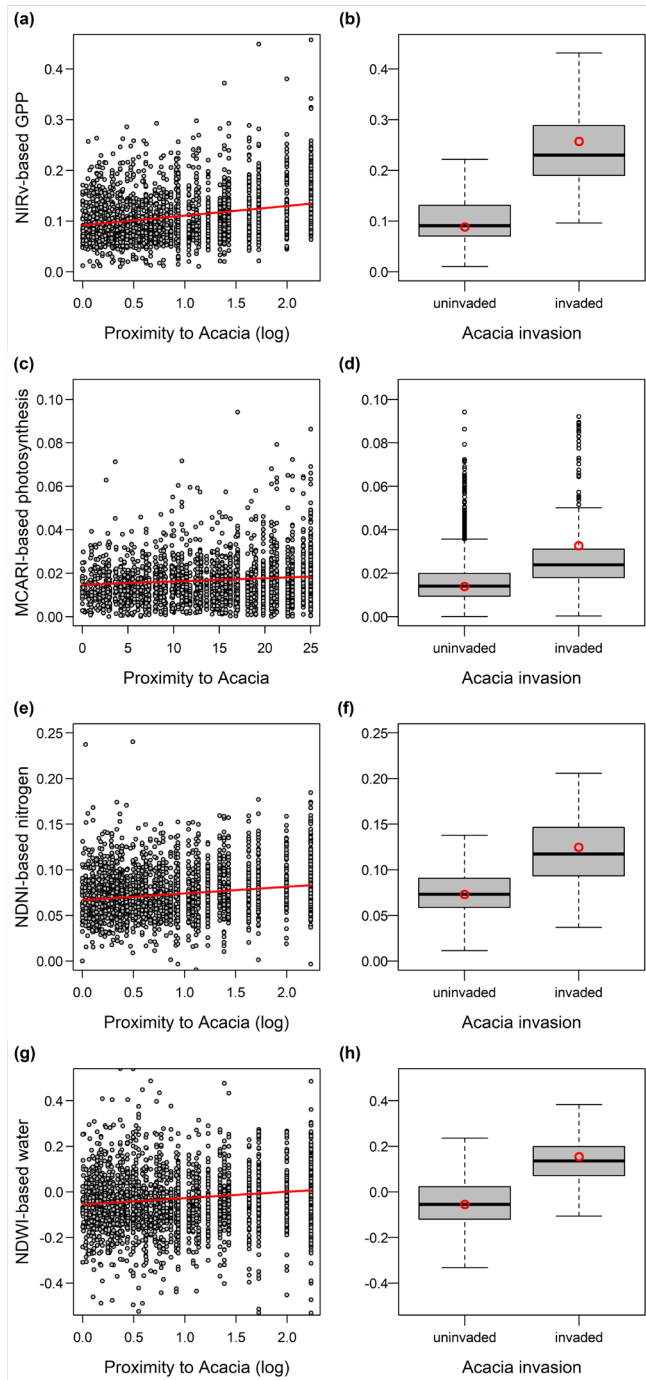


Figure 2: Local effects of proximity to and presence of *Acacia* on ecosystem functions. Proximity was measured as inverted distance from raster cells classified as *Acacia* (centroid-centroid distance) within a buffer of 27 m, so that cells adjacent to invasive stands received a proximity value of 25 (27-2) and cells at 27 m distance would have a proximity of 0 (27-27). All slopes and differences between boxes were significant at $p < 0.001$. Red circles in boxplots indicate expected values given median values of Topographic Wetness Index and vegetation cover.

At landscape level, *Acacia* substantially increased the scores of primary productivity, photosynthesis and nitrogen (Fig. 3a-c). Concerning water, the score of the stand impact model (93,007) was within the confidence limits of the background value ($90,675 \pm 1,242$, upper limit: 93,160), while the total impact model was above this range (94,897). Thus, *Acacia* increased the water score significantly indicating a higher vegetation water content adjacent to *Acacia*, but this effect was small (+ 4.7 % total impact based on the full model; Fig. 3d). Generally, the impacts on ecosystem functions that occurred

outside of the stands of *Acacia* (spatial impacts) were as large as or larger than the impacts inside the stands (stand impacts). In particular, the spatial impact on photosynthesis outweighed the stand impact (Fig. 3b). Hence, the impacted area extended far beyond the invasive stands (Fig. 4; Appendix Figs. A1-A3).

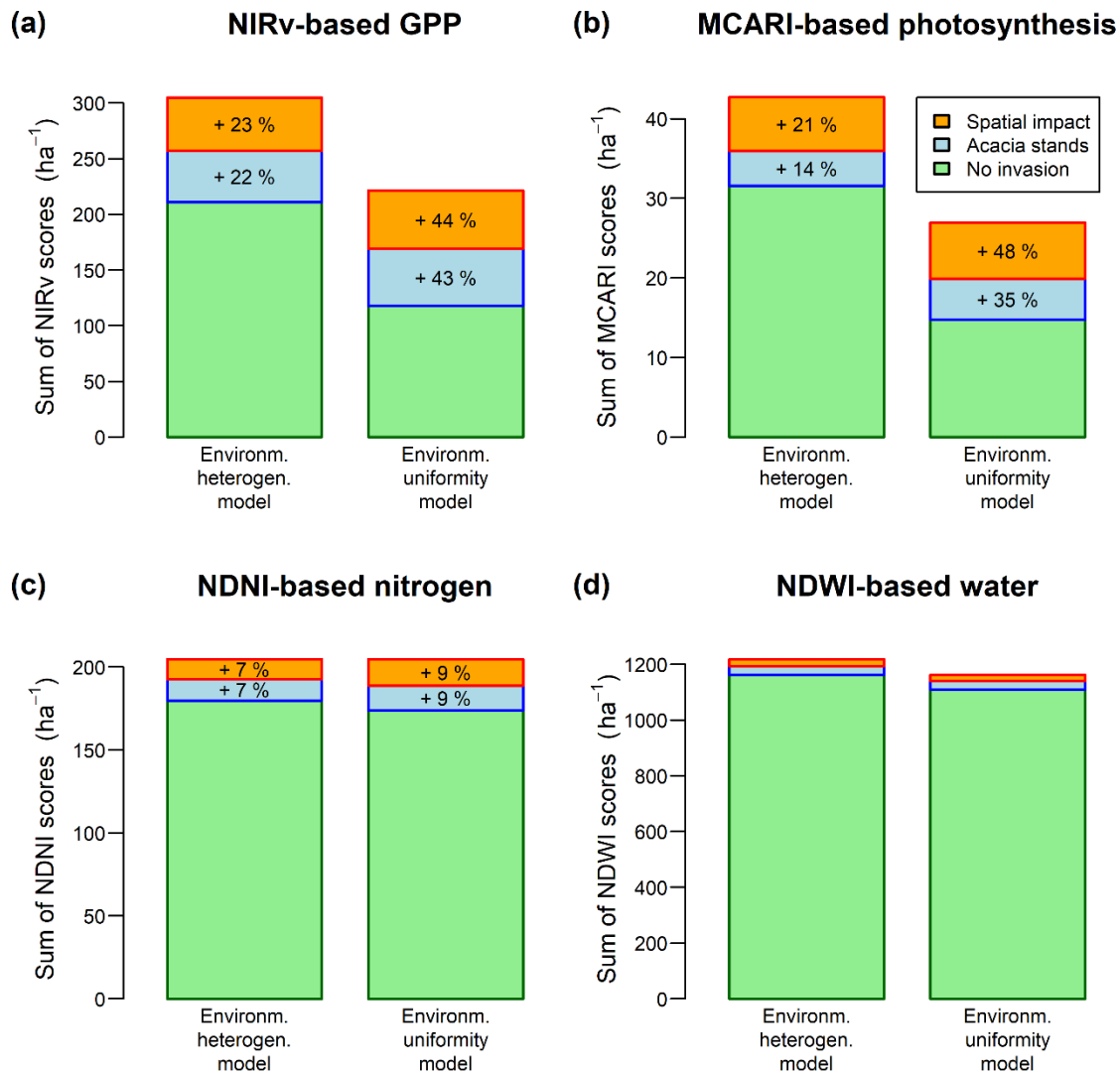


Figure 3: Impacts of *Acacia* on ecosystem functions of Mediterranean dunes in Portugal at landscape level. The scores are the sums over all raster cells up to 27 m beyond invasive stands of predicted proxy values of ecosystems functions (hyperspectral indices). Background scores were estimated based on environmental variables ("Full" model) or based on the intercepts of models disregarding environmental heterogeneity ("Basic" model). Stand impact is the added score due to the effect of presence of *Acacia*. Spatial impact is the additional impact outside of the invasive stands that was modelled through effects of proximity (horizontal and elevational) and size of the closest stands of *Acacia*.

Environmental heterogeneity

Disregarding environmental heterogeneity had a strong influence on the estimated background values of primary productivity and photosynthesis (Fig. 3a-b). The basic model, without environmental variables, predicted lower background values and,

consequently, the relative impacts of *Acacia* increased. Regarding nitrogen and water, the differences between the full and basic models were minor (Fig. 3c-d).

The environmental variables consistently had significant effects on the estimation of background values of ecosystem functions. The most important predictor was vegetation cover that had positive effects on all ecosystem functions (Appendix A1, Tables A1, A3, A5, A7). The Topographic Wetness Index (TWI) had positive effects on nitrogen and water, but negative ones on primary productivity and photosynthesis. However, in all cases the effects of TWI were small. The landforms ‘ridges’ and ‘valleys’ had the highest values of ecosystem proxies, while ‘plains’, ‘slopes’ and ‘drainages’ had lower values, but differences were moderate throughout (Appendix A1, Tables A1, A3, A5, A7).

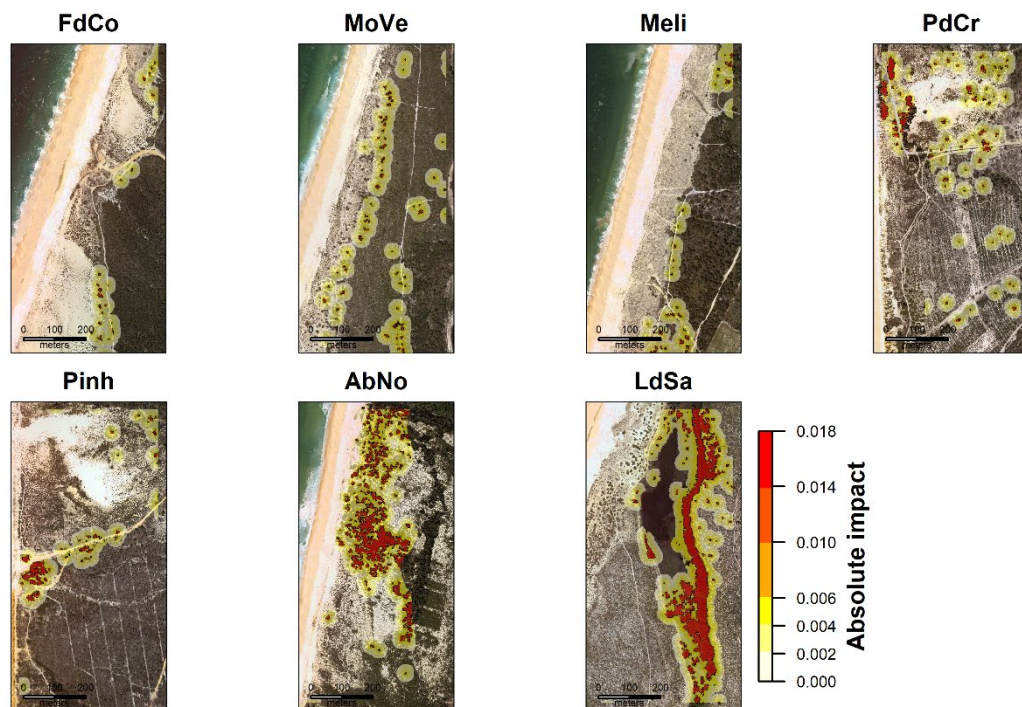


Figure 4: Maps of impacts of *Acacia* related to photosynthetic activity from our seven study sites from low to high impact. The MCARI vegetation index was derived from hyperspectral data as a proxy of photosynthetic activity. Spatial impacts were modelled up to 27 m around invasive stands. Map backgrounds show aerial images that were taken simultaneously with the hyperspectral images.

Invasion stage

The spatial impact of *Acacia* depended on the stage of invasion expressed as cover percentage of the invader within landscapes windows (26×26 m). Regarding primary productivity, the proportion of spatial impact amongst total impact, i.e. the sum of cell-level impact scores of both the *Acacia* presence ('stand impact') and of the spatial impact, increased rapidly from early stage of invasion up to 20 % invader cover and,

then, gradually decreased, but still showed positive trends across all cover ranges until the whole area was covered by the invader (Fig. 5a). The same pattern was found for nitrogen and water. However, with respect to photosynthesis, spatial impact was most prevalent at very early stages of invasion (close to 0 % cover) and declined steadily with increasing invader cover (Fig. 5b).

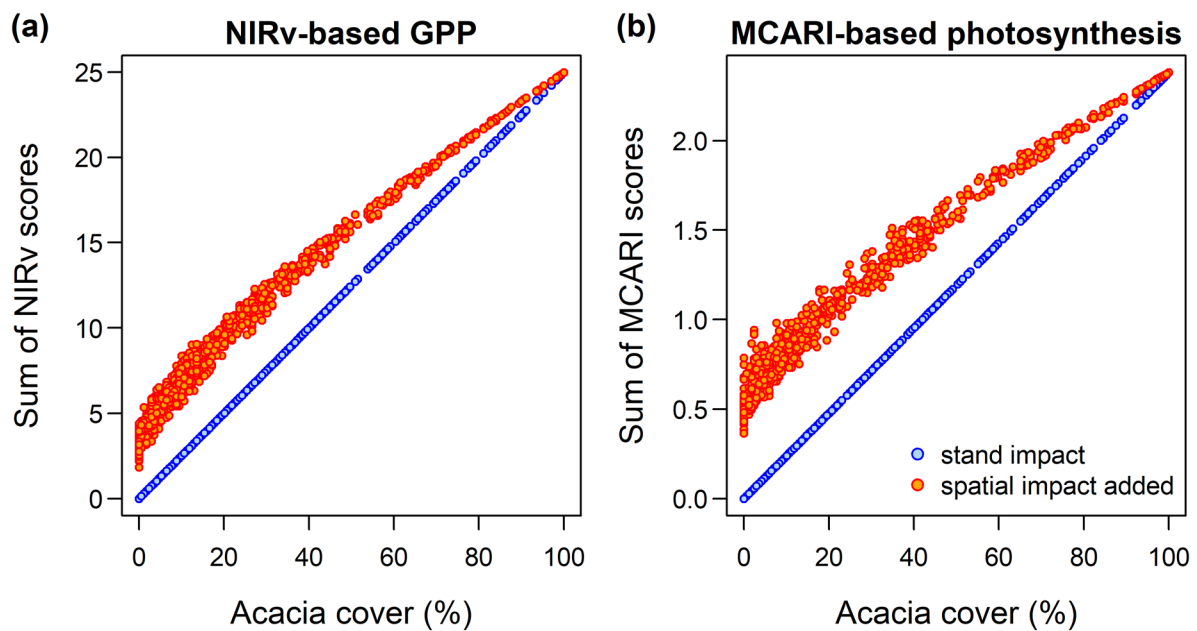


Figure 5: Sums of impact scores of *Acacia* vs. its cover percentage in moving windows of 26×26 m with respect to (a) the NIRv index as a proxy of gross primary production and (b) MCARI as a proxy of photosynthetic activity. Impact scores were calculated per raster cell as the difference in predicted values of NIRv or MCARI between models that included *Acacia* invasion and background models for uninvaded sites. Stand impact: only presence-absence of *Acacia* was used for modelling impacts. Spatial impact added: impact models included both presence and proximity of *Acacia*. The difference between ‘stand impact’ and ‘spatial impact added’ equals the spatial impact that occurred outside of the invasive stands.

Functional diversity

Acacia had a spatial impact on functional diversity as the multidimensional Rao’s Q index decreased with increasing proximity to the invader (Fig. 6a) in both the basic model and the model including environmental heterogeneity (Appendix A1, Tables A9, A10, Figure A4). Functional diversity was higher in uninvaded areas with native vegetation compared to *Acacia* canopies where the Rao’s Q index reached its minimum (Fig. 6b). However, Rao’s Q index reached its maximum in the zone close to *Acacia* (Fig. 6b), and proximity to *Acacia* and ‘Edge of *Acacia* stands’ had marked positive effects in

both models (Appendix A1, Tables A9, A10, Figure A4) indicating functional differences between the invader and the native vegetation.

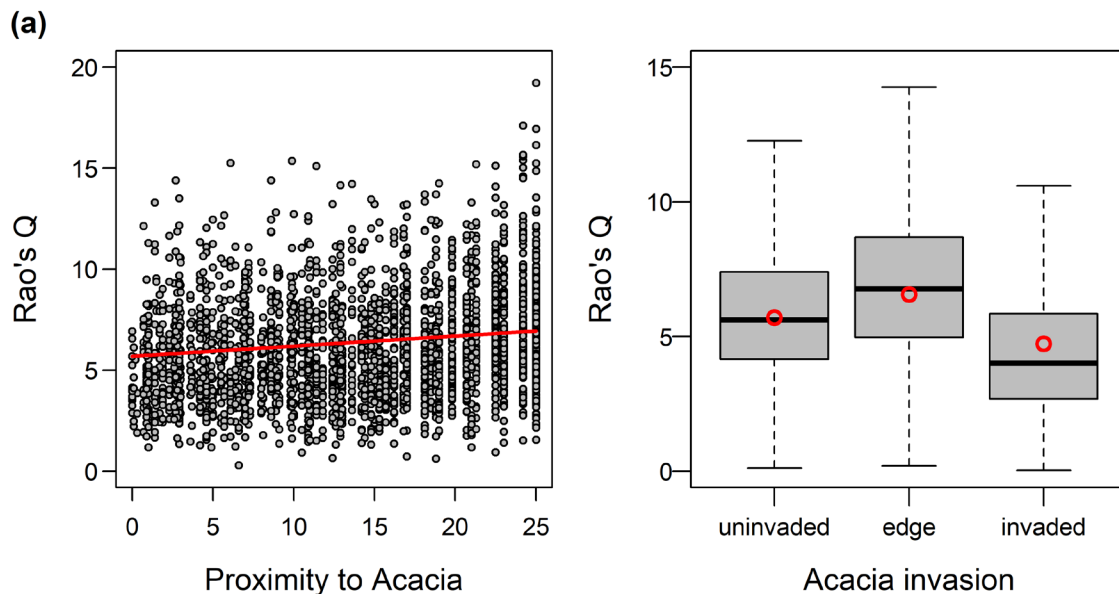


Figure 6: Local effects of proximity to and presence of *Acacia* on functional diversity in terms of spectrally derived Rao's *Q* based on the vegetation indices NIRv, MCARI, NDNI and NDWI. (a) Proximity was measured as inverted distance from raster cells classified as *Acacia* (centroid-centroid distance) within a buffer of 27 m, so that cells adjacent to invasive stands received a proximity value of 25 (27-2) and cells at 27 m distance would have a proximity of 0 (27-27). (b) Rao's *Q* diversity was compared in detail for *Acacia* stands ("invaded"), the area of ± 2 m around the borders of *Acacia* stands ("edge"), and not invaded area ("uninvaded"). All slopes and differences between boxes were significant at $p < 0.001$. Red circles in boxplots indicate expected values given median values of Topographic Wetness Index and vegetation cover.

Discussion

The overall aim of this study was to assess the impacts of an invasive tree on ecosystem functioning at the landscape scale using remote sensing. We demonstrate that a) impacts can be mapped by means of hyperspectral vegetation indices and b) that the integration of hyperspectral and LiDAR data improves mapping spatial effects beyond the invasive stands. Our study generated new insights on identifying high impacts at early stages of invasion, considering environmental heterogeneity in impact assessments at the landscape scale and tracking effects on functional diversity after invasion. These findings enhance our understanding of remote sensing-driven impact assessments of invasive plant species.

Impact at landscape scale

The impact assessments at landscape scale confirm that *Acacia* has substantial effects on ecosystem functioning. Remotely sensed proxies of nitrogen in plant biomass (NDNI),

chlorophyll/photosynthesis (MCARI), vegetation water content (NDWI) and primary productivity (NIRv) all increased in invasive stands. These results match those observed in field-based studies. Indeed, *Acacia* enriches invaded ecosystems with nitrogen (Hellmann et al., 2011; Marchante et al., 2019; Ulm et al., 2017b), it changes water cycling (Hellmann et al., 2016b; Rascher et al., 2011b), it shows high vitality productivity indicated by a high growth rate (Hellmann et al., 2011), it increases the Leaf Area Index and it causes densification of the vegetation structure (Rascher et al., 2011a).

Impacts on ecosystem functions are also typical for other invasive *Acacias* (Kumschick and Jansen, 2023; Le Maitre et al., 2023) and other invasive plant species in general (Kumschick et al., 2015; Vilà et al., 2024), and such impacts have occasionally been assessed using remote sensing-based approaches (Müllerová et al., 2023). However, most remote sensing-based studies still focus on mapping invader occurrence (Bolch et al., 2020; Müllerová et al., 2023), and this also applies to well-studied species groups such as invasive *Acacias* (Große-Stoltenberg et al., 2023). At the same time, availability of remote-sensing data as well as capacities for data analysis to study landscape structure and ecosystem functioning and dynamics across scales are increasing (Crowley and Cardille, 2020; Senf, 2022), which led to progress in the field of plant invasions (Müllerová et al., 2023; Saranya et al., 2024). Thus, a solid basis of knowledge and data on plant-invasion impact on ecosystem functioning exists, and together with recent technological progress there is high potential for future research on integrating field-based with remote sensing driven approaches to assess ecological impacts of plant invasions.

Spatial impacts beyond invader canopy

In this study, the impacts of *Acacia* can be traced outside of the stands of the invader, and their spatial dimension differs. Even though absolute impacts are substantially lower outside of the stands compared to inside, the sum of spatial impacts is considerable. These spatial impacts do not increase linearly with progressing invasion, but are particularly prevalent in rather early stages (~20 % invader cover at landscape level). Therefore, impact assessments of the studied *Acacia*, and likely also other *Acacia* species (Le Maitre et al., 2023) or nitrogen-fixing invaders, such as *Morella faya* (Ait.) Wilbur and *Ulex europaeus* L., that belong to the 100 of the world's worst invasive species (Lowe et al., 2000; Luque et al., 2014), will markedly underestimate impacts

especially at early stages of invasion if spatial effects (see also Cuddington and Hastings (2004)) are neglected.

In addition, *Acacia* creates homogeneous stands, which are functionally less diverse than the native vegetation, and stark functional differences occur at the edge of *Acacia* canopies. This is in line with earlier research showing the functional diversity of the studied system and the distinct traits of invasive *Acacias* compared to the native tall shrubs and trees (Große-Stoltenberg et al., 2018a) including tendencies to form dense, monospecific thickets (Große-Stoltenberg et al., 2018b; Rascher et al., 2011a). Recent progress in remote sensing technology allows examining plant-plant interactions at both fine scale and large extents (Chen et al., 2022), and offers a large but untapped potential to analyse invader-ecosystem interactions (Werner et al., 2024). We argue that this technological progress facilitates to identify or to screen for such functional changes at the neighbourhood scale, which are difficult to decipher otherwise (Goyal and Sharma, 2019; Jarić et al., 2019). For example, the availability remote sensing data with very high spectral and spatial resolution is increasing (Crowley and Cardille, 2020), which facilitates trait-based approaches to examine invasion impacts (Niphadkar and Nagendra, 2016; Saranya et al., 2024) such as alterations of forest canopy chemistry (e.g., Ewald et al., 2018). Future directions include trait retrieval using hybrid approaches combining machine learning with physical models (Berger et al., 2020) as well as multi-trait retrieval using deep learning (Cherif et al., 2020) in the context of impact assessments (Werner et al., 2024). Regarding remote sensing of belowground impacts (e.g., Rakotoarivony et al., 2024), invasive species might change (Lekberg et al., 2013) or be limited by (Pringle et al., 2009) mycorrhizal traits, and first studies show that such traits can be derived from hyperspectral data (Sousa et al., 2021; Jantzen et al., 2023), which could be an avenue for future research. Thus, a broad range of tools and methods are at hand, which combined could enhance the understanding of invader-ecosystem interactions (Werner et al., 2024).

While we present a showcase for the spatial dimension of impact, the temporal aspect of remote sensing-based impact assessments could be a future avenue of research. For example, resource use and competition, e.g., increased water use under drought conditions (Rascher et al., 2011b), are important parameters that guide invasion management (Kumschick et al., 2015). Remotely sensed land surface phenology, in addition to derive precise distribution maps (Lake et al., 2022), could be used to study such changes of resource use (Dronova and Taddeo, 2022). Therefore, we envision that advancements in remote sensing together with spatial (and temporal) modelling will

facilitate tracing the spatial effects of invasive species on ecosystem functioning including functional homogenisation and, by doing so, improve insights into abundance-impact relationships and support early detection of different types and magnitudes of ecological impacts at broad spatial extents.

The role of environmental heterogeneity

While neglecting spatial effects leads to underestimation of impact, neglecting environmental heterogeneity may lead to overestimation of invader impact. Here, the effects of environmental heterogeneity on ecosystem functioning, especially regarding landforms, were mostly constant, but slight differences occurred between the studied proxies, emphasizing that effects of heterogeneity on ecological impacts can be function-specific. In fact, context-dependency is still a major challenge in invasion research (Ricciardi et al., 2021). Indeed, spatial environmental heterogeneity in terms of topography is a strong driver of species richness (Stein et al., 2014), and it shapes vegetation structure, e.g., in dune ecosystems (Sewerniak and Jankowski, 2017). Regarding impact modelling, spatial heterogeneity caused by "patchy" processes, such as disturbances or land use, may entail spatial auto-correlation in the data when working on contiguous landscape sections, such as aerial images. To safeguard valid impact estimates, spatial auto-correlation should be considered in the models, e.g., using spatial auto-correlation structures (Dorman et al. 2007). Airborne LiDAR remote sensing is a powerful tool to characterize topographical heterogeneity and vegetation patterns in coastal dunes with high spatial detail and broad coverage, and LiDAR-derived proxies of ecosystem functioning agree well with proxies derived from optical sensors and field measurements (Yousefi Lalimi et al., 2017). Regarding ecological impacts of invasive plant species, LiDAR-derived proxies of environmental heterogeneity are well suited to map invader impacts, e.g., regarding N-fixation, across sites (Hellmann et al., 2017). The toolbox to characterize the 3D structure of ecosystems is rapidly evolving (Valbuena et al., 2020), and there is large potential to study plant-plant interactions (Chen et al., 2022) including effects of invasive species on ecosystem structural variability (Barenblitt et al., 2024) using 3D data. Therefore, the spatial environmental heterogeneity matrix is an important habitat characteristic that shapes ecological impacts of invasive species, and 3D remote sensing offers new opportunities to characterize heterogeneity at multiple scales in a standardized way, which is extremely useful to advance in the field of context-dependency of plant invasion impact.

Perspective on upscaling to satellite-based observations

In this study we presented a proof-of-concept for mapping spatial impacts of an invasive tree species on ecosystem functioning in a Mediterranean dune ecosystem considering landscape heterogeneity. To do so, we used single-time airborne hyperspectral and LiDAR data with very spatial resolution that was acquired in spring during the greening up phase (Große-Stoltenberg et al., 2018b). Upscaling this approach using satellite data would be desirable as it would provide the means to screen for plant invasion impacts over large spatial extents as a prerequisite for understanding invasion processes (Werner et al., 2024), for a continuous monitoring (Müllerova et al., 2023,) and to guide management in a spatially explicit way (Saranya et al., 2024), but challenges integrating remote sensing information with in-situ observations apply (Cavender-Bares et al., 2022). The core challenge is to select a sensor or sensor-combination that captures data at appropriate spatial, spectral and temporal scales to examine the respective impact caused by the invader (Werner et al., 2024). This mirrors the challenges when inferring biodiversity metrics from remote sensing data to test the transferability of the SVH (see Torresani et al., 2024). Clearly, as a first step the local process of invader - ecosystem-interaction need to be understood as a precondition for upscaling using remote sensing (Gholizadeh et al., 2024; Werner et al., 2024, this study). In our example, the spatial effect of *Acacia* on functional properties of the surrounding native vegetation was first identified using in-situ measurements of stable isotopes (Rascher et al., 2012; Hellmann et al., 2016a,b), then spatial heterogeneity of the landscape was derived from airborne LiDAR point clouds gridded to fine resolution and integrated in spatial models to account for environmental context (Hellmann et al., 2017), and, finally, hyperspectral vegetation indices related to the identified impacts from in-situ measurements covering the VNIR-SWIR part of the electromagnetic spectrum were computed at fine spatial resolution and combined in the Rao's Q index to map context-dependant-spatial effects across large spatial extents (this study). Our findings and approach might be upscalable to satellite data but with some caveats. First, stand impact might be identifiable at sub-pixel level of medium-resolution remote sensing data with a pixel size of 30m (Große-Stoltenberg et al., 2018b), and such corresponding multitemporal satellite data with high temporal resolution is freely available (Crowley and Cardille 2020), so even scaling across time could be tested. Second, spatial impacts in terms of ^{15}N -enrichment were observed in a distance up to 6-8 m to *Acacia* canopy (Hellmann et al. 2017), and the airborne data, i.e. hyperspectral vegetation indices as well as the Rao's Q index, were computed at 2m resolution, which was sufficient to map the spatial impacts using

remote sensing. Such data is, with limitations in terms of resolution, available from commercial providers and has successfully been applied to map invasive plant species in complex landscapes (Lake et al., 2022), and might be considered in this context. However, it would be an open question if high temporal, but lower spatial resolution (3m) and spectral coverage (VNIR) Planetscope imagery (Lake et al., 2022) would be able to capture the fine-scale effects in close vicinity to invader canopy, or if low temporal, but higher spatial resolution and spectral coverage Worldview data (Lake et al., 2022) would be necessary and/or sufficient. Therefore, using such data not only for mapping but also for spatial impact assessments could be a future avenue of research. Third, spatial heterogeneity in our example was computed based on airborne point-cloud data gridded with a grain size of 2m (Hellmann et al., 2017, this study), and a high spatial resolution is likely to be required in this complex Mediterranean dune ecosystem. While availability of 3D information derived from satellites is increasing, their spatial resolution is coarser compared to airborne data (Valbuena et al., 2020). It would need to be tested to which degree which type of 3D metric (e.g., topographical parameters, proxies of vegetation structure) could be upscaled in spatial impact models to still capture the spatial heterogeneity that shapes the invader-ecosystem under study. If no airborne 3D data is available, drone-based LiDAR or photogrammetry (Müllerova et al., 2023) could be used for testing upscaling, and very high-resolution spaceborne synthetic aperture radar (Shennan and Crabbe, 2024) could be a promising alternative for large scale mapping of spatial heterogeneity in the context of plant invasions. In conclusion, first proofs-of-concept to link in-situ observations of spatial impacts of invasive plants species on ecosystem functioning to remotely-sensed information have been developed. Analogue to the SVH (Torresani et al., 2024), challenges in terms of transferability and upscaling likely apply, but a variety of sensor technologies and modelling approaches exist to support future research.

Conclusion

The invasive tree *Acacia longifolia* is able to alter ecosystem functioning, and we mapped its impacts by means of hyperspectral indices related to nitrogen in plant biomass, chlorophyll/photosynthesis, vegetation water content and primary productivity even beyond invasive stands by integrating airborne LiDAR in our spatial impact models. By doing so, we showcase that both 2D and 3D remote sensing data complement each other in remote sensing-driven impact assessments. Further, we illustrate that the spatial dimensions differ between impacts, and that while the total

score of these spatial impacts was low, the sum of spatial impacts beyond invader canopy was substantial. Moreover, spatial impacts did not increase linearly with progressing invasion, but were relatively high when invader cover was still relatively low (~20 % cover at landscape level). In addition, we showed that while neglecting spatial effects could lead to underestimation of impact, neglecting environmental heterogeneity would have led to overestimation of invader impact. Therefore, we emphasize that both spatial effects and environmental heterogeneity, e.g. derived from airborne LiDAR data, need to be considered to neither under- nor overestimate ecological impacts of invasion, and that such effects are function-specific. Finally, *Acacia* creates homogeneous stands, which are functionally less diverse than the native vegetation, and stark functional differences occur at the edge of *Acacia* canopies, which we mapped using the spectral version of the Rao's Q index based on the aforementioned impacts. That being the case, we argue that remotely sensed proxies of functional diversity allow for both identifying pronounced functional differences at the interface between the invader canopy and the native vegetation, and invader-induced functional homogenisation of the landscape. Together, mapping these spatial effects provides data to guide management, e.g., to derive thresholds for intervention, and accounting for environmental heterogeneity informs on the context-dependency of ecological impacts. Challenges to upscale the approach to satellite-based observations, but could be a promising avenue of research due to progress in sensor technology and analytical approaches.

Acknowledgements

We are grateful to the Instituto da Conservação da Natureza e das Florestas Portugal and the Estabelecimento Prisional de Pinheiro da Cruz for granting access to the field sites, and to Cristina Máguas for logistical support. Funding for this project was provided by the DFG (OL 417/1-1, TH 1295/4-1, WE 2681/ 8-1), EUFAR (DeInVader, EUFAR11-06, grant to AGS), LAsTools (LASmoons grant to AGS), DAAD (field studies AGS), and "Studienstiftung des Deutschen Volkes" (Fellowship CH). We thank NERC's Airborne Research Facility and Data Analysis Node for conducting the airborne survey.

Authors' Contributions Statement

AGS and JT conceived the ideas and designed methodology; AGS and JO processed the data, JT analysed the data with inputs from AGS; AGS led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Chapter 8

Identifying urban vegetation stress factors based on open access remote sensing imagery and field observations

Irina Cârlan^{1,}, Bogdan-Andrei Mihai², Constantin Nistor², André Große-Stoltenberg³*

¹University of Bucharest, Faculty of Geography, Simion Mehedinti Doctoral School, 1 Nicolae Bălcescu Blvd, Bucharest 010041, Romania

²University of Bucharest, Faculty of Geography, Department of Geomorphology-Pedology-Geomatics, 1 Nicolae Bălcescu Blvd, Bucharest 010041, Romania

³Justus Liebig University Giessen, iFZ Research Centre for Biosystems, Land Use and Nutrition, Institute of Landscape Ecology and Resource Management, Division of Landscape Ecology and Landscape Planning, Heinrich-Buff Ring 26-32, 35392 Giessen, Germany

*Corresponding author

Abstract

Healthy vegetation in cities provides ecosystem services, which contribute to the overall well-being of urban populations, especially in times of climate change and increasing urbanization. More specifically, vegetation monitoring is needed in the context of intensifying and mitigating factors of the Urban Heat Island (UHI) effect. Therefore, fast and low-cost, but reliable approaches are needed for monitoring the status of urban greening. A satellite-based monitoring scheme based on freely available data could ensure the provision of key urban ecosystem services, and guide both policy maker and practitioners. Thus, the main objective of this paper is to investigate the impact of urbanization and urban green management on vegetation status of park trees during summer season in Bucharest, the capital city of Romania, using remote sensing. This city is known to be affected by air pollution and the UHI effect. Further, it is an example of a city with limited green spaces compared to other European cities. Hence, spatial data on vegetation status and potential impacts as a basis for management schemes are required to maintain a healthy urban green infrastructure. Vegetation indices related to chlorophyll, senescence, greenness and water stress were calculated from Sentinel-2 imagery as response variables to vegetation stress. Vegetation status was then predicted for each park using spatial environment factors (e.g. presence of irrigation systems) in a mixed model approach to account for heterogeneity among parks. The most important predictors of vegetation stress were irrigation systems, land surface temperature, distance to a lake and proximity to roads. However, the effect of these predictors on the vegetation status differed among parks. Therefore, a mixed effect model approach is suggested to quantify the effects of urbanization on green spaces in cities, and there is a high potential to use freely available satellite data for a spaceborne-monitoring service of urban green infrastructure.

Keywords

Vegetation stress, Urban green infrastructure, Sentinel-2, Landsat 8, Vegetation indices, Urban heat island, Mixed effect model

Introduction

Urban vegetation provides important ecosystem services related to human well-being, biodiversity and carbon storage (Breuste et al., 2013; Dobbs et al., 2014; Sugiyama et al., 2018). Humans gain benefits from urban greens as they mitigate effects of urban heat islands (UHI) and contribute to air filtration, noise reduction, rainwater drainage, as well as sewage treatment (Meerow and Newell, 2017; Nowak et al., 2018). However, increasing urbanization leads to an increase in both demand for and pressure on these services (Bastian et al., 2012; Nastran et al., 2019). As status and availability of natural areas in urban settings are connected to human health (van den Bosch and Nieuwenhuijsen, 2017), new approaches are required to deliver and to visualize spatially explicit information on urban vegetation status in a timely manner.

Remote sensing is a powerful option to retrieve continuously environmental data for the scale of a city, which would be difficult to obtain otherwise (Buchanan et al., 2015). Especially open access data such as collected by the Sentinel-2 mission have the potential to deliver low-cost and up-to-date maps about distribution and status of urban green infrastructure. Sentinel-2 images include detailed spectral information in three bands situated in the red-edge region, which are correlated with chlorophyll content (Cho and Skidmore, 2006; Ramoelo et al., 2015; Wu et al., 2008). Because chlorophyll is sensitive to stress factors such as drought, extreme temperatures, lack of light and air pollutants (Jim and Chen, 2008; Tomašević et al., 2005; Van Wittenberghe et al., 2013), chlorophyll vegetation indices can be appropriate urban vegetation health indicators. In addition to that, spatial data about Land Surface Temperature (LST), which is an important parameter to assess the UHI, can be retrieved from the thermal infra-red (TIR) bands of Landsat 8 images (Cheval and Dumitrescu, 2014; Roberts et al., 2015). Therefore, both the Sentinel-2 and the Landsat 8 missions deliver baseline information to ensure long-term and continuous vegetation monitoring (Recanatesi et al., 2018) such as in urban areas.

The spectral response of vegetation can give insights about vegetation stress and early senescence (Lausch et al., 2016, 2018). Many previous studies dealing with monitoring plant stress in urban environments are based only on very high resolution imagery (Degerickx et al., 2018; Ramoelo et al., 2015), which are not publicly available (Malthus and Younger, 2000; Nouri et al., 2013). Few urban studies are based on free high-resolution imagery. Among these studies, some are focused on the spatial analysis of the distribution of green areas (Lakes and Kim, 2012; Yan et al., 2018), whilst others

include mapping of biomass or vegetation structure (Guo et al., 2017; Raciti et al., 2014) or discriminating among tree species (Alonzo et al., 2014; Tigges et al., 2013). Thus, we identify a research gap for using open access high spatial resolution images for assessing urban vegetation health.

Few studies combine qualitative field observations with spaceborne data to assess urban vegetation physical and biochemical parameters of vegetation within parks (Dimitrov et al., 2018; Vanuytrecht et al., 2014). Most studies focus on urban forests (Livesley et al., 2016; Recanatesi et al., 2018), urban horticulture (Säumel et al., 2012) or laboratory experiments (De Jong et al., 2012). In addition, many studies consider only a limited number of factors to explain urban vegetation stress. They focus mainly either on traffic-related pollution (Asmaryan et al., 2013; Gheorghe and Ion, 2011; Malthus and Younger, 2000) or on drought stress (Keeling, 2018; Roberts et al., 2015; Swain et al., 2017; Vanuytrecht et al., 2014). Previous studies emphasize the difficulty in discriminating between the impact of multiple factors on urban vegetation stress. While the ecophysiological status of urban trees can be accurately mapped using very high resolution multispectral data (Degerickx et al., 2018; Xiao and McPherson, 2005), identifying and disentangling the factors that lead to a poor vegetation status based on earth observation remains a challenge. Thus, further research is required for a spatially-explicit, remote sensing driven approach to monitor urban vegetation status in relation to multiple external factors.

In this study, we selected Bucharest, the capital city of Romania, as a suitable example of a large European city, which faces several environmental challenges due to global warming (Radulovic et al., 2015). Firstly, the UHI effect is intense in Bucharest due to the increase of impervious surface within the city (Grădinaru et al., 2013; Ioja, 2009; Mihai et al., 2015; Rusanescu et al., 2011). Secondly, Bucharest's traffic follows an increasing trend, mainly due to the extended car use. Cars are becoming more and more numerous, ~1.5 million vehicles per day present in Bucharest for 1.85 million inhabitants (Ioja et al., 2011), compared to EU average of 505,000 passenger cars per 1 million inhabitants (European Commission, 2017). Thirdly, another source for air pollution within the city is heating based on fossil fuels such as coal and natural gas (Ioja, 2009). Air pollutants like CO₂, NO₂, SO₂ and O₃ were recorded to exceed critical limits for vegetation over several years, which presumably hamper vegetation development (Lakkaraju et al., 2010; Gheorghe and Ion, 2011; Constantin et al., 2012;). Finally, Bucharest records one of the lowest values of square meters of green space/ inhabitant in the European Union. The World Health Organization mentions the minimum value of

50 sqm of green space/inhabitant (Mănoiu et al., 2016). The urban green space in Bucharest occupies 2275 ha, that is 23.9 sqm of green space/inhabitant (Iojă et al., 2011). Therefore, Bucharest is an example of a city with a relatively small amount of green space, but with an increasing pressure on vegetation due to traffic and urbanization, which puts stress on the provision of urban ecosystem services.

Thus, healthy urban vegetation is the basis for urban ecosystem services. Here, we investigate how to assess the impact of factors that cause urban vegetation stress using earth observation and spatial geodata. The objective is to identify which external factors have an impact on urban vegetation and what vegetation indices are proxies for vegetation stress. The resulting maps provide baseline information for a sustainable management of urban green areas in the light of climate change. To achieve these results, the approach taken is based on qualitative field observations and open access remote sensing imagery to ensure transferability to other case studies, and comply with existing monitoring schemes such as the European Copernicus Land Monitoring Service.

Materials and methods

Study area

Bucharest hosts 1.85 million inhabitants over 226 km², resulting in a high population density of 8.185 inhabitants/sqkm. This value is double compared to other cities of similar area: Prague records 4410 inhabitants/sqkm and Amsterdam 3882 inhabitants/sqkm (EuroStat, 2016). The city of Bucharest is continuously growing since the beginning of the 20th century (Mihailescu, 2003). It is characterized by the socialist industrialization which transformed the semi-rural structures at the border of the built-up area into blocks of flats districts (Cina, 2010), alternating with the emerging industrial zones and transportation areas along the railways and the main roads (Sandric et al., 2007; Suditu, 2016).

This study focused on 10 parks within the city of Bucharest (Table 1). These parks were selected to cover a great range of park typologies based on area, location within the city (Fig. 1), number of tree species, number of fountains and presence of adjacent congested boulevards.

Table 1: Main features of the analyzed park areas including irrigation types in the city of Bucharest. Source: Field campaign, April 2017.

Park name (acronym)	Park name (long name)	Area (ha)	Sprinkler irrigation	Other irrigation solutions
CIS	Cișmigiu Park	16	X	X
UNI	Unirii Park	3.5		X
KIS	Kiseleff Park	31	X	
CAR	Carol Park	41		X
HER	Herăstrău Park	110	X	X
TEI	Tei Park	9	X	
DRU	Drumul Taberei Park	30	X	
PAN	Pantelimon Park	52	X	
PAC	Păcii Park	2.5	X	
BAZ	Bazilescu Park	14	X	

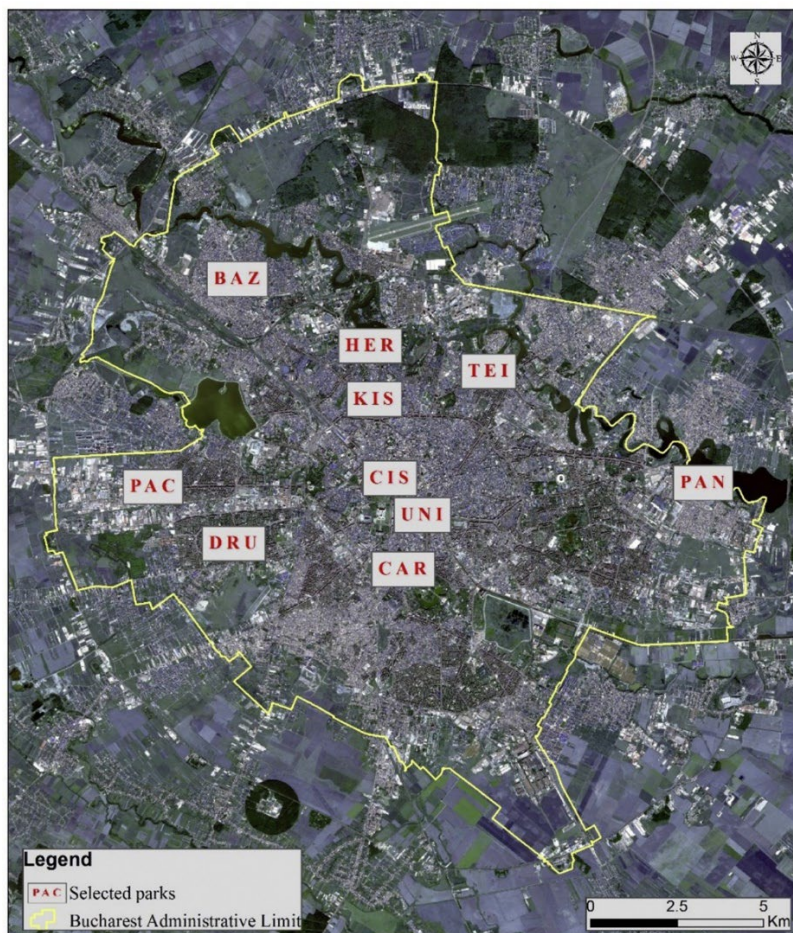


Figure 1: Spatial distribution of studied parks in the city of Bucharest (Table 1). Source of the basemap: Sentinel-2 true colour image, European Space Agency (ESA), acquired on August 8th, 2016.

Field data

A field campaign took place in April 2017. Qualitative data based on field observations was recorded for each park: number and density of the most common tree species in Bucharest, presence of fountains, presence of construction sites, presence and type of irrigation systems and shading status in relation to tall buildings nearby the parks (Table 2).

Table 2: Factors that were extracted from the field campaign and included as predictor variables in the statistical analysis.

Predictor	Description
<i>Number of tree species</i>	Species' richness represents the approximated number of tree species for each park.
<i>Distance to fountains</i>	Each fountain inside the parks was mapped; Euclidian distance from trees to the nearest fountain.
<i>Distance to construction sites</i>	Each construction site around the parks was mapped; Euclidian distance from trees to the nearest construction site.
<i>Presence and type of irrigation system</i>	Irrigation system is described by three categories: sprinkle irrigation system; other solution (water is transported by cars or by hoses from the lake); both solutions are applied.
<i>Level of shade</i>	Parks were examined if they are surrounded by tall buildings and if trees are deprived of light for > 4 h a day. The parameter is defined by the number of hours/ day that a portion of the park is shaded by tall buildings nearby. The level of shade was mapped using a quadrant-based method: each park was divided into 4 quadrants and each quadrant was assessed whether or not it was shaded by tall buildings nearby the parks. If the quadrant was shaded, the estimated number of hours with shaded quadrant was provided.

Some species are known to be sensitive to drought and air pollution, finding suitable trees as green infrastructure is important (Maria Raquel C de S et al., 2016). Among the most tolerant to SO₂ and O₃ species are linden tree (*Tilia cordata*) and oak tree (*Quercus robur*), whereas the most sensitive species are pine (*Pinus sylvestris*), poplar (*Populus tremula*), ash (*Fraxinus excelsior*), and maple (*Acer pseudoplatanus*) (Appleton et al., 2014; Oswalt and Clatterbuck, 2004; Rozas et al., 2009). Therefore, it is necessary to have a-priori knowledge about the existing tree species and their sensitivity to external factors when investigating vegetation health.

Impacts and mitigation measures can be manifold. Irrigation systems can compensate the lack of water in drought periods, but not all parks are equipped with such infrastructure. Further, fountains and lakes have a local impact on vegetation because

they regulate the microclimate around them within a buffer area of 40 m (Xue et al., 2015). Construction sites are a source of air pollutants. They have an impact on vegetation because of the particulate matter which deposits on leaves (Gheorghe and Ion, 2011). Finally, lack of light in urban areas due to shading by nearby buildings can affect the process of photosynthesis (Iakovoglou et al., 2001).

GIS & remote sensing data

Open access remote sensing images were integrated in this study to extract spatial information about vegetation health and LST. More specifically, information from VIS-NIR and TIR parts of the spectrum from Sentinel-2 and Landsat 8 was explored as a basis of a remote sensing driven monitoring scheme for assessing urban vegetation stressors. Moreover, open access GIS datasets such as Open Street Map were also included in the analysis (Table 3). Five factors such as distance to roads, distance to lakes, LST within park, LST around park and park were extracted from free GIS and remote sensing datasets and included as predictor variables in the statistical analysis together with the aforementioned field data (Section 2.2).

Table 3: Factors that were extracted from the open access datasets and included as predictor variables in the statistical analysis.

Predictor	Description
<i>Distance to roads</i>	Euclidean distance from trees to the nearest boulevard.
<i>Distance to lakes</i>	Euclidean distance from trees to the nearest lake.
<i>LST within parks</i>	LST as extracted from Landsat 8.
<i>LST within 150-buffer around park</i>	Average LST as extracted from Landsat 8 within a 150-buffer around each park.
<i>Park area</i>	Total area of each park.

Spaceborne sensors such as Landsat 8 and Sentinel-2 acquire images at a medium (30 m) and high resolution (10-20 m) (Addabbo et al., 2016; Pesaresi et al., 2016). Here, Landsat 8 was used for LST estimation and Sentinel-2 for calculating the vegetation indices. The Sentinel-2 image, which was acquired on August 8th, 2016, is composed of 13 spectral bands. Firstly, the image was atmospherically corrected and spectrally calibrated using the SNAP toolbox and Sen2Cor. The atmospheric correction is based on scene classification, aerosol retrieval and cloud detection using the Bands 10, 11 and 12 from the Sentinel-2 image (Louis et al., 2016). Next, vegetation indices were calculated. All the spectral bands were interpolated to have 20-m spatial resolution to match the resolution of the bands in the red-edge region.

Vegetation indices are simple numerical indicators that reduce multispectral (two or more spectral bands) data to a single variable for predicting and assessing vegetation characteristics (Delegido et al., 2011). For this study, four vegetation indices covering a large range of vegetation characteristics such as plant water stress (Moisture Stress Index (MSI)), greenness (Normalized Difference Vegetation Index (NDVI)), plant senescence (Plant Senescence Reflectance Index (PSRI)) and chlorophyll content (Red Edge Normalized Difference Vegetation Index (RENDVI)) were computed as proxies for vegetation health. They were used as response variables in the statistical analysis (Table 4).

Table 4: Vegetation indices and biophysical parameters used to assess urban vegetation status.

Parameter	Index name	Index abbreviation	Formula (Sentinel-2 bands)	Reference
Plant water stress	Moisture Stress Index	MSI	$\frac{B11}{B8}$	(Hunt and Rock, 1989)
Greenness	Normalized Difference Vegetation Index	NDVI	$\frac{B8A - B4}{B8A + B4}$	(Goward et al., 1991)
Plant senescence	Plant Senescence Reflectance Index	PSRI	$\frac{B4 - B2}{B5}$	(Sims and Gamon, 2002)
Chlorophyll	Red Edge Normalized Difference Vegetation Index	RENDVI	$\frac{B6 - B5}{B6 + B5}$	(Sims and Gamon, 2002)

For LST estimation, we used one Landsat 8 image, which was acquired on August 5th, 2016 and provided by United States Geological Survey (USGS). Landsat 8 OLI/TIRS delivers information in 11 spectral bands, among which two thermal infrared bands resampled at 30 m spatial resolution. LST was estimated based on a single-channel algorithm (Sobrino et al., 2004). This method was successfully used for LST retrieval from Landsat 8's TIR band 10. It was noted that Band 10 shows better results than Band 11 (Jimenez-Munoz et al., 2014; Yu et al., 2014).

Statistical analysis

To assess the status of urban trees, random points were generated in relation to the parks' area with an average of 5 points/1 ha. The sum of points was 1546 for all parks. For these points, the predictor and the response variables were derived. The study considered only pixels with reflectance of trees. Mixed pixels containing other elements such as water (lakes, fountains), roads, grass and elements other than trees were not included in the analysis.

Vegetation status and parameters describing the parks and their surrounding were examined using Linear mixed-effect models (LMMs). These models are suitable for testing the interactions between multiple factors where random effects can be

expected (Nakagawa and Schielzeth, 2013). Vegetation indices, as proxies of vegetation health, were used as response variables in the LMMs as a function of the parameters (predictor variables) characterizing the local settings (e.g. distance to roads, LST, closeness to fountains, closeness to construction sites). Ten predictor variables were extracted from satellite images, GIS datasets and from field observations (see also Section 2.3, 2.4).

The parks were considered as clusters or random effects which group the predictors' impact on the vegetation indices (Bates and Pinheiro, 2018). Predictor and response variables were checked for correlation higher than 0.75, and “LST within 150m-buffer around park” and “distance to construction sites” as predictor variables were removed from the dataset.

Finally, a linear mixed effect model for each vegetation index with park as a random effect was computed using the lme4 package (Bates et al., 2015) of R statistical software (R Development Core Team, 2011). The most important predictor variables were selected using backward based on the Akaike information criterion (AIC).

Results

The number of trees and tree species composition varied across the city. The parks characterized by the highest level of vegetation diversity were Carol Park (> 40 tree species), Kiseleff Park and Cismigiu Park (31-40 tree species). Unirii Park and Drumul Taberei Park contained < 20 tree species, thus their tree vegetation was more homogenous (Fig. 2).

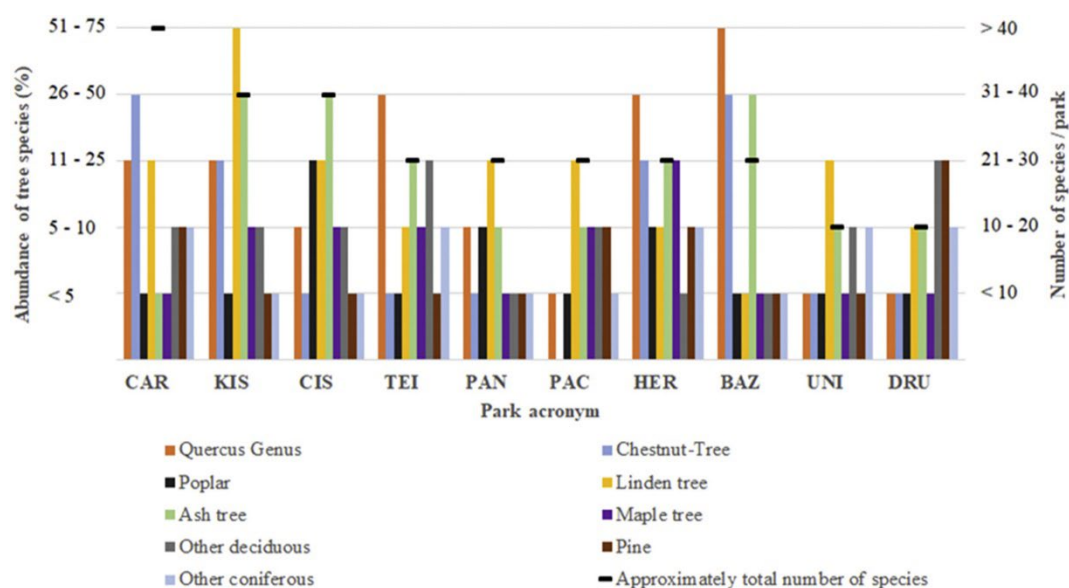


Figure 2: Summary of existing species across analyzed parks.

For example, in Carol Park, out of > 40 different tree species, chestnut-tree (*Castanea sativa*) was the most abundant species, followed by oak tree and linden tree. Kiseleff Park was covered mainly by linden tree, followed by ash tree. Cismigiu Park was characterized by three species: ash tree (26-50%), poplar and linden (each with 11-25% abundance). Unirii Park was mainly covered by other deciduous tree species, such as hornbeam (*Carpinus betulus*) and elm tree (*Ulmus laevis*), but also ash tree (11-25%). For Drumul Taberei Park, out of almost 20 different tree species, the most predominant species were pine (21-30%) and other deciduous species, such as willow (*Salix alba*), black locust (*Robinia pseudoacacia*) and cherry tree (*Prunus* genus) (21-30%) (Fig. 2). Thus, the parks of Bucharest were heterogenous in terms of tree species and density. Vegetation status in terms of chlorophyll content and moisture as derived from vegetation indices was most affected by the presence of irrigation systems, LST inside the park, distance to lakes and distance to roads. RENDVI, NDVI, MSI and PSRI proved statistically significant interaction to these individual factors with $p < .001$. Greenness (NDVI) and chlorophyll related indices (RENDVI) correlated with the presence of irrigation system, LST inside the park, distance to a lake and distance to a road (Table 5). Stress indicators for early senescence or water-related stress (MSI, PSRI) were explained by type of irrigation systems, temperature and distance to lakes.

Table 5: Summary of Linear Mixed Effect Models of the factors in relation to vegetation indices (*** $p < .001$; ** $p < .01$). Marginal R^2 with fixed factor only. Conditional R^2 with random and fixed factors.

Response variable	Explanatory Variables			Marginal R^2	Conditional R^2
MSI	Irrigation**	LST_in_park***	dist_lake***	0.19	0.77
NDVI	Irrigation***		dist_lake*** dist_roads***	0.26	0.70
PSRI		LST_in_park***	dist_lake***	0.15	0.70
RENDVI		LST_in_park***	dist_lake***	0.19	0.89

Park as a random factor explained between 0.44 and 0.6 (difference between marginal and conditional R^2) of the variation in the dataset, while the fixed factors explained between 0.15 and 0.26 of the variation. Together, random and fixed factors capture between 0.70 and 0.89 of the variation (Table 5). The tree conditions varied among the parks as indicated by the diverging estimates of the vegetation indices (Fig. 3). The estimates for greenness (NDVI) and chlorophyll content (RENDVI) were consistently opposite the estimates for moisture stress (MSI) and plant senescence (PSRI). For example, Unirii Park (UNI) reflected stressed vegetation: both MSI and PSRI were above average as indicated by the blue colored dots, while the NDVI and the RENDVI were below average as indicated by the red colored dots. The only exception was Pantelimon

Park (PAN) where PSRI was above average together with RENDVI and NDVI, and MSI was below average (Fig. 3). An example for a park with non-stressed trees was Kiseleff Park (KIS). Even though it is surrounded by congested boulevards at all edges, the neighboring area was not affected by high LST because of a lower degree of soil imperviousness. This park is covered almost entirely (75%) by a tolerant to air pollutants and drought tree species (linden tree) and it is also watered regularly through sprinklers. Moreover, it also contains a small lake (Fig. 4).

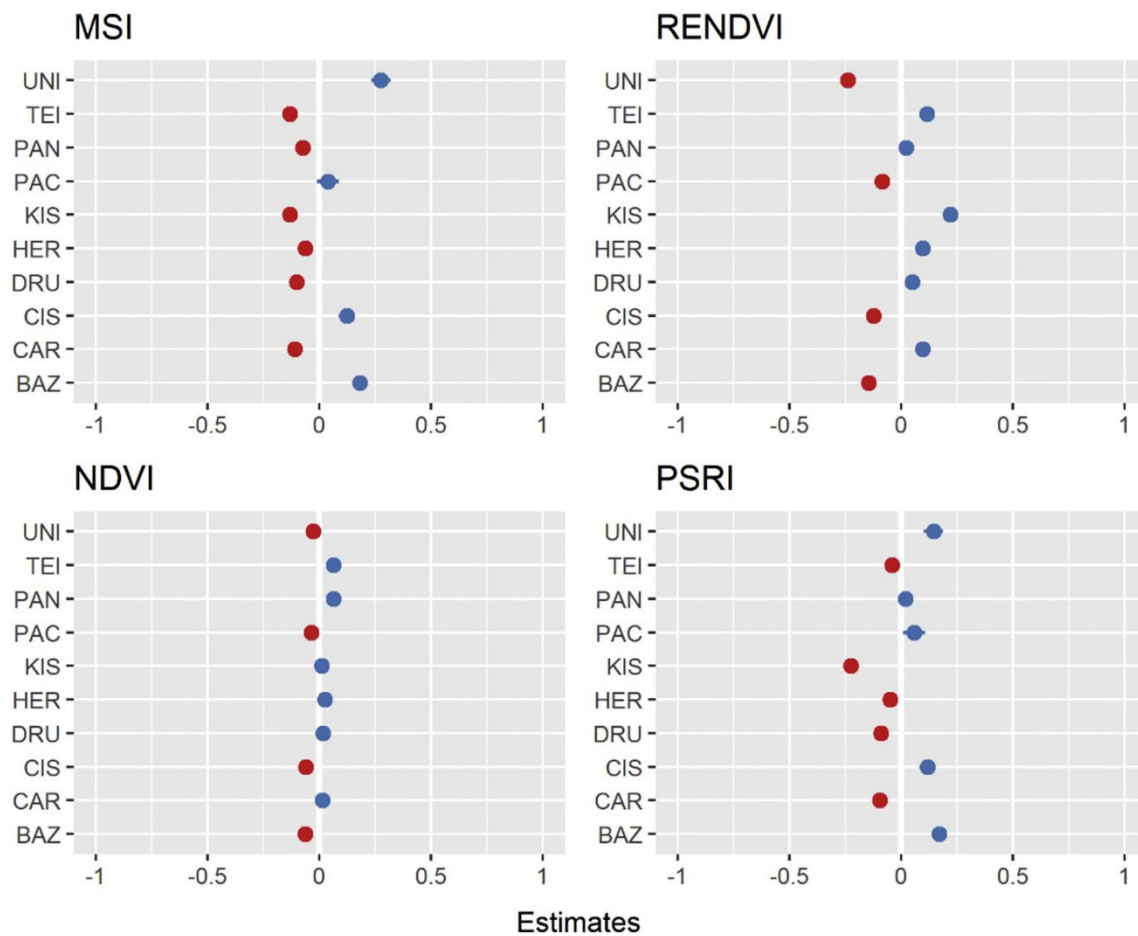


Figure 3: Summary of linear mixed effect models for each vegetation index: red colored dots indicate estimates below average (below "0"), and blue colored dots indicate estimates above average.

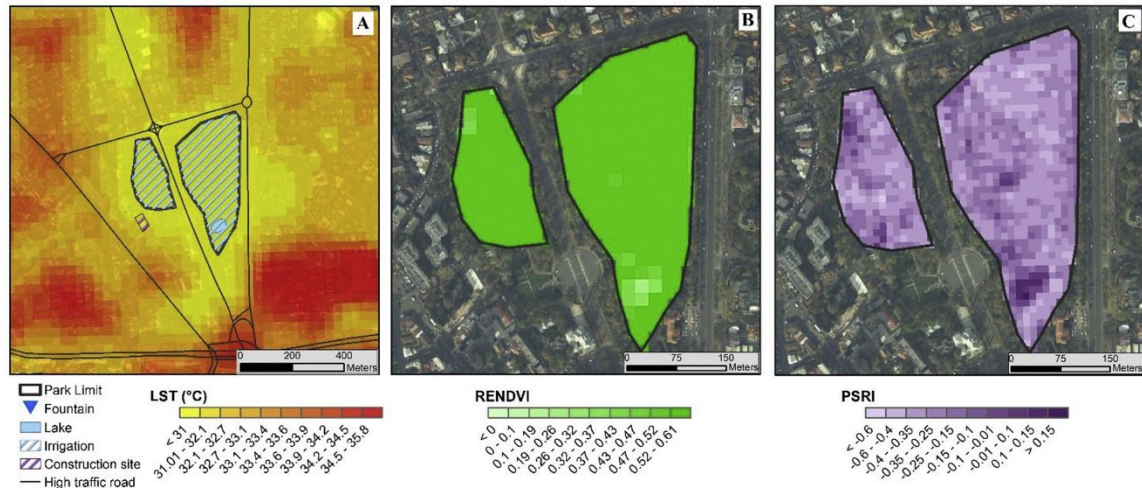


Figure 4: Estimated LST (A), RENDVI (B) and PSRI (C), detailed maps for KIS (vegetation not stressed).

In contrast, for both Unirii Park (UNI) and Bazilescu Park (BAZ) plant stress was detected. Both parks recorded low values of chlorophyll content (RENDVI) (Fig. 5, Fig. 6) and increased plant senescence in terms of elevated PSRI values (Fig. 5, Fig. 6). Unirii Park (UNI) is a small park located in the city center, surrounded by high traffic and high LST. The park was irrigated, but the second most abundant tree species was ash tree, which is sensitive to air pollutants. Bazilescu Park (BAZ) is a medium-size park located in the northern part of the city. The dominant species here were oaks, chestnut and ash. Trees from *Quercus* genus are tolerant to drought, and the park was irrigated and there was a fountain in the center. However, PSRI was increased indicating increased canopy stress for trees around the fountain (Fig. 6).

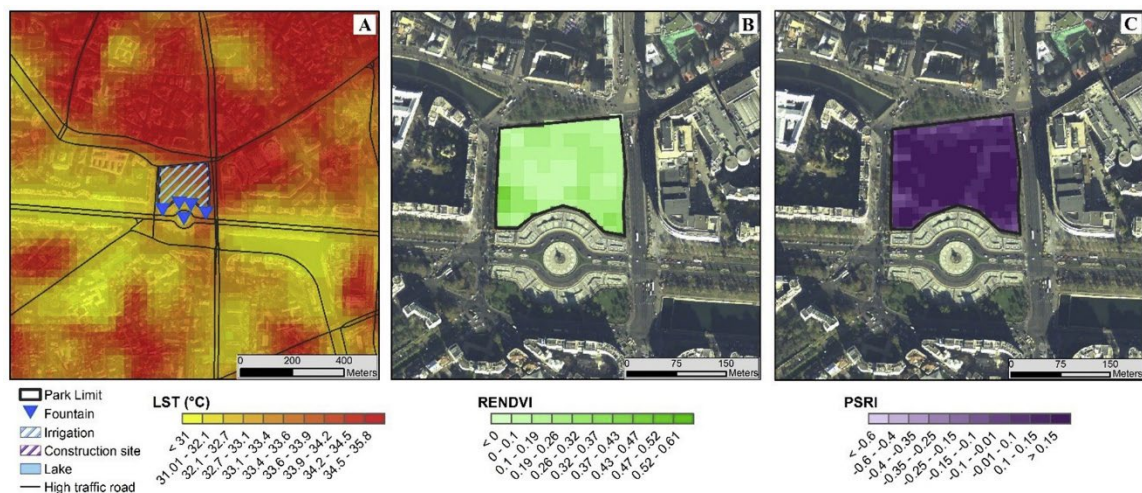


Figure 5: Estimated LST (A), RENDVI (B) and PSRI (C), detailed maps for UNI (stressed vegetation).

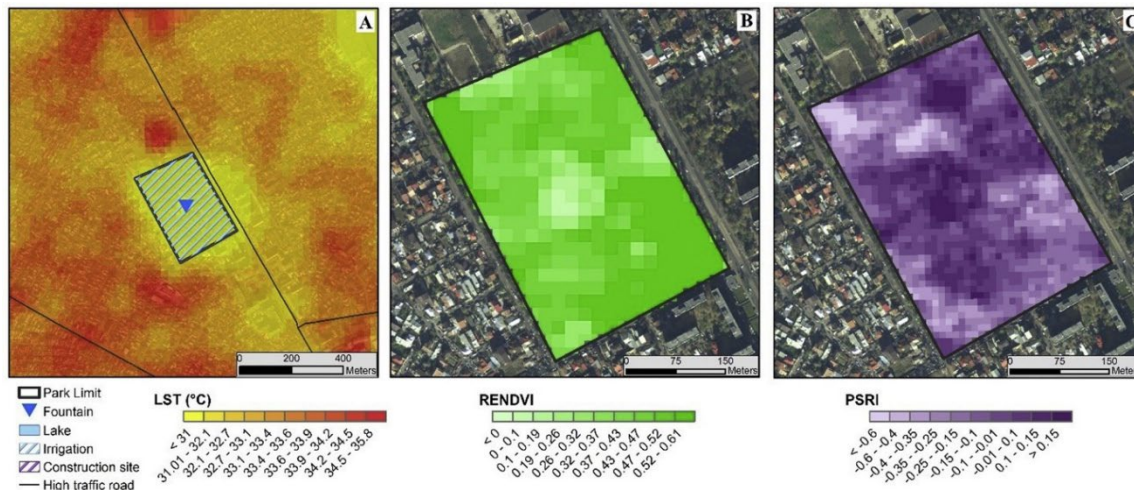


Figure 6: Estimated LST (A), RENDVI (B) and PSRI (C), detailed maps for BAZ (stressed vegetation). Source: Processed LST and PSRI datasets based on Landsat 8 and Sentinel 2 images; ortho-photo basemap offered by National Agency for Cadaster and Land Registration, 2014.

In summary, MSI and PRSI on the one hand, and NDVI and RENDVI on the other hand, showed consistently contrary patterns as response variables. Regarding the explanatory variables, the distance to lakes had a clear and significant impact on all indices (Fig. 7). The impact of stress factors depended evidently on the further park settings as shown by the high explanatory power of the random effect “park” in the mixed model approach.

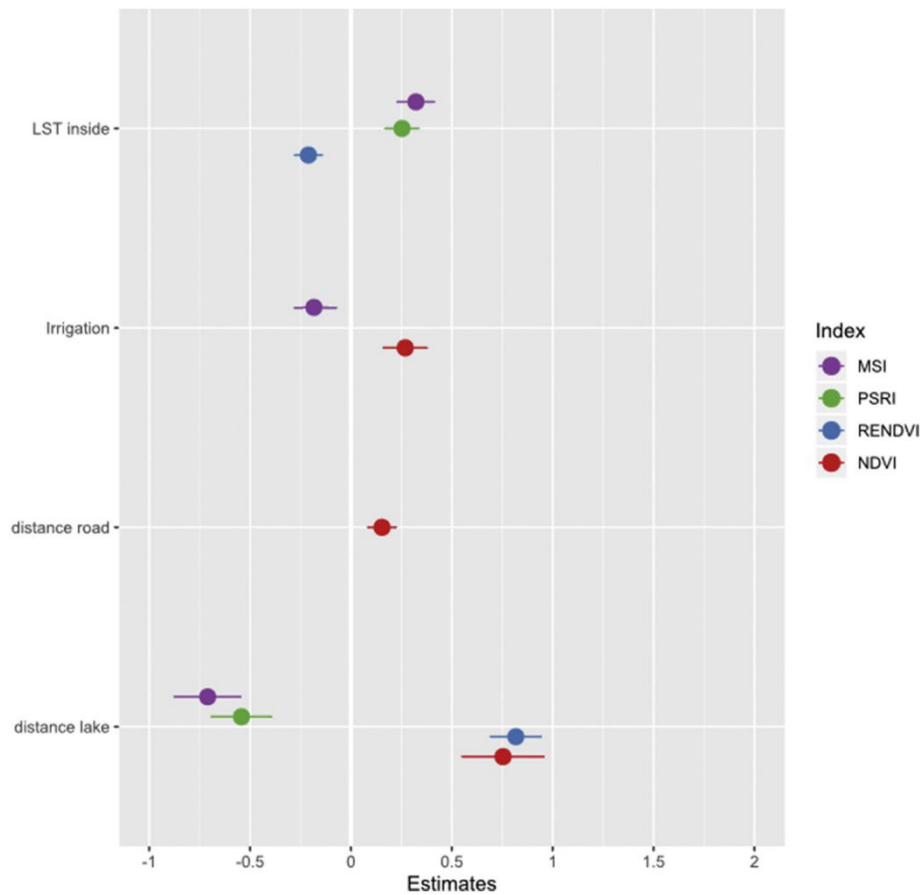


Figure 7: Forest plot showing the effect of Land surface Temperature, irrigation, distance to lakes and distance to roads to the vegetation indices MSI, NDVI, RENDVI and PSRI as proxies for vegetation health (only predictors with p level are displayed, according to Table 5).

Discussion

In our study, we explored the potential of satellite imagery to identify stressing factors for urban vegetation. Compared to similar studies that used very high resolution or hyperspectral images to assess urban vegetation health (Kundu et al., 2016; Malthus and Younger, 2000; Ramoelo et al., 2015), our study also reached encouraging results using lower spectral and spatial resolution images. The data from both EO missions, Sentinel-2 and Landsat, are freely available on a continuous and frequent basis with a spatial resolution that is appropriate for assessing urban vegetation health. Thus, spatially explicit information on urban tree health and its affecting stress factors can be assessed and visualized in a timely manner.

Specifically, we investigated at the city scale the joined impact of ten environmental stress factors on urban trees, and we identified four main factors that have an effect on urban vegetation health: presence of irrigation systems, land surface temperature, distance to lakes and distance to roads. However, we also showed that these effects

are parkspecific, and the variability among the parks needs to be considered. Earlier investigations mainly focused on specific parameters, either on traffic-related pollutants (Malthus and Younger, 2000), on heat and drought (Colombo et al., 2008) or on lack of light (Richardson and Berlyn, 2002). Other studies focused on classifying the vegetation into two classes, “healthy” or “unhealthy”, but not revealing the sources which could have had a negative impact on trees (Xiao and McPherson, 2005). There is a challenge to identify the stress factors for vegetation, especially in an urban environment where relations between natural and artificial elements are dynamic. Consequently, other studies tried to assess the impact of five different types of stress (drought, drought-and- heat, light deprivation, total saturation and chlorine poisoning) on vegetation in a controlled environment (De Jong et al., 2012). In our study, we assessed the combined impact of ten external factors on urban vegetation, for an entire European capital-city, using freely available satellite and geospatial data. As the mixed model approach showed, this study does not identify all stress factors on vegetation in a complex urban environment. Further, the importance of vegetation indices as stress indicators varies across stress factors, and a large part of the variation is explained by the random factor “park”. However, we think this study can be a starting point for future studies examining in more detail which factors impact urban tree health the most. This evaluation can guide urban vegetation management in times of climate change and urban growth. Heterogeneous site conditions can be accounted for in mixed effect models, which aim to assess ecosystem conditions based on remote sensing data (Gurung et al., 2009; Hellmann et al., 2017). Thus, we suggest joining qualitative field data (e.g. presence of irrigation systems) with quantitative publicly available geodata (e.g. vegetation indices), and applying mixed modelling approaches. By doing so, transferability to other cities would be enabled in terms of data availability, and differences of urban settings could be accounted for.

We used vegetation indices related to greenness (NDVI, RENDVI) and water stress (MSI, PSRI) as proxies for vegetation health. The response of the vegetation indices as stress indicators was not consistent across stress factors. Only for the distance to lakes, all indices indicated stressed vegetation. Thus, tree vitality was affected if there was no lake nearby. Water sources can contribute to air cooling (Völker et al., 2013), and, thus, might reduce the UHI effect on trees such as moisture stress (Cregg and Dix, 2001) and pest damage (Meineke et al., 2013). On the other hand, for the distance to roads, only the NDVI showed the effects on tree health. Trees are preferable planted close to roads because they are known to reduce noise (Kalansuriya et al., 2009; Watts et al., 1999)

and to mitigate the effect of traffic-related pollutants such as NO₂ (Tomašević et al., 2005; Soares et al., 2011; Grundström and Pleijel, 2014; Nowak et al., 2018), PM_{2.5} and coarse PM (Viippola et al., 2018).

Regarding the presence of irrigation systems, the NDVI and the MSI were found to be important predictors for vegetation health for the sampling period (August, mid of summer). Indeed, the continuous heat waves that struck Bucharest in the past years led to premature loss of chlorophyll and even early defoliation of the tree crown starting with the month of June. Usually, the lack of water is compensated by irrigation systems. However, irrigation systems in the parks of Bucharest do not cover the entire green area or they are scarce (Nae and Turnock, 2011) or sometimes malfunction. Field observations noted some countermeasures such as cars draining water from the nearby lakes to substitute the lack of proper irrigation systems. The NDVI based on very high resolution data has been linked to the evapotranspiration of urban trees (Nouri et al., 2013), while the MSI was successfully applied to map soil moisture and vegetation water content of crops (Benabdelouahab et al., 2015). Further, the MSI can be an indicator of environmental pollution (Nouri et al., 2013; Ozigis et al., 2019), which can result in water stress. Considering that the type of irrigation system had a relation with all analyzed vegetation characteristics, park management should find proper solutions for meeting the need of water supply. In future studies, it could be tested if these measures can be guided and monitored using the NDVI and MSI derived from satellite data. Similarly, LST inside the park is another factor which affects the greenness and, overall, the stress level. As in other studies (Paunescu et al., 2013; Scherrer et al., 2011), high temperatures and water stress had a major impact on vegetation status. Here, in addition to the MSI, which is related to water content (Nouri et al., 2013), the PSRI and the RENDVI were important proxies of vegetation status. While the PSRI can indicate changes of phenology due to changes of temperature (Lang et al., 2019; Nouri et al., 2013), as well as leaf senescence (Castro and Sanchez-Azofeifa, 2008), the RENDVI is related to chlorophyll content (Lang et al., 2019; Sims and Gamon, 2002), but it was also linked to drought-related changes of leaf photosynthetic rates (Lang et al., 2019; Sims and Gamon, 2002) and water stress (Castro and Sanchez-Azofeifa, 2008; Van Beek et al., 2013). In sum, no single vegetation index indicated stressed vegetation for all potential factors. Therefore, the choice of vegetation indices to assess urban tree health needs to be considered carefully. As urban ecosystems are characterized by distinct environmental gradients related to plant stress (Calfapietra et al., 2015; Cârlan et al., In press), further studies are encouraged to establish links between remotely

sensed proxies of vegetation health and field ecophysiological measurements in contrasting urban settings. Parks as a random effect had a great influence in the predictive models. This points out that the configuration of the parks has to be examined further to find additional factors that have an effect on vegetation health. For example, RENDVI shows decreased tree health in Unirii Park (UNI), Pacii Park (PAC) (Figs. 8, 9), Cismigiu Park (CIS) and Bazilescu Park (BAZ). The first two parks are small-sized, while the last two are medium-sized. All of them are surrounded by high LST values due to a high degree of soil imperviousness. A small-sized park characterized by drought stress could be a trigger for early senescence, as parks deliver ecosystem services according to their size (Vieira et al., 2018). Unirii Park is located in the city center, at the crossroad of four main boulevards. Pacii Park is the only green area the western part of the city, along a main boulevard. The congested traffic every day is the main source of NO₂ emissions. When its critical levels are exceeded for extended periods of time, it has a negative impact on trees (Mills, 2017). In contrast, Kiseleff Park (KIS) is an example of a park with less stressed vegetation than others. Here, the species composition is heterogeneous, but the dominant species is linden tree. It covers almost 75% of the entire park's area. This air-pollutant resilient species has regular access to water through irrigation system and it can deliver proper ecosystem services. Therefore, in this park, trees are properly managed and the people can benefit from their regulatory services. As the impact of pollutants on tree health could be species dependent, we recommend for future studies to include spatiotemporal data on air pollutants together with tree species maps along urban-rural gradients. Considering that only healthy vegetation can deliver proper ecosystem services, we stress the importance of monitoring vegetation status using low-cost, fast and reliable methods based on open access satellite images. These images have suitable characteristics for urban studies (Bolund and Hunhammar, 1999; Malthus and Younger, 2000). We identified important environmental predictors and their interactions in relation to vegetation indices as proxies for vegetation health. However, it is worthwhile to emphasize that more factors need to be identified, for example through satellite time series analysis to identify early warning indicators of plant stress due to climate change (Liu et al., 2019), by linking further field physiological with geospatial data (Calfapietra et al., 2015), and in standardized trans-city comparisons. The availability of free and open data as used in this study are essential for this kind of analysis. Consequently, new satellite missions are being developed that focus on plant stress due to drought such as the FLEX mission by the European Space Agency (Coppo et al., 2017), which will measure photosynthetic

activity, and ECOSTRESS by NASA (Hulley et al., 2017), which is mapping evaporative stress. Thus, we see a high potential for monitoring urban green infrastructure and the impact of the urban heat islands in times of climate change and increasing urbanization using publicly available earth observation data, which can guideline decision-making process for a sustainable development of cities.

Conclusions

Open access remote sensing data along with qualitative field observations enable the identification of stress factors and their combined interaction on tree status in urban parks. However, the effects of these factors on vegetation status can vary across sites in heterogeneous urban environments. In addition, a combination of remote sensing indices related to different vegetation properties might be required to map the effect of stressing factors on vegetation status. Thus, mapping the status of trees in complex urban environments is possible, but the local environmental context needs to be considered. Furthermore, both the stress indicators and the stress factors need to be assessed with care. The approach in this study ensures transferability because it is based on publicly available data and free software, and because it uses mixed models that can account for the context dependency, which is necessary for comparative studies. Further studies along urban-rural gradients are encouraged. We emphasize the potential to link data from new satellite missions, which map evaporative stress and photosynthetic activity at a high temporal resolution, with detailed field data on tree physiology and environmental pollutants. This would facilitate identifying and disentangling biotic and abiotic stress factors, and, therefore, account for the context dependency of urban tree stress. Altogether, there is a high potential to use free remote sensing data as a basis for monitoring schemes of urban green infrastructure to ensure the provision of important urban ecosystem services in times of global change.

Acknowledgements

The authors are thankful to Dr. Jens Oldeland (University of Hamburg, Germany) for supervising the statistical work and for stimulating discussions. We also appreciate the valuable comments of the editor and two anonymous reviewers that greatly improved the manuscript.

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Chapter 9

Mapping heat and traffic stress of urban park vegetation based on satellite imagery - A comparison of Bucharest, Romania and Leipzig, Germany

Irina Cârlan^{1,}, Dagmar Haase^{2,3}, André Große-Stoltenberg^{4,5}, Ionut Sandric⁶*

¹Simion Mehedinti Doctoral School, University of Bucharest, Faculty of Geography, 1 Nicolae Balcescu Blvd, 010041 Bucharest, Romania

²Department of Geography, Lab for Landscape Ecology, Humboldt Universität zu Berlin, Rudower Chaussee 16, 12489 Berlin, Germany

³Department of Computational Landscape Ecology, Department of Environmental Immunology, Helmholtz Centre for Environmental Research—UFZ, Permoser Straße 15, 04318 Leipzig, Germany

⁴Institute of Landscape Ecology, University of Münster, Heisenbergstr. 2, 48149 Münster, Germany

⁵Division of Landscape Ecology and Landscape Planning, Institute of Landscape Ecology and Resource Management, iFZ Research Centre for Biosystems, Land Use and Nutrition, Justus-Liebig University Gießen, Heinrich-Buff Ring 26-32, 35392 Giessen, Germany

⁶Department of Regional Geography and Environment, University of Bucharest, Faculty of Geography, 1 Nicolae Balcescu Blvd, 010041 Bucharest, Romania

*Corresponding author

Abstract

Large and comparatively compact European cities such as Bucharest and Leipzig struggle with considerable urban heat island (UHI) effects characterized by heat and drought together with high concentrations of air pollutants (NO_2 , SO_2 , O_3 , CO_2). However, a healthy urban green infrastructure is necessary to reduce the impacts of UHI on human health. Therefore, continuous monitoring schemes are required for green infrastructure in order to improve human life in such cities. Satellite remote sensing can provide the means for monitoring urban vegetation status. In this study, vegetation indices, mostly based on the spectral bands located in the red-edge region, were computed from Sentinel-2 imagery, and land surface temperature (hereafter LST) was estimated from Landsat 8 data. The aim was to assess the individual and cumulative effects of both vicinity to roads and estimated LST on tree vegetation health in urban parks using analysis of variance. Vegetation indices indicated stressed vegetation. However, tracking urban tree health required a combination of indices, and therefore of spectral ranges, rather than one specific index alone, as the effect sizes varied between parks, cities and along the centre-periphery gradient. Therefore, spaceborne data can provide spatially-explicit indicators for stressed urban vegetation and, thus, decreasing ecosystem services delivery. Future studies are encouraged to decipher further the relation the spatial configuration of urban systems and remote sensing based stress indicators of urban trees using publicly available datasets to enable comparative studies.

Keywords

Land surface temperature, Air pollution, Green infrastructure, Stressed vegetation, Landsat 8, Sentinel-2

Introduction

Among the most pressing environmental features that European cities face nowadays are air pollution and the urban heat island effect (Weber et al. 2014b). These stressors have an effect on urban vegetation status (WHO 2000b; Mills 2017; Smithers et al. 2018) and, ultimately, on the human health (Currie and Bass 2008; Baró et al. 2014). The pollutants responsible for deteriorating urban air quality and affecting human health directly are oxides of nitrogen (NO_x), sulfur dioxide (SO_2), carbon monoxide (CO) and particulate matter (PM) (Gulia et al. 2015). The main urban sources of air pollution are traffic and industrial activities, as well domestic fuel burning for heating facilities (Karagulian et al. 2015). Traffic is increasing in many European cities, mainly due to the extended car use (Weber et al. 2014a). The urban heat island effect describes the phenomenon of increased temperatures in urban areas when compared to their rural surroundings (Nastran et al. 2019). Assuming that only little pervious surface exists within a city, meaning that less energy is used in evaporating water, then less solar energy is reflected and more heat is stored by buildings and the ground in urban compared to rural areas (Schwarz et al. 2011; Nastran et al. 2019).

Urban vegetation can deliver a full range of ecosystem services and counteract both heat and air pollution stress (Baró et al. 2014; Livesley et al. 2016; Vieira et al. 2018). Previous studies showed vegetation's role in mitigating the effects of urban heat island (Georgi and Zafiriadis 2006; Weber et al. 2014b; Smithers et al. 2018) and in decreasing air pollution (Nowak et al. 2018). Both ecosystem services result in an improvement of the citizen's life. Vegetation performs better when it is in a good physiological state and thus being able to collect particles on the leaves and capture NO_2 , SO_2 and O_3 by stomata processes (Lausch et al. 2016; Vieira et al. 2018). Therefore, it is necessary to assess vegetation's health in order to determine whether or not and how well urban vegetation can provide urban ecosystem services related to the Sustainable Development Goal (SDG) of human well-being (UN General Assembly, 2015).

Vegetation health can be studied using non-invasive reliable tools, which assess spectral traits. State-of-the-art Earth Observation technology acquires important information over large areas, which can be both basis and support for decision-making processes in urban planning (Lausch et al. 2016). In particular, vegetation indices based on two or more spectral bands are promising means to extract physical, biochemical, and ecophysiological characteristics of vegetation. The spectral and spatial characteristics of publicly available remote sensing data acquired by Landsat 8 (Zhao et al. 2017) and

Sentinel-2 (Drusch et al. 2012) have high potential for urban applications (Frampton et al. 2013; Addabbo et al. 2016; Pesaresi et al. 2016). Sentinel-2 acquires multispectral data in narrowband, valuable for assessing vegetation state (Frampton et al. 2013). Previous studies clearly show a relationship between environmental factors and vegetation state. The impact of air pollutants is explored by research such as of Tomašević et al. (2005), Säumel et al. (2012), Van Wittenberghe et al. (2013), while the urban heat island effect characterized by heat and drought is investigated by Nouri et al. (2013), Paunescu et al. (2013) and Kunz et al. (2016). Moreover, Landsat-8 delivers images with thermal infrared (TIR) bands which allow the estimation of LST over large areas and also canopy temperature, a key monitor of photosynthesis, respiration and transpiration (Roberts et al. 2015). Previous studies focus on very high resolution, commercial data (Nouri et al. 2013).

Thus, we identified a research gap for combining high spatial resolution open access data from multiple platforms sensors to assess urban vegetation health, especially in compacted densely populated areas. Since most studies analyze urban vegetation stress as a response to only one parameter (Säumel et al. 2012; Kunz et al. 2016), we will address the combined effect of multiple environmental factors on urban vegetation status.

Two cities with similar urban structure were chosen for this study: Bucharest, Romania, and Leipzig, Germany. Both cities are very well comparable in terms of their size, the distribution of land cover classes within the city, the existing tree species and environmental changes and pressures that both cities underwent in the past and recent years. This is due to the cities' post-socialist past including suburban sprawl, increasing car numbers and increasing built-up densities (Chiriac et al. 2009; Weber et al. 2014a), housing vacancies in the inner city and large industrial brownfields and unused places across the cities' area (Haase et al. 2017). Both cities record an exceedance of NO₂ and SO₂ critical values for vegetation in and around the city center (WHO 2000a; Leeuw and Ruysenaars, 2011; Mills 2017). Air pollution increases during the winter because of heating based on fossil fuels like coal and natural gas, which affects vegetation on long-term (Iloja 2009).

Urban environments represent complex ecosystems where numerous elements mutually interact and where the relationship of causality is very dynamic (McPhearson et al. 2016). The difficulty for an accurate statistical modelling of causal relationships or chains initiated e.g. by urban heat in urban environments comes from the multiple elements and their connecting variables that form each feature. Everything adds up to

the complex aggregate that is the urban environment (Breuste et al. 2013). Thus, urban ecosystems are heterogeneous, and the impact on urban vegetation health is context dependent, so the results from single sites might not be transferable. As a consequence, we propose an approach to identify the most affected parks across two cities using freely available remote sensing data.

The specific objectives of this study are 1) to compare public parks' vegetation status in Bucharest and Leipzig along an urban-to-rural gradient, and 2) to assess the impact of the vicinity to roads and LST on vegetation vitality and their joined impact on each park based on open access remote sensing data.

Material and methods

Study areas

Bucharest and Leipzig are characterized by an intensive urbanization after the communist fall in 1989 (Mihai et al. 2016) and the German reunification in 1990 (Weber et al. 2014b). This process is represented mainly by land cover conversion (e.g. pervious surfaces transformed into residential facilities or large commercial areas), which lead to an overall increase of built-up areas.

Bucharest is located at 44°25' North latitude and 26°06' East longitude and it covers 230 km², with a population of approximately 2 million inhabitants. Leipzig is located at 51°20' North latitude and 12°23' East longitude and it covers 300 km², with approximately 600.000 inhabitants. Annual mean temperatures of both cities are similar. Bucharest records 10 °C (Ioja 2009) and Leipzig 9 °C (Weber et al. 2014b), with tendency to increase in the future years. (Ioja 2009; Weber et al. 2014b).

In order to provide a standardized comparison method from the center to periphery, the two cities were split into five multirings that cover their entire administrative areas. The radius of each ring is 2-km, based on the urban development phases observed during field campaigns. These multi-buffers deliver a straightforward understanding of the land cover variation from the city center to periphery (Fig. 1). What is more, it provides the context for visualizing the variation of LST and air pollutants across the five circular sections.

Both city centers are mostly covered by built-up area, almost 90%, followed by urban green area, varying from 9 to 10%. Comparing the rest of the circular sections, built-up coverage decreases in favor of pervious land cover classes such as agricultural land or forest (Table 1). Leipzig records a larger percentage of green urban areas because its

parks are larger than the ones in Bucharest thanks to the floodplain forests in the heart of the town (Haase 2003). Also, agricultural area is present in the outskirts of Leipzig due to intensive land use for farming and fertile loess soils, a tradition that was never abandoned around German cities (Haase et al. 2017). In Romania, newly built residential neighborhoods replaced abandoned areas or agricultural land in the city's outskirts after 1990 (Mihai et al. 2016).

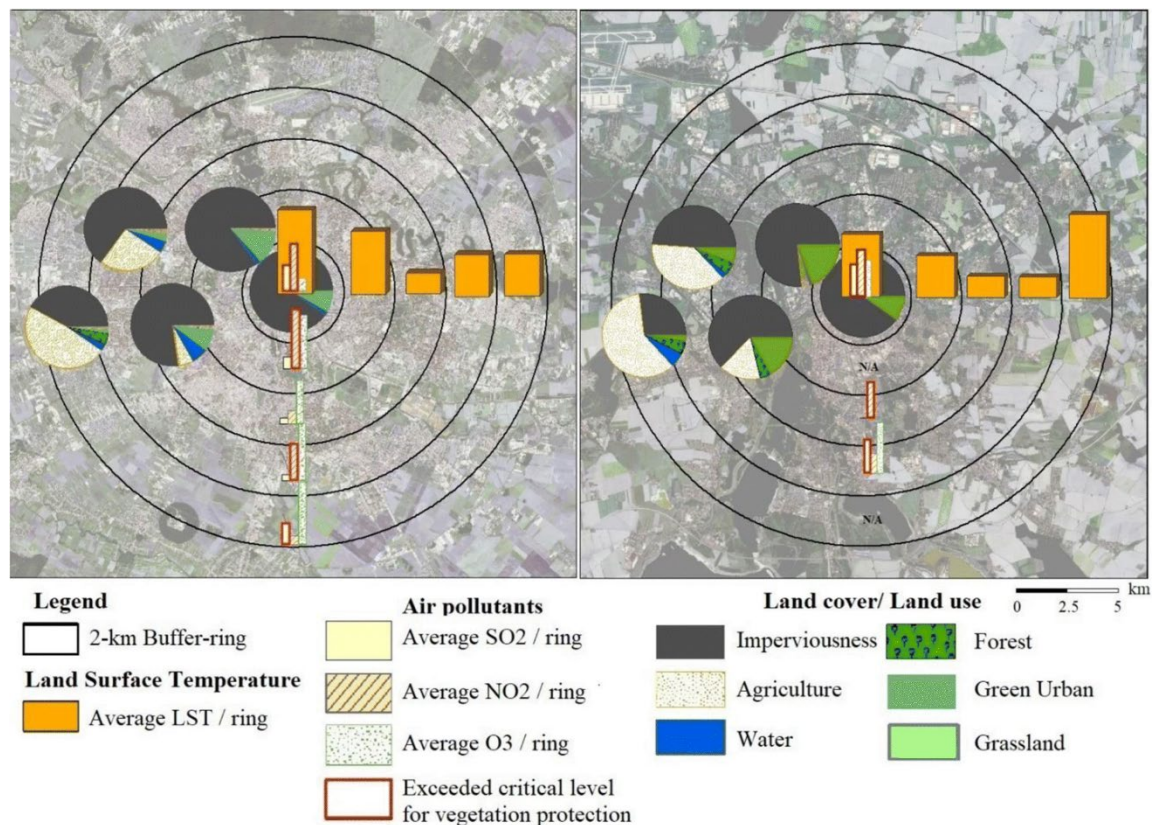


Figure 1: Multi-ring buffer around city center. Images show percentages of LCLU classes for each ring, average values of LST for each buffer ring and the annual means of air pollutants for each buffer ring. Source: Processed Air pollution data from National Agencies (No data available for Leipzig for all rings); Land cover/ Land use data from Urban Atlas 2012 (Meirich 2008); Processed LST data from Landsat 8 imagery; Basemap from Sentinel-2 imagery.

Temperature values in Bucharest are overall higher than the ones recorded in Leipzig due to its more southern location. However, some distribution patterns can be observed according to which average temperature values computed for each ring decrease from city center to suburbia. The fifth ring of Leipzig is covered mainly by agricultural land. Critical thresholds for NO₂ are exceeded in and around the city centers, while closer to suburban areas SO₂ critical thresholds are exceeded. Exceeded values are indicated with red borderline for each air pollutant (WHO 2000a; Leeuw and Ruysenaars, 2011; Mills 2017).

Table 1: Land cover and land use class percentages for each city and mean LST values per each buffer-ring (with B = Bucharest, L = Leipzig). Source: Land cover/ Land use data from Urban Atlas 2012 (Meirich 2008); Processed LST data from Landsat 8 imagery.

	Multi-Ring Buffer	Built-Up	Green	Urban Areas	Agriculture	Forest	Grassland	Water	LST (°C)
1		89.8	8.6	-	-	0.2	1.4	33.5	
2		84.6	12.1	0.8	-	1.0	1.5	32.9	
B 3		76.9	8.9	5.9	0.3	1.4	6.5	32	
4		64.1	2.7	25.9	0.8	1.9	4.6	32.3	
5		41.8	1.3	48.7	4.5	1.0	2.6	32.3	
1		89.0	9.8	-	-	1.2	-	25	
2		75.8	18.7	3.0	0.1	1.2	1.2	24.6	
L 3		61.9	17.2	15.7	3.7	0.8	0.8	23.7	
4		49.0	5.8	37.5	5.4	0.8	1.5	23.8	
5		27.1	1.8	60.1	5.1	0.4	5.6	25.5	

Both countries have similar proportion of passenger cars in terms of used engine fuel. However, alternative energy is preferred by 1.58% of all cars in Germany, whilst in Romania the market for environment-friendly fuel is expanding slowly; only 0.14 of all cars use alternative energy (European Commission 2017). On the other hand, both countries are above the average values in the European Union in terms of emissions of CO₂ per km (Fig. 2). Thus, traffic is still a major contributor to air pollution throughout old cars which run on diesel or petrol.

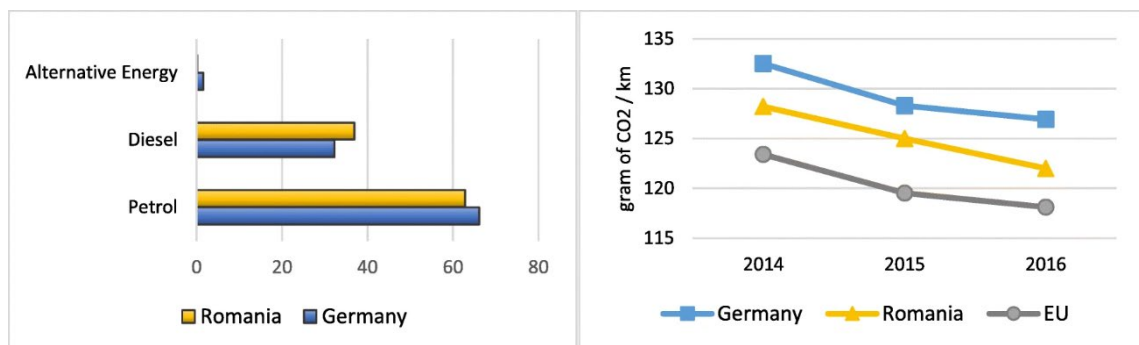


Figure 2: Proportion of passenger cars by combustion (left) and Average CO₂ emissions per km from new passenger cars (right). Source: Eurostat, Passenger cars in the EU, European Commission, 2017.

For the vegetation vitality comparison, ten parks within each city were selected (Fig. 3). The parks have different characteristics: their sizes range from 3.5 ha to 110 ha for Bucharest and from 1 to 109 ha for Leipzig; they are located across all five urban circular sections; they have different irrigation systems; their micro-climates are characterized by different temperature values (Table 2).

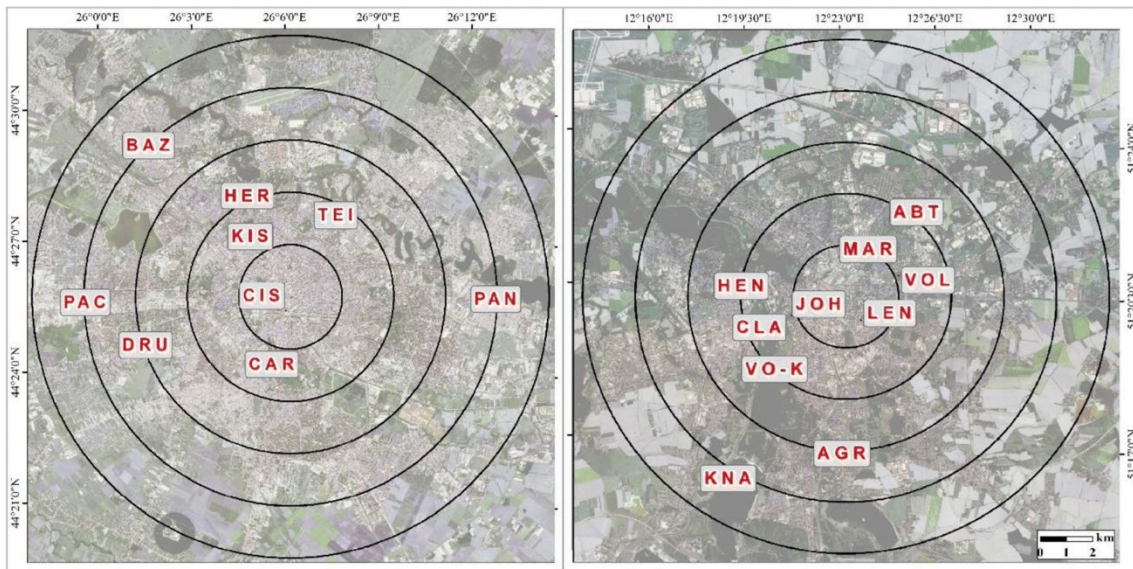


Figure 3: Spatial distribution of selected parks for Bucharest (left) and Leipzig (right). Source: Basemap from Sentinel-2 imagery.

Field observations revealed that parks in Leipzig are only irrigated by sprinkler systems, whilst for Bucharest the management system requires complex preservation with complementary solutions: sprinkler systems and, for some parks, additional solutions such as water transported by cars or by garden hoses from the nearby lakes (Table 2). Parks are popular among citizens as they deliver a good environment for spending time, no matter their location inside the city or their size. Generally, parks with a small area are cleaner than the ones with a large area, possibly because they are easily maintained. CIS is a famous park in Bucharest which is visited by many citizens and tourists because it delivers great vegetative landscape with many species and because it is the biggest park located in the city center. It was built on top of a swamp and nowadays it contains a lake. KIS is a well-maintained park, one of the cleanest parks in Bucharest, also centrally located, but the number of visitors is reduced because the average time for visitors is limited to a couple of minutes.

In Leipzig, the sample includes two different types of parks: old, 19th and early twentieth century founded, public parks that are mostly in the style of former English landscape gardens such as MAR, VOL or ABT. Other parks are considerably younger created after 1990 in line with a larger-scale revitalization of industrial and railway brownfields in the inner parts of the city such as LEN or HEN. The latter park type is different concerning its biophysical conditions as brownfield soils are often less deep, less humid and more porous than the natural loamy soils the old parks and their trees stock on. Moreover, the water holding capacity of the brownfield- parks is considerably

lower than that of the old parks. Last but not least, the age of the trees in both revitalized areas, LEN and HEN, is less than in all other parks although we also find there some old trees being remnants of the former (railway side green) land use (Haase 2001).

Table 2: Park characteristics and information

City	Park Name (acronym)	Park Name (long name)	Area (ha)	In-ground irrigation	Other solutions for irrigation	Visitors	Cleanliness
B	CIS	Cismigiu Gardens	16	X	X		
	UNI	Union Park	3.5		X		
	KIS	Kiseleff Park	31	X			
	CAR	Carol Park	41		X		
	HER	Herastrau Park	110	X	X		
	TEI	Tei Park	9	X			
	DRU	Drumul Taberei Park	30	X			
	PAN	Pantelimon Park	52	X			
	PAC	Peace Park	2.5	X			
	BAZ	Bazilescu Park	14	X			
L	LEN	Lene-Voigt-Park	5				
	MAR	Mariannenpark	19				
	VOL	Volksgarten	4				
	ABT	Abtnaundorfer Park	19				
	CLA	Clara-Zetkin-Park	109	X			
	JOH	Johannapark	11				
	HEN	Henriettenpark	1				
	VO-K	Volkspark	45				
		Kleinzschocher					
	AGR	Agra-Park	13	X			
	KNA	Knauthainer Park	10	X			

Datasets and methods

In Earth Observation, there is usually a compromise between spatial and spectral resolution because of the mixed spectral response within a pixel and the free availability of data (Thenkabail et al. 2012). Here, multispectral satellite imagery (Landsat 8 and Sentinel-2) that matched vegetation peak season (August) was combined with additional spatial information such as air pollution data from National Environmental Agencies, road network from Open Street Map and datasets distributed within the framework of Land Copernicus Program (Table 3).

Remote sensing based spectral indices offer information related to plant traits such as leaf biochemistry, photosynthetic processes and canopy structure (Homolová et al. 2013). However, vegetation indices based on spectral bands located in the red-edge region have lower background effect and are known to be positively correlated to

pigments and nutrients, especially chlorophyll (Ramoelo et al. 2015; Gholizadeh et al. 2016). Satellite images were used to extract information for each park.

Table 3: Datasets used in analysis and sensor characteristics

Dataset	Sensor/ Source	Provider	Acquisition date Bucharest	Acquisition date Leipzig	Resolution/ MMU	Spectral Bands
Land Surface Temperature	Landsat 8 imagery	USGS	August 5, 2016 (DOY 218)	August 18, 2016 (DOY 231)	30 m (15 m panchromatic)	11 Spectral Bands
Vegetation indices	Sentinel-2 imagery	ESA	August 8, 2016 (DOY 221)	August 27, 2016 (DOY 240)	10, 20, 60 m	13 Spectral Bands
Land Cover/ Land Use	Urban Atlas	ESA - Copernicus Land Program	2012	2012	1 ha	-
Degree of imperviousness	Imperviousness Layer	ESA - Copernicus Land Program	2012	2012	20 m	-
Monthly mean values of air pollution	Air pollution data	National Agencies http://www.anpm.ro http://statistik.leipzig.de/statcity/index.aspx	2012	2012 (No data available for Leipzig for all stations)	-	-

Firstly, images from spaceborne sensors were atmospherically corrected and spectrally calibrated using the appropriate bands for aerosol retrieval and cloud detection (Louis et al. 2016). Secondly, narrowband and broadband vegetation indices as proxies for biophysical and biochemical plant parameters such as chlorophyll content, moisture and foliar structure were extracted from Sentinel-2 images using ENVI software (Exelis Visual Information Solutions, v5.3) and SNAP Toolbox (SNAP - ESA Sentinel Application Platform, v5.0) (Table 4). LST was estimated based on a single-channel algorithm as developed by (Sobrino et al. 2004) using ENVI software. This method was successfully used for LST retrieval from Landsat 8's TIR band 10. Previous studies show that band 10 shows better results than band 11 (Jiménez-Muñoz et al. 2014; Yu et al. 2014).

Table 4: Vegetation indices used in urban vegetation stress/state analysis

Indicated parameter	Index name	Index abbreviation	Formula	Reference
Chlorophyll	Chlorophyll Red-Edge	Chl Red-edge	$\frac{B7^{-1}}{B5}$	(Gitelson et al. 2006)
Chlorophyll	Red Edge Normalized Difference Vegetation Index	RENDVI	$\frac{B6 - B5}{B6 + B5}$	(Sims and Gamon 2002)
Chlorophyll	Plant Senescence Reflectance Index	PSRI	$\frac{B4 - B2}{B6}$	(Sims and Gamon 2002)
Chlorophyll; LAI	Simple ratio	SR	$\frac{B8}{B4}$	(Blackburn 1998)
Water	Moisture Stress Index	MSI	$\frac{B11}{B8}$	(Ceccato et al. 2001)

Analysis

Due to a given normal distribution of the data values of all samples, correlations were reported using the Pearson coefficient which is frequently used in many environmental studies (Govindaraju et al. 2012; Tote et al. 2014). Here, the Pearson coefficient was used to test the strength of the association between (a) LST and imperviousness degree and (b) LST and park's area. Moreover, the relationship between vegetation indices and average LST estimated inside a buffer zone around parks was tested. This analysis provides the context for assessing the strength of vegetation for decreasing temperatures around it, within a buffer of 150 m (Du et al. 2017). The number of random points distributed across each city is $n = 375$.

Analysis of variance (ANOVA) was applied to investigate the individual impact of traffic, temperatures and their joined interaction on vegetation status. Values of the vegetation indices were taken as the response variable and parameters, which characterize the local settings were integrated as explanatory variables. Vegetation indices were considered significant at the $p < 0.10$ level (Dahiru 2011). In addition, the effect size η was calculated for each ANOVA test in order to identify how important the difference between the groups is. The values of η were reported from 0 to 1 (Richardson 2011). Results were reported using three classes of effect size magnitude: small, medium, large (Richardson 2011).

All statistical analyses were done using SPSS Statistics 13.0 (IBM Corp 2013). Three NULL hypotheses were tested for each park:

- (1) H_0 : Distance to roads has no significant effect on vegetation indices.

(2) H0: Land surface temperature recorded within park has no significant effect on vegetation indices.

(3) H0: Joined interaction of distance to roads and land surface temperature has no significant effect on vegetation indices.

The threshold of $p < 0.10$ was used to reject the NULL hypotheses and to accept the alternative hypotheses:

(1) H1: Distance to roads has significant effect on vegetation indices.

(2) H1: Land surface temperature recorded within park has significant effect on vegetation indices.

(3) H1: Joined interaction of distance to roads and land surface temperature has significant effect on vegetation indices.

Results

One major result of our study is the finding for the correlation between high LST and high degree of imperviousness. Leipzig records a higher value of positive correlation $r = .710$ at p value = 0.01 than Bucharest. Leipzig reports an overall larger variance of LST across the entire city compared to Bucharest. Bucharest records a $r = .666$ at a p value = 0.01. In the case of testing the linear association between the average LST within the 150-m buffer around the parks' areas ($n = 10$), r reveals a negative correlation.

The context of vegetation indices was studied using boxplots representing average values of vegetation indices for each analyzed park (Fig. 4). The processed data was cleaned and the outliers were removed.

Average LST values calculated around the parks in Leipzig reveal a strong positive correlation with Chl Red-Edge, PSRI, RENDVI (chlorophyll content indicators) and MSI (moisture stress indicator) (Table 6). On the opposite pole, the correlations between the average values of vegetation indices and average LST around the parks in Bucharest are not similarly strong. Some indices get close to a good positive correlation ($r \sim 0.5$). Another important result of our study shows the impact of traffic-related pollution and heat, taken as two individual factors, on vegetation health. Moreover, their combined impact is tested for being a cumulative stress for vegetation. Values of effect sizes were used for mapping the individual and the cumulative stress of the two analyzed factors on urban trees. All the charts corresponding to each park were mapped for Bucharest and Leipzig, showing the differences between the groups.

Comparing the summary results of the Two-way ANOVA between the external factors and vegetation status and tree vegetation, we can observe that some parks report a

higher number of vegetation indices with statistical significance: CAR, HER, PAC, BAZ in Bucharest and CLA, AGR in Leipzig (Table 7).

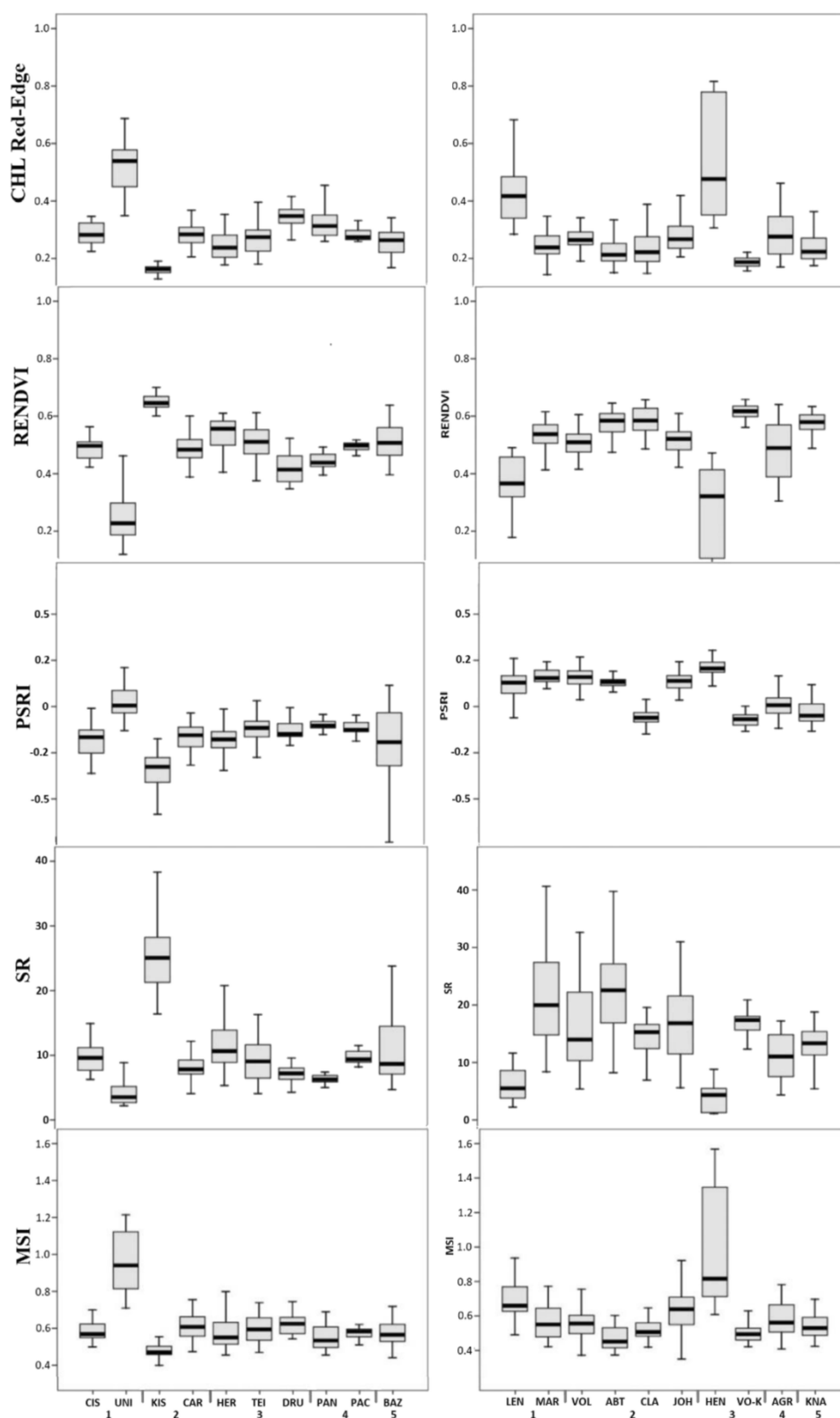


Figure 4: Boxplots showing the average values for each vegetation index in relation to each park, categorized by the five buffer rings. Left column: Bucharest; Right column: Leipzig. Source: Processed data from Sentinel-2 images.

Table 5 Pearson correlation between LST and surface imperviousness and LST and park's area.
 *Correlation is significant at the 0.05 level. **Correlation is significant at the 0.01 level

	Bucharest Leipzig	
LST - Imperviousness	.666**	.710**
LST - Park area	-.645*	-.617**

Some parks in Bucharest (CIS, KIS, DRU) and Leipzig (LEN, MAR, ABT, JOH, VO-K) are reported to have only one parameter affected by either traffic or high temperatures. CIS reports a combined influence of the two factors $\eta = 0.304^{**}$ for MSI (Fig. 9) and for the rest of the vegetation indicators there is a statistical significance with LST. LEN reports a combined influence for SR with $\eta = 0.358^{**}$ (Table 7).

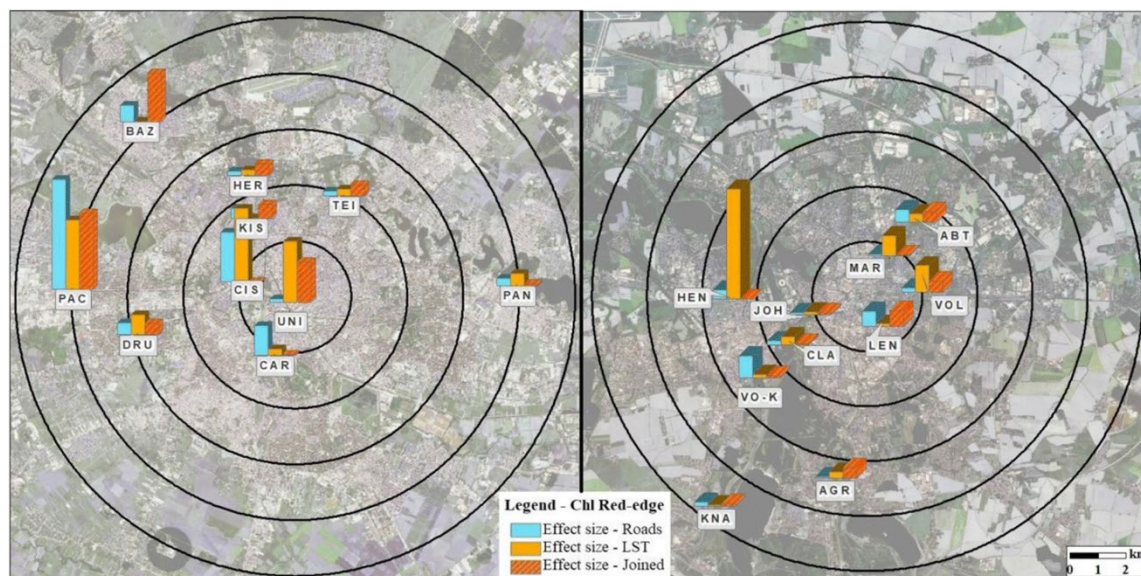


Figure 5: Map of effect size in ANOVA for the impact of traffic and LST on vegetation, taken individually and joined, related to Chl Red-edge in Bucharest

Effect sizes of ANOVA are used for mapping the impact's level of the two analyzed factors on tree vegetation. Vegetation in Bucharest is affected no matter the location in the buffer-rings. However, to be noted that the less affected parks are the ones located to the north of the city, in areas with a low degree of imperviousness (Figs. 5, 6, 7, 8, 9). Leipzig reveals a concentric layout of the effect size bars, as they decrease from the city center towards the periphery. One park (HEN) stands out as it reports the highest values of effect size for all analyzed indices (Figs. 5, 6, 7, 8, 9).

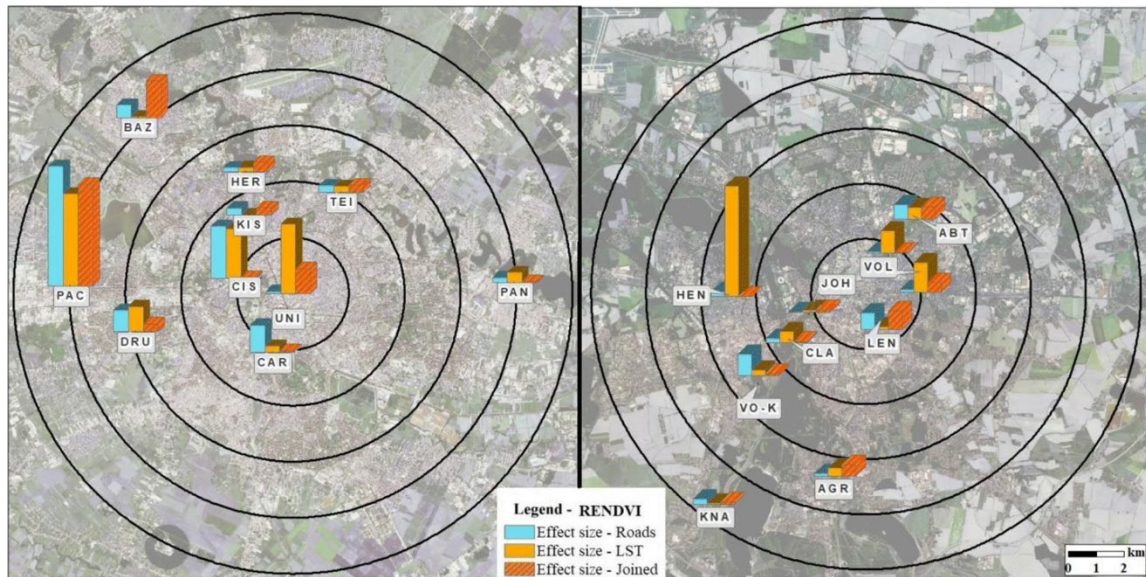


Figure 7: Map of effect size in ANOVA for the impact of traffic and LST on vegetation, taken individually and joined, related to RENDVI in Bucharest (left) and Leipzig (right).

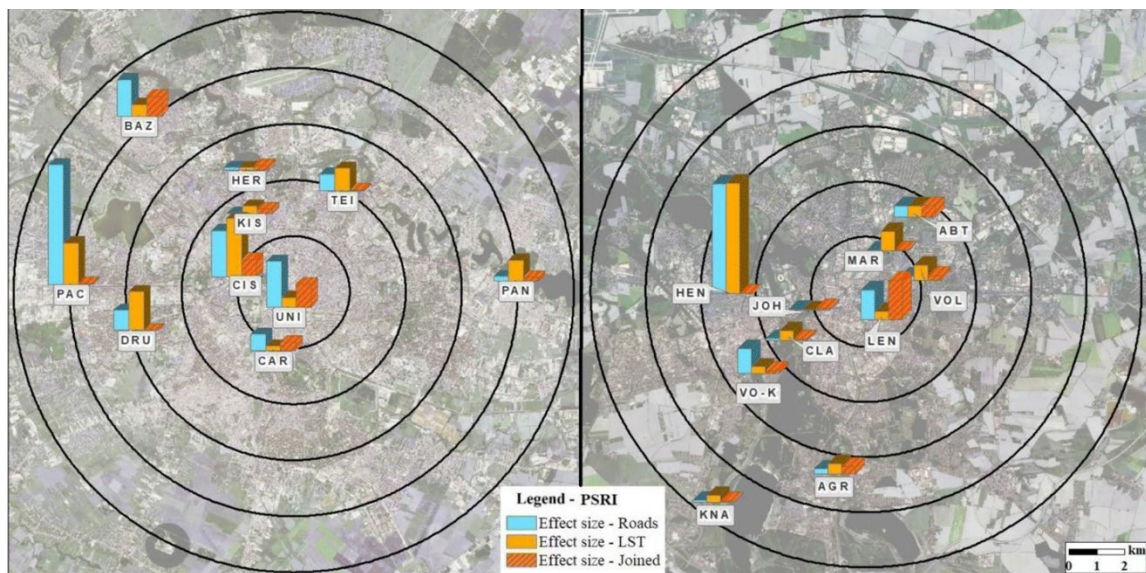


Figure 6: Map of effect size in ANOVA for the impact of traffic and LST on vegetation, taken individually and joined, related to PSRI in Bucharest (left) and Leipzig (right)

Table 6: Pearson correlation coefficient between vegetation indices and estimated LST around the parks (150 m). **Correlation is significant at the 0.01 level. *Correlation is significant at the 0.05 level

		LST around parks	
		Bucharest	Leipzig
Chl red-edge	Chl red-edge	.493	.875**
	RENDVI	-.441	-.888**
	PSRI	.498	.744*
	SR	-.142	-.613
MSI	MSI	.471	.885**

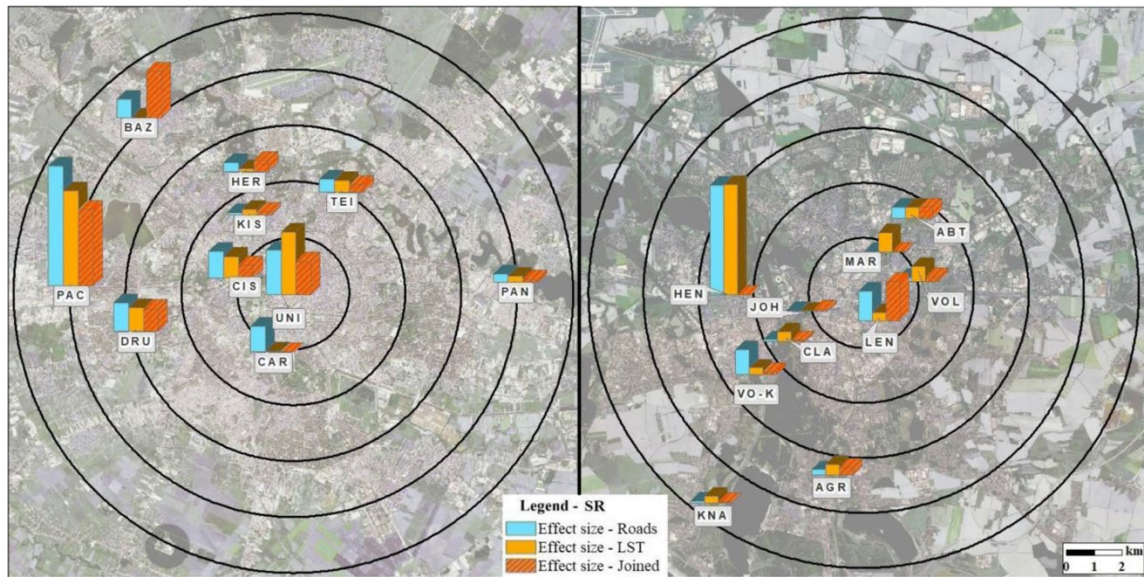


Figure 9: Map of effect size in ANOVA for the impact of traffic and LST on vegetation, taken individually and joined, related to SR in Bucharest (left) and Leipzig (right)

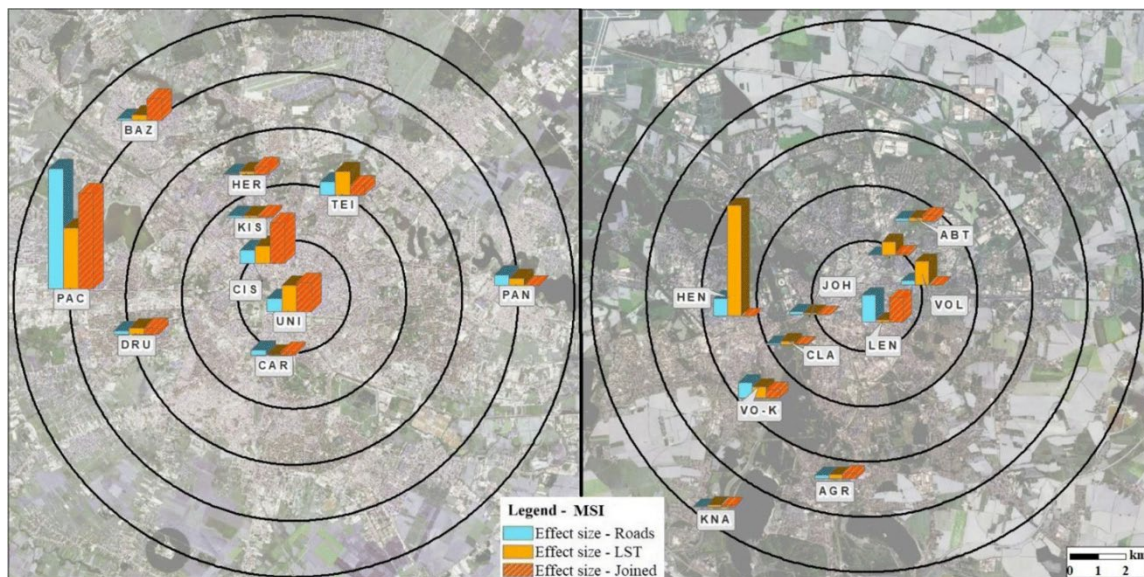


Figure 8: Map of effect size in ANOVA for the impact of traffic and LST on vegetation, taken individually and joined, related to MSI in Bucharest (left) and Leipzig (right)

Table 7: Effect size of ANOVA for assessing the impact of external factors on vegetation. *Significant level 0.1, **Significant level 0.05, ***Significant level 0.01. Small effect: <0.01, Medium effect: 0.01-0.06, Large effect: > 0.06. Parks are listed from city center to periphery. Cells are categorized based on result's magnitude (Richardson 2011). Source: Processed data from Sentinel-2 and Landsat 8 imagery and OSM dataset

	Chl R-e	RENDVI	PSRI	SR	MSI	Chl R-e	RENDVI	PSRI	SR	MSI
	B: CIS					L: LEN				
Roads	0.231*	0.321**	0.269*	0.190	0.099	0.130	0.134	0.038	0.273*	0.233*
LST	0.343**	0.306**	0.338**	0.154	0.130	0.020	0.022	0.228*	0.075	0.014
Roads x LST	0.001	0.009	0.102	0.092	0.304**	0.136	0.151	0.055	0.358**	0.215
	B: UNI					L: MAR				
Roads	0.015	0.015	0.262	0.314	0.096	0.011	0.011	0.048	0.008	0.004
LST	0.282	0.423*	0.056	0.440*	0.192	0.174***	0.184***	0.113***	0.174***	0.115***
Roads x LST	0.188	0.154	0.132	0.236	0.216	0.005	0.006	0.016	0.007	0.015
	B: KIS					L: VOL				
Roads	0.047**	0.043**	0.004	0.013	0.013	0.038	0.022	0.151	0.036	0.037
LST	0.004	0.001	0.043**	0.038*	0.016	0.230	0.243	0.255	0.135	0.208
Roads x LST	0.066**	0.046*	0.027	0.024	0.018	0.096	0.078	0.051	0.042	0.005
	B: CAR					L: ABT				
Roads	0.139***	0.167***	0.095***	0.181***	0.037**	0.107***	0.117	0.021	0.098**	0.021
LST	0.031**	0.038**	0.028*	0.008	0.008	0.071**	0.097**	0.009	0.099**	0.029
Roads x LST	0.005	0.011	0.051***	0.002	0.028*	0.091**	0.103**	0.039	0.104**	0.053
	B: HER					L: CLA				
Roads	0.021***	0.026***	0.015**	0.063***	0.006	0.038***	0.038***	0.032***	0.019***	0.015**
LST	0.025***	0.027***	0.015**	0.019**	0.023***	0.075***	0.092***	0.037***	0.092***	0.036***
Roads x LST	0.056***	0.060***	0.028***	0.078***	0.057***	0.013**	0.011**	0.025***	0.015**	0.010**
	B: TEI					L: JOH				
Roads	0.023	0.041	0.096	0.093	0.100	0.020	0.006	0.001	0.009	0.027
LST	0.032	0.038	0.130**	0.081	0.176**	0.027	0.022	0.035	0.007	0.016
Roads x LST	0.051	0.047	0.006	0.054	0.072	0.021	0.027	0.015	0.023	0.005
	B: DRU					L: HEN				
Roads	0.054	0.130*	0.116	0.198**	0.026**	0.077	0.039	0.688	0.995***	0.156
LST	0.093	0.154*	0.221**	0.163**	0.048	0.957	0.913	0.697	1.000**	0.964
Roads x LST	0.054	0.049	0.001	0.157**	0.050	0.001	0.001	0.001	0.001***	0.001
	B: PAN					L: VO-K				
Roads	0.036	0.031	0.026	0.056**	0.077**	0.196***	0.180***	0.062***	0.227***	0.135***
LST	0.057**	0.063	0.119**	0.043	0.049	0.031**	0.047***	0.004	0.062***	0.099***
Roads x LST	0.009	0.007	0.022	0.022	0.001	0.018	0.021	0.004	0.029	0.074***
	B: PAC					L: AGR				
Roads	0.509	0.727**	0.686**	0.836***	0.893***	0.013	0.022	0.041	0.047	0.031
LST	0.321	0.559*	0.237	0.662**	0.451	0.052	0.067	0.103	0.096	0.034
Roads x LST	0.351*	0.618**	0.006	0.533**	0.715***	0.090*	0.096*	0.010	0.068	0.046
	B: BAZ					L: KNA				
Roads	0.075*	0.078*	0.209***	0.127**	0.015	0.033	0.043	0.026	0.016	0.002
LST	0.003	0.006	0.067	0.001	0.040	0.012	0.011	0.001	0.061	0.019
Roads x LST	0.226***	0.224***	0.114**	0.325***	0.161***	0.023	0.020	0.018	0.013	0.016

Discussion

The main finding of our study is that Bucharest is more affected by the urban heat island effect than Leipzig is. Bucharest records overall higher temperatures and longer intervals of heat waves than the German city (Rusanescu et al. 2011; Cheval and Dumitrescu 2014), but also Leipzig is becoming more and more affected (Weber et al. 2014b).

Similar to other studies, it is demonstrated that the higher the surface sealing is, the higher the LST is (Gusso et al. 2014) (Table 5). This correlation can be seen along the buffer rings: the imperviousness coverage decreases in relation to LST, from the center to periphery. However, the values for Bucharest indicate that the UHI effect is strong even in areas facing a rather low degree of surface sealing. The analysis includes sample points with no soil sealing but with extreme high LST because of agricultural land, which stores heat, particularly in dry periods (Sun et al. 2011; Omran 2012). This applies mainly for the fifth multi-ring buffer in Leipzig, which records the highest values of LST due to the lack of vegetation on agricultural land in that timeframe. Soil properties play an important role here but also the state of the soil after longer drought periods, especially in peripheral agricultural lands (Haase 2009).

Moreover, our analysis shows that not all vegetation in Bucharest is able to mitigate the temperatures as indicated by LST during summertime. Based on the results of the negative correlation between the average LST within 150-m buffer around the park and its area, it can be interpreted that the lower the park's area is, the higher the LST is. In Leipzig, the conditions are different: in and around parks, the temperatures are lower than the ones corresponding to impervious surfaces. Large parks perform better for mitigating the temperatures around them, compared to small parks. This result is supported by the findings of Vieira et al. (2018).

In order to analyze if vegetation contributes differently to decreasing temperatures around parks based on its health, we tested the correlation between vegetation indices and LST within a buffer of 150 m around the parks (Du et al. 2017).

For Leipzig, the positive correlations between indicators and estimated LST around the parks show that the better the vegetation health in the German city is, the lower the LST recorded around it. Vegetation successfully delivers air temperature cooling and thus effectively mitigates the impact of the urban heat island (Maes et al. 2016). For Bucharest, the correlation coefficients are not as strong as for Leipzig. This can be explained by the fact that the Romanian city experiences an overall stronger heat island

effect over the entire city area (Cheval and Dumitrescu 2014). Thus, its LST variance is not large from one buffer ring to another. The urban vegetation in a limited number of parks in Bucharest deliver cooling ecosystem services by mitigating high temperatures. Based on these correlations, we conclude that even though the UHI effect is more intense in Bucharest compared to Leipzig, the parks in both cities have an overall positive impact for mitigating the heat island effect measured by the proxy of LST.

Park vegetation must be in a healthy state to provide their claimed services properly and to mitigate the external pressures such as heat and air pollution. We shall further discuss our findings in terms of vegetation health conditioned by two environmental factors, which was our second objective in this study.

Here, we map the impact of traffic and heat-stress on urban park vegetation, similar to previous studies (Malthus and Younger 2000; Xiao and McPherson 2005; Asmaryan et al. 2013), but we answer directly the question: Which parks are most affected by traffic and LST? Whereas earlier studies focused on the health of urban forests or street trees (Malthus and Younger 2000; Oswalt and Clatterbuck 2004; Gusso et al. 2014; Livesley et al. 2016) or contamination of urban horticulture (Säumel et al. 2012), we focused our study on trees within parks. The majority of these studies succeed in classifying the vegetation in healthy or unhealthy as a response to one decisive parameter: either pollution (Vacek et al. 1999) or drought (Bhuiyan et al. 2017). To our knowledge, this study may be the starting point for mapping the joined influence of traffic-related pollutants and heat stress on selected parks from two big European cities.

The results of the study clearly show which parks are affected by traffic and high temperatures as indicated by spectral indices sensitive to biochemical and biophysical parameters.

The results are mapped using an urban-rural gradient in order to understand the local context of each park. Using remote sensing images, we can inspect for each park which parameters were affected by these external factors.

Some parks in Bucharest (CAR, HER, PAC, BAZ) and Leipzig (CLA, AGR) report a high number of vegetation indices with statistical significant effect size. This can be explained by the fact that more parks in Bucharest are sensitive to external factors compared to Leipzig, meaning that the closer to the road a tree is situated and stressed by high temperatures, the poorer is the vegetation state. The individual impact of LST shows an intense influence on the tree's fitness. In Bucharest, effect sizes are large across all buffer-rings, mainly within UNI, CIS, DRU, PAC. In Leipzig, effect sizes decrease from city to periphery, as described by LEN, HEN, VOL, VO-K (Figs. 5, 6, and

7). AGR and KNA, located in the fourth and fifth buffer rings, show the lowest influence from roads and LST on vegetation status.

Other parks in Bucharest (CIS, KIS, DRU) and Leipzig (LEN, MAR, ABT, JOH, VO-K) indicate vegetation stress for one parameter, mostly because they are medium-sized and thus easier to be maintained as they are located in a central area of the city. This is explained by the fact that the local authorities treat them with priority thanks to the recreational values they bring to citizens and tourists and thus indirectly contribute to cash flows from tourism.

For CIS in the first ring in Bucharest, only temperature acts as a decisive parameter on decreasing the vegetation status revealed by chlorophyll-related indices and moisture indicator. Also for CIS, both combined factors have an impact on the moisture indicator. For HEN in the third ring in Leipzig, SR indicates that vegetation is affected by both external factors. However, HEN in Leipzig records the highest values for effect sizes for each analyzed index, meaning that in this small park, the response of the trees located closest to the roads are very different from the ones furthest from the roads.

The parks that did not reveal any statistical significance for the interaction of the two factors on vegetation state are UNI, TEI, PAN and VOL, KNA. We can observe that UNI and TEI reveal a strong statistical significance for the individual impact of LST on vegetation status and PAN for both factors, but taken individually. UNI is a small park located in an ultra-central area in Bucharest, with high soil sealing which leads to the highest temperatures inside the city: average LST around this park is 33.33 °C. Therefore, temperature has an overwhelming impact on vegetation over traffic. VOL from Leipzig is similar to UNI from Bucharest because it is located close to the city center and the average LST around it is the second one among the analyzed parks: 24.58 °C.

In conclusion, integrating freely available remote sensing data from different sensors enables investigating the vegetation state in Bucharest and Leipzig and, more specifically, the factors which have an impact on trees: heat or traffic-related pollutants. Moreover, our study emphasizes the role of healthy vegetation in delivering ecosystem services, especially cooling services.

Conclusions

The results of this study show that Bucharest records a stronger urban heat island effect than Leipzig; therefore, the role of vegetation in delivering ecosystem services is limited. Here, analysis of public remote sensing data reveals that urban vegetation

status can be affected by air pollutants due to high traffic and by high temperatures due to surface imperviousness. However, the impact of these factors is context dependent and it is related to the parks' location, area and management. The vegetation in Leipzig records lower influence of these factors in suburban areas than the central one, whilst vegetation in Bucharest is affected by traffic and heat stress throughout all five circular sections, except for the few parks with efficient management. The two analyzed external factors influence vegetation at different levels from physical parameters and moisture content to photosynthesis processes based on chlorophyll. Hence, there is great potential to combine complementary public remote sensing data with high acquisition rates and spatial coverage such as Landsat 8 and Sentinel 2 imagery for monitoring urban vegetation's health related to current issues: traffic and high temperatures. Therefore, we point out that free earth observation data can contribute to reach the Sustainable Development Goal of human wellbeing in urban areas.

Acknowledgements

Dagmar Haase wishes to thank our colleagues from the FP7 collaborative project GREENSURGE (FP7-ENV.2013.6.2-5- 603567), the BiodivERsA project ENABLE (COFUND 2015-16), and the Horizon 2020 innovation action CONNECTING (COproductionN with NaturE for City Transitioning, Innovation and Governance; No 730222-2) for financial support.

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Chapter 10

Tracking effects of extreme drought on coniferous forests from space using dynamic habitat indices

Mojdeh Safaei^{1,}, Till Kleinebecker^{1,2}, Manuel Weis³,
André Große-Stoltenberg^{1,2,**}*

¹Division of Landscape Ecology and Landscape Planning, Institute of Landscape Ecology and Resource Management, IFZ Research Centre for Biosystems, Land Use and Nutrition, Justus Liebig University Giessen, Heinrich-Buff Ring 26-32, 35392, Giessen, Germany

²Center for International Development and Environmental Research (ZEU), Senckenbergstrasse 3, 35390, Giessen, Germany

³Hessian Agency for Nature Conservation, Environment and Geology (HLNUG), Rheingaustraße 186, 65203, Wiesbaden, Germany

^{*}, ^{**} Corresponding authors

Heliyon 10:e27864 (2024), doi: 10.1016/j.heliyon.2024.e27864

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.heliyon.2024.e27864>.

Abstract

Terrestrial ecosystems such as coniferous forests in Central Europe are experiencing changes in health status following extreme droughts compounding with severe heat waves. The increasing temporal resolution and spatial coverage of earth observation data offer new opportunities to assess these dynamics. Dense time-series of optical satellite data allow for computing Dynamic Habitat Indices (DHIs), which have been predominantly used in biodiversity studies. However, DHIs cover three aspects of vegetation changes that could be affected by drought: annual productivity, minimum cover, and seasonality. Here, we evaluate the health status of coniferous forests in the federal state of Hesse in Germany over the period 2017-2020 including the severe drought year of 2018 using DHIs based on the Normalized Difference Vegetation Index (NDVI) for drought assessment. To identify the most important variables affecting coniferous forest die-off, a series of environmental variables together with the three DHIs components were used in a logistic regression (LR) model. Each DHI component changed significantly across non-damaged and damaged sites in all years (p-value 0.05). When comparing 2017 to 2019, DHI-based annual productivity decreased and seasonality increased. Most importantly, none of the DHI components had reached pre-drought conditions, which likely indicates a change in ecosystem functioning. We also identified spatially explicit areas highly affected by drought. The LR model revealed that in addition to common environmental parameters related to temperature, precipitation, and elevation, DHI components were the most important factors explaining the health status. Our analysis demonstrates the potential of DHIs to capture the effect of drought events on Central European coniferous forest ecosystems. Since the spaceborne data are available at the global level, this approach can be applied to track the dynamics of ecosystem conditions in other regions, at larger spatial scales, and for other Land Use/Land Cover types.

Keywords

Dynamic habitat indices, Coniferous forest, Ecosystem health, Extreme drought events, Germany

Introduction

Severe drought events and heatwaves currently represent major driving forces behind forest die-off [1-3], and the risk of megadrought events is likely to increase [4]. This can push forest ecosystems beyond their historic range of disturbance [5] and thereby posing a threat to forest resilience [3,6-9] and can cause vast changes in vegetation dynamics [10-13]. Forests in Germany, as in other central European countries, have encountered droughts and heatwaves of various magnitudes in recent years [9]. The extreme droughts between 2018 (with 3.3 °C higher than the long-term average from 1961 to 1990 [14]) and 2020 severely affected Central Germany, where in certain parts in central Germany up to two-thirds of coniferous forests died [15] and certain tree species such as Spruce Scots pine (*Pinus sylvestris* L.) potentially having reached tipping point [16].

Remote sensing of vegetation indices enables the monitoring of drought conditions at large spatial extents and could support monitoring and management efforts accounting for the dynamic nature of ecosystem health [7,17,18]. For example, continuous space-borne measures such as phenological metrics [19] provide more direct links to ecosystem functioning than discrete classifications [20]. Consequently, metrics calculated from remotely sensed time series data such as Dynamic Habitat Indices (DHIs), which rely on productivity properties, such as vegetation greenness or degree of vegetation seasonality, provide a baseline of the (natural) variability in ecosystem health and degradation [21,22].

DHIs are useful tools to summarize measures of vegetative productivity including the cumulative and minimum annual productivity as well as variation in annual productivity [21]. DHIs have been derived at 1 km spatial resolution for Australia [23], Canada (Coops et al., 2008), and recently at global scale [24]. The availability of remote sensing products such as the Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), the fraction of light absorbed by the vegetation (fPAR), or estimates of Gross Primary Productivity (GPP) derived from globally available MODIS satellite data clearly facilitates the calculation of DHIs [21,25]. However, with the increasing availability of remote sensing products with high temporal resolution, for example from the European Copernicus Land Monitoring service that provides global NDVI data at 300 m resolution with an interval of 10 days [26], these high temporal scale data products have a great potential for exploring ecosystem dynamics using composite vegetation indices such as the DHI.

The increasing temporal extent of baseline data to compute DHIs also allows for analyzing changes in DHIs over successive years across Land Use Land Cover types [27]. For example, identifying significant deviations from the long-term mean or a baseline state can facilitate to demarcate regions undergoing changes in ecosystem conditions [21,25,28,29]. To the best of our knowledge, DHIs have not been used to explore the health characteristics of coniferous forests affected by drought, yet. This is even more remarkable as DHIs may hold a substantial potential to refine the understanding between vegetation dynamics [24,28] and severe drought events [15]. Here, we present a detailed spatiotemporal analysis of a NDVI-based DHI across coniferous forests of Hesse, Germany. The specific objectives include (1) establishing a Hessian dynamic habitat index (DHI_{Total}) using spaceborne NDVI data at 300 m resolution, (2) identifying the DHI based health status of the coniferous forest before the severe drought event in 2018 and its potential recovery afterwards, (3) identifying where the drought event had strongest effects using spatiotemporal analysis, and (4) exploring the relationship between the environmental drivers, DHI components and coniferous health status.

Material and methods

Study area

This study was conducted in the federal state of Hesse, Germany (Fig. 1). The mean annual temperature (1981-2010) is 8.8 °C. It increased from 8.2 °C between 1951 and 1980, and it is still rising. There is a considerable spatial variation of annual increase ranging from almost 0 in some northern parts to +1.4 °C in the south. The annual precipitation increased slightly from 735 mm (1901-1930) to 807 mm (1981-2010). As for precipitation, there is a clear spatial variability of precipitation ranging from around 500 mm in the Upper Rhine Valley to 1400 mm at the higher elevations of e.g. the Vogelsberg or the Rhön [30].

According to the Climate Protection Scenario in Hesse, an increase in the number of particularly hot days with temperatures above 30 °C is very likely [30]. Precipitation is predicted to shift from summer to winter and will be more likely fall as rain instead of snow in winter. The probability and the severity of heavy precipitation and drought events will increase in the future [31].

In Hesse, forests cover more than 40 % of the land surface (about 894,000 ha). More than half of these are dominated by broadleaved tree species such as *Fagus sylvatica* L. (Beech) and *Quercus robur* L. (Oak). Beech and oak together account for 43.8% of the

forest area. Conifers make up almost 40%. The main coniferous tree species are *Picea abies* (L.) Karst. (Spruce), *Pinus sylvestris* L. (Scots pine), *Pseudotsuga menziesii* Franco (Douglas fir), and *Abies alba* Mill. (silver fir) [32]. As a result of storm events (and subsequent bark beetle infestation), the area of spruce forests decreased by more than 20,000 ha between 2002 and 2012. This was associated with an increase in deciduous forests and Douglas fir, which is more and more used as a “replacement” for spruce [32].

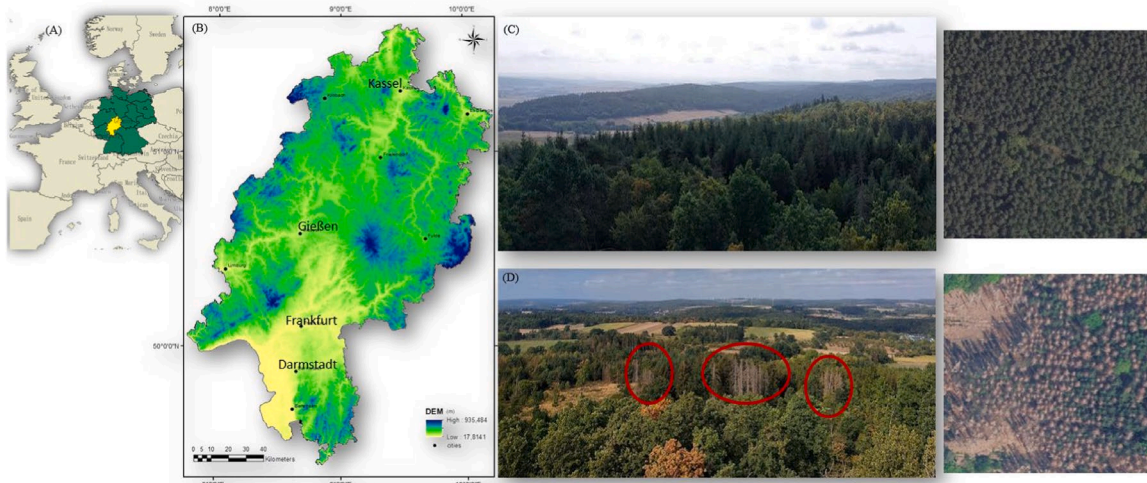


Figure 1: (A) Location of the federal state of Hesse in central Germany and in Europe (B) the digital elevation model (DEM) [33] ranging between 75 and 950 m above sea level. Photos show some indication of the health status of coniferous forests: (C) example of a non-damaged site and (D) of a damaged site. Photos were taken by the first-author in August 2022 in the Vogelsberg region and aerial overview pictures are derived from digital orthophotos of the Hessian geoportal [34].

Data

Satellite data

To compute the DHI_{Total} , we used the NDVI product of the Copernicus Global Land Service with a spatial resolution of 300 m [26]. It is a 10-daily synthesis product derived from PROBA-V observations [26]. We used data from Jan 01, 2017 until Dec 31, 2020, that showed consistent data value ranges, to calculate the Hessian DHIs to examine the sudden effects of the extreme drought of 2018. Recent studies demonstrated the applicability of the DHI for similar temporal ranges [35–37]. Further, recent analysis of annual, satellite-derived NDVI data showed the effect of the 2018 drought on ecosystem conditions in Europe [38] including central European forests [14,39]. Notably, such data can potentially be applied to track coniferous forest health [16]. In addition to NDVI data, a satellite-based digital elevation model (DEM) [33] was used to derive elevation

above sea level as an topographical predictor of the health status of coniferous forests (Table 1).

Table 1: Datasets and extracted variables used in this study.

Dataset	Abbreviation	Temporal res. and coverage	Spatial res.	Variables
Normalized difference vegetation index Copernicus [26]	NDVI	10 days, 01.01.2017- December 31, 2020	300 m	Annual Productivity Minimum cover Seasonality
Digital elevation model [33]	DEM	February 11, 2000 to February 21, 2000	30 m	DEM
CORINE Landuse/land cover [49]	LULC	2018	100 m	LULC
Monthly total precipitation (mm) [40]	MTP	30 days, 01.01.2017- 31.12.2020	1000 m	Cumulative Minimum
Mean of the monthly averaged minimum daily air temperature (1/10 °C) [41]	MMT	30 days, 01.01.2017- 31.12.2020	1000 m	Variation of each climate dataset
Monthly total sunshine duration (h) [42]	MTS	30 days, 01.01.2017- 31.12.2020	1000 m	
Monthly drought index (de Martonne index) [43]	dMI	30 days, 01.01.2017- 31.12.2020	1000 m	
Coniferous forest damage map [47]		2018 and 2019	10 m	Damaged area
Orthophotos [50]		2018 and 2019	20 cm	Identify and verify Damaged and non-damaged sites

Climate data

Various climate datasets related to vegetation and ecophysiology of plants were obtained from the Climate Data Center (CDC) (<https://cdc.dwd.de/portal/>) including grids of monthly total precipitation [40], monthly mean of minimum daily air temperature in 2 m height above ground [41], monthly total sunshine duration [42], as well as grids of monthly drought index (de Martonne index = dMI [43,44]). The dMI is calculated based on Equation (1).

$$[44]: dMI = \frac{P}{T+10} \quad (1)$$

T refers to the temperature in degrees Celsius from temperature grids and P refers to the precipitation in mm from precipitation grids. This index shows the aridity of regional

climate zones and provides information on the drought level at a given site [45]. Lower dMI values indicate drought while increased values indicate more water is available for trees. The dMI has been used to describe the extreme drought conditions for summer 2018 in Central Germany [46].

In order to investigate the relationship between DHI and climatic drivers, we calculated the cumulative, minimum, and variation of the climate variables (Table 1).

Coniferous forest data

Geodata on the damage of coniferous forests were obtained from the Hessian state forestry service [47]. Since bark beetle outbreaks following the deep depression Friederike in January 2018, the forestry service regularly monitors coniferous forest health in early summer [47]. Damaged forests are detected based on multispectral Sentinel 2 data and pixel-based change detection using the NDVI [47]. Random Forest [48] was used to generate a spatial analysis mask, describing the exact distribution of coniferous forests in summer 2017, before the winter storm Friederike and the associated bark beetle outbreak. This mask allows to define sharp thresholds for damage detection resulting in complete spatiotemporal patterns of forestry damage [47]. To identify non-damaged areas, the CORINE Land-use and Land cover (LULC) map was used to extract coniferous forests in Hesse [49]. Coniferous forest patches displaying a homogenous green texture based on digital orthophotos (DOP) from the geoportal of Hesse [50] were classified as non-damaged. (Fig. 1C). After that, we applied spatial thinning using “spThin”, and spatial autocorrelation was checked using “acf” R package [51]. We found no spatial autocorrelation in our dataset.

The Hessian Dynamic Habitat Index (DHI_{Total})

NDVI data from 2017 to 2020 were recorded with an interval of 10 days [26], thus three tiles were collected per month resulting in 36 tiles for each year and a total of 144 tiles for the full 4-year dataset. For each year, yearly NDVI composites were used to obtain the three DHI components, i.e., cumulative DHI (DHI_{Cum}), minimum DHI (DHI_{Min}), and variation DHI (DHI_{Var}). Here, the three components of DHI_{Total} were computed over the time period 2017-2020 from the NDVI layers based on Equation (2) [52]:

$$DHI_{Cum} = \sum p_t \quad DHI_{min} = \min(p_t) \quad DHI_{Var} = \frac{\sigma(p_t)}{\mu(p_t)} \quad t = 1..n \quad (2)$$

where p represents vegetation productivity at different periods (t) during a year [25,53]. DHI_{Cum} refers to the cumulative productivity values for all time periods over a year,

DHI_{Min} refers to the minimum productivity value within a year, and DHI_{Var} refers to the seasonality of the productivity calculated based on the coefficient of variation using the standard deviation and the mean ($\sigma(\text{pt})/\mu(\text{pt})$) [25,53]. In addition, the long-term mean of each indicator was calculated as the median over the full four-year period. Further details on DHI calculation are described by Refs. [21,25,28,54]. To reveal the extent to which the three DHI components complement each other [55], we performed Spearman correlation analyses between DHICum, DHIMin, and DHIVar. In addition, we tested the correlation of the DHI components with the climatic variables under study.

Yearly comparison

One-way analysis of variance (ANOVA) was performed to test differences in DHI components across damaged and non-damaged coniferous forests within each of the four years using the “car” package [51]. We met the assumptions of one-way ANOVA using the Shapiro-Wilk test, Q-Q plot of residuals, and Bartlett’s Test [56]. To test for immediate or time-delayed effects of the severe drought in 2018 and for possible recovery, we calculated the change of the DHI components between each combination of years.

We performed Theil-Sen’s test and Ordinary Least Squares (OLS) with a moving widow [57,58] to investigate the overall trends of the three DHI components. Theil-Sen’s test is a non-parametric and robust method concerning missing values and non-normal distributions [59]. To assess the effect of drought on the observed trends, we first classified cumulative drought into four zones including arid, semi-arid, semi-humid, and humid and identified areas with high aridity over time. These classes which indicated the aridity of regional climate zones came from equal intervals of cumulative drought maps. To figure out which cells had a considerable trend across the time we applied a 20% threshold on the DHIs components on the entire distribution of trend values [54,60]. Finally, we used the positive-to-negative trend ratio to understand how health status was affected by which arid zone.

Environmental variables across health status

To distinguish which variables were related to the health status, and to gain a better understanding of the trend analysis, we added further environmental variables such as cumulative, minimum, and variation precipitation, temperature, sunshine duration, and monthly drought index (Table 1) to our analysis. Strongly intercorrelated variables ($|R|$

>0.8) were removed [61]. We used logistic regression (LR) as a subtype of generalized linear models (GLM) and chose binomial distribution [62] as the response data are binary (damaged, non-damaged) using the “glm” function in R statistical software [51]. The model was built based on Equation (3).

$$p(X) = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}} \quad (3)$$

p: the probability of occurrence of an event, β_0 : model constant, β_i : regression coefficients, and X_i : environmental variables [63]. To assess how well the LR model fits the data, McFadden’s R^2 using “pR2” function from the “pscl” package was employed. Values close to 0 indicate low goodness of-fit, and values over 0.40 indicate a very good model fit [64]. The importance of each environmental variable using the “varImp” function from the “caret” package was computed. To minimize effects of multicollinearity, variables with variance inflation factor (VIF) > 5 were removed [65]. All statistical and geospatial analyses were performed in R statistical software ver. 4 [66] and QGIS ver. 3.22 LTR Białowież’a and gdal wrap [67]. The general framework of our study is summarized in Fig. 2.

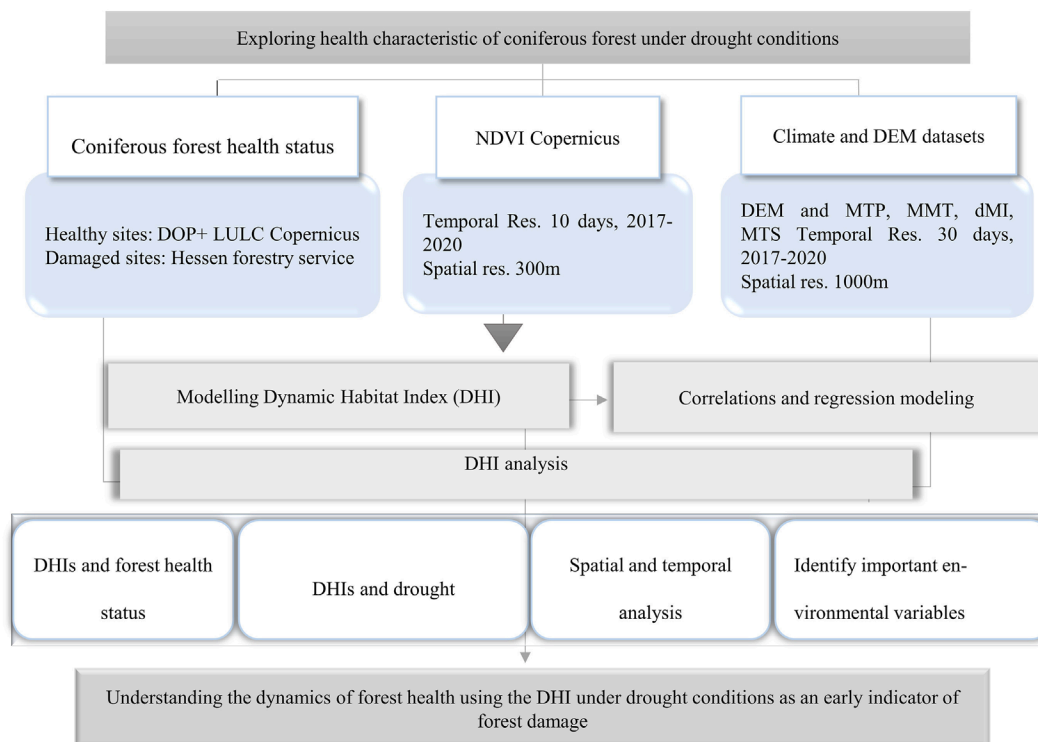


Figure 2: Methodological steps of the inputs, analysis, and outputs. DOP: Digital orthophotos, DEM: digital elevation model, MTP: monthly total precipitation, MMT: mean of the monthly averaged minimum daily air temperature, dMI: Monthly drought index (de Martonne index), and MTS: monthly total sunshine duration, DHI: Dynamic habitat index, and LULC: Land Use Land Cover.

Results

The Hessian Dynamic Habitat Index (DHI_{Total})

The three components of the DHI_{Total} varied across time and space (Fig. 3A, B, C) as did the DHI_{Total} (Fig. 3D). DHI_{Cum} (annual productivity) dropped in 2018 (Fig. 3A), while DHI_{Min} (minimum coverage) clearly decreased in 2020 (Fig. 3B). DHI_{Var} (seasonality) in 2018 is different from all other years (Fig. 3C). DHI_{Total} captured the variability in the vegetative productivity patterns during 2017-2020, and the contribution of each DHI component to DHI_{Total} varied between the years (Fig. 3D). For example, while some regions were characterized constantly by high seasonality, low annual productivity and low minimum cover (blueish colours), the location of areas with moderate seasonality, high annual productivity and low minimum cover (reddish purple) varied (Fig. 3D).

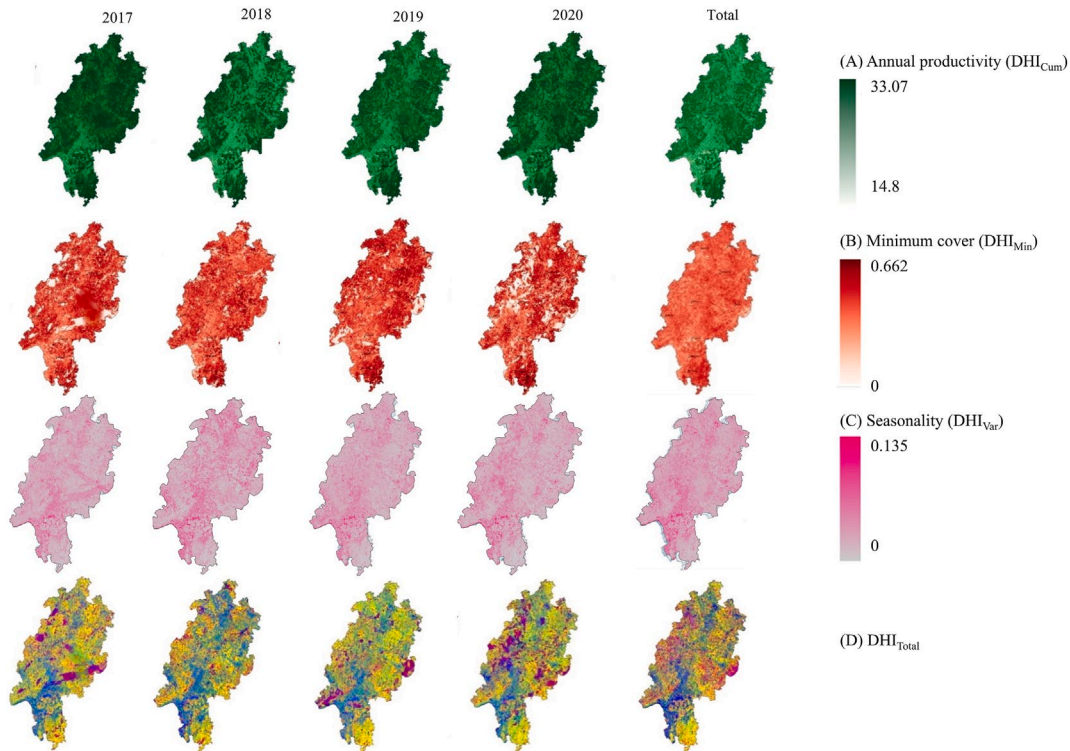


Figure 3: Maps of each year and for all years combined of the DHI components (A) annual productivity (DHI_{Cum}), (B) minimum cover (DHI_{Min}), and (C) seasonality (DHI_{Var}), which are calculated based on 10-day NDVI data per year, and (D) of the merged components (DHI_{Total}) over the 4 years of observations from January 01, 2017 to December 31, 2020.

Three DHI_{Total} components were moderately to strongly correlated with each other (Fig. 4). There was a positive correlation between annual productivity and minimum cover values ($R^2 = 0.42$). Seasonality was negatively correlated to minimum cover and annual productivity ($R^2 = -0.71$ and -0.66 , respectively) (Fig. 4B and C). This indicated that the highest values of DHI_{Var} occurred at the lowest DHI_{Min} and DHI_{Cum} . The DHI

components correlated moderately positively with precipitation, drought, and temperature variables (See Table S1 and Fig. S3).

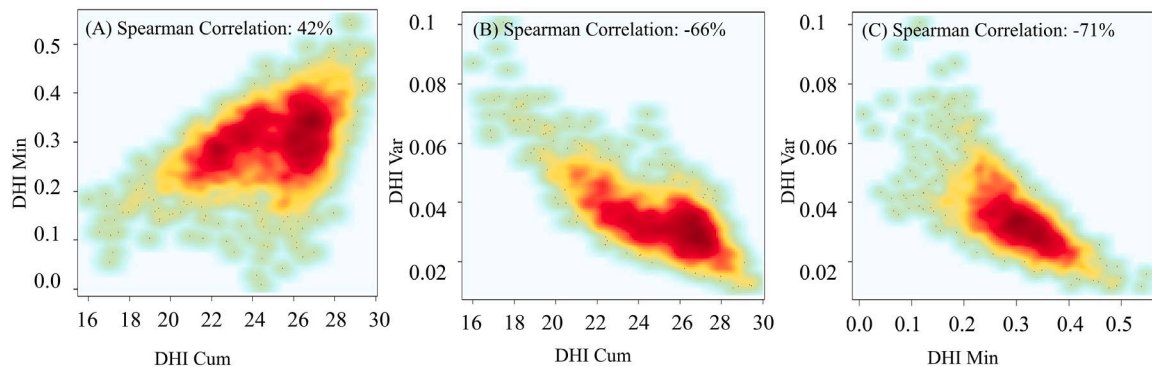


Figure 4: Correlations among the three DHI_{Total} components derived from NDVI. The three DHI_{Total} components were moderate to strongly correlated with each other. DHI_{Cum} : Annual Productivity, DHI_{Min} : Minimum cover, and DHI_{Var} : Seasonality. The color range is based on the density of points. Dense points of each scatter plot were shown with red color and by decreasing points density it changed to orange, yellow, and then green. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Yearly comparison between non-damaged and damaged coniferous forests

Annual productivity and minimum cover were significantly higher for non-damaged sites compared to damaged sites throughout the years (Fig. 5A and B). The seasonality component was constantly significantly lower (Fig. 5C) meaning that in non-damaged sites less variation (seasonality) occurred.

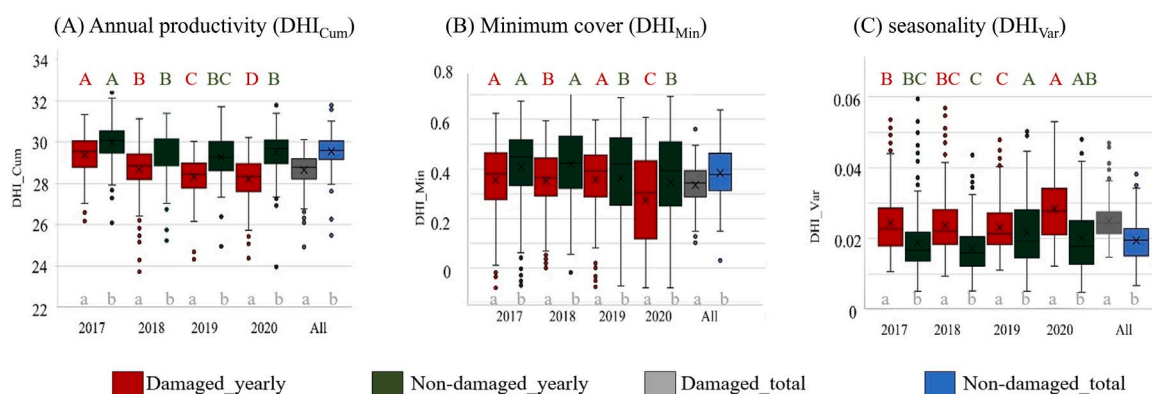


Figure 5: Comparison of damaged and non-damaged coniferous forests for each DHI component for each year (A, B, and C). The capital letters indicate significant differences related to the non-damaged (green letters) and damaged sites (red letters) between years. The lowercase letters in grey indicate significant differences regarding the health status within each year using the Tukey post hoc test (p -value < 0.05). For example, grey lowercase letters in 2017 mean that there is a significant difference related to the non-damaged and damaged sites. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

When analysing the changes of the DHI components in damaged sites between the years (Fig. 6A), annual productivity first decreased with the most negative changes being observed between 2017 (pre-drought) and 2019 but showed partial recovery in 2020

where it reached its maximum. In contrast, minimum coverage significant decreased in 2020 (Fig. 6B). So, while annual productivity and minimum cover were moderately positively correlated for the whole time span (Fig. 4), yearly comparison showed different and partly opposing trends. The third DHI component seasonality first decreased, but then continuously increased since 2019 (Fig. 6C). Thus, annual productivity in damaged sites was mostly negative, but showed a positive trend and became positive in 2020, while the seasonality increased across all the years apart from a decrease due the 2018 drought event. Minimum cover increased towards 2019 but was negative otherwise. So, all DHI components differed significantly between non-damaged and damaged sites, and they did so even before the drought event 2018 (Figs. 5 and 6). Compared to 2017, damaged sites showed different characteristics after the drought for all DHI components. While annual productivity showed a partial recovery, minimum cover rather decreased and seasonality rather increased (Fig. 6 and Fig. S1).

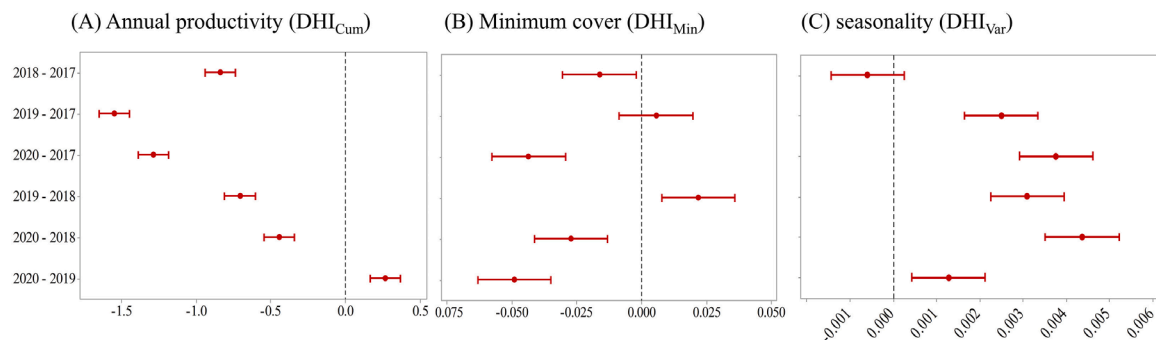


Figure 6: Visualizations of the drought effects across damaged sites. The plots show Tukey's simultaneous tests for differences in DHIs means within years. The confidence intervals display the likely ranges for all of the differences in the means. If an interval does not intersect the zero line, the corresponding means are significantly different ($p\text{-value} < 0.05$).

Spatial and temporal dimension of coniferous forest health status

We explored the spatial dimension of DHI changes of coniferous forest from 2017 to 2020 (Fig. 7A) and identified a set these changes into relation with the aridity zones after de Martonne index (Fig. 7B). We then explored the negative or positive trends of the DHI components for different aridity zones based on the dMI (Fig. 7C and Table 2). The area of coniferous forest for each aridity zone equalled 42,284 ha for arid zone (16% of the total coniferous forest area), 165,542 ha for semi-arid zone (62%), 55,108 ha for semi-humid zone1 (21%), and 3243 ha for humid zone (1%). Most positive trends of the DHI components were found at the rather humid end of the dMI aridity gradient (Table 2). For example, the most positive trend of DHI_{Cum} considering all years (2.65, Table 2) was observed when the drought effect decreased (semi-humid zone), while the least

positive trend (1.39) was observed when drought increased (semi-arid zone, Table 2). Coniferous forests rarely occurred in areas which were characterized by strong drought effect (arid zone), and this could explain the positive trend in this zone (Fig. 7C). The highest coniferous coverage occurred in the semi-arid zone. The overall trends were similar for non-damaged and damaged forest (Table 2). However, in damaged sites the positive-to-negative ratios of DHI_{Cum} were lower, but DHI_{Var} was higher compared to non-damaged sites (Table 2). DHI_{Min} was generally lower in damaged forest apart from rather humid zone (Table 2).

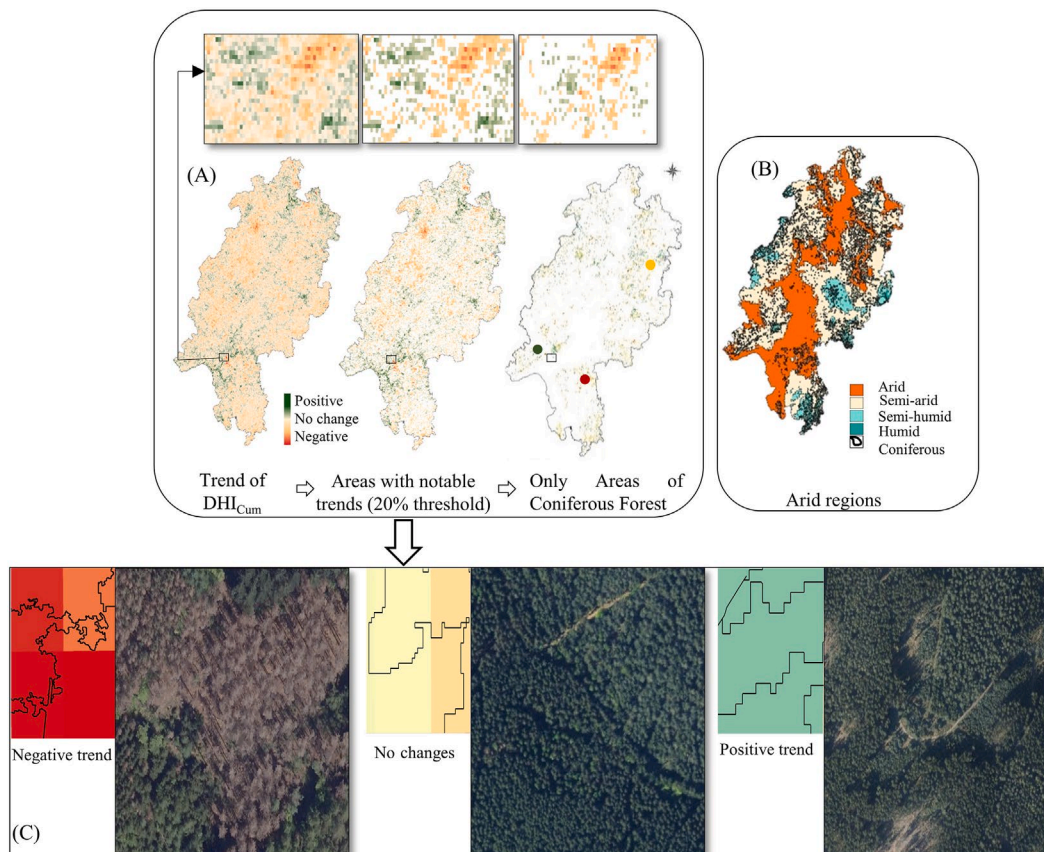


Figure 7: Results of spatial analysis to capture the effects of drought on the DHI's trend (A) Example of DHI_{Cum} trend analysis spanning from 2017 until 2020 (See Fig. S2 for more maps) for coniferous forests. Small boxes above are zoomed in the area to see more details. (B) The accumulated drought map based on the de Martonne index (dMI) ranging from “low accumulated drought” (dark green) to “high accumulated drought” (orange) overlaid with (in black) a coniferous forest map. (C) Examples of coniferous forests showing negative (red), indifferent (yellow) or positive (blue) trends over four years. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Analysis revealed that most damages of the coniferous forests did not occur in the areas where maximum accumulated drought was located, but rather in the semi-arid zone, where most of the coniferous forest occurred (Table 2). Consequently, most damaged coniferous forests were observed at altitudes lower than 350 m with pronounced, but not maximum cumulative drought. Most of the non-damaged forests occurred at higher

altitudes of 350 and lower cumulative drought (semi-humid zone, and $y = 12.867x - 147.27$ with $R^2 = 0.73$) (Fig. 8).

Table 2: The ratio of the positive trend to the negative trend of the area in each arid zone for each DHI component across health status. Sparklines refer to the ratios across arid zone for each DHI component.

The ratio of positive to negative trend of the area under aridity zones after de Martonne index (dMI).						
arid zones		Arid	Semi-arid	Semi-humid	humid	Sparkline
DHI Components						
Total	DHI _{Cum}	2.08	1.39	1.65	2.65	
	DHI _{Var}	0.30	0.17	0.04	0.02	
	DHI _{Min}	0.89	1.21	2.59	2.72	
Damaged	DHI _{Cum}	0.16	0.26	0.33	0.51	
	DHI _{Var}	0.55	0.43	0.09	0.04	
	DHI _{Min}	0.70	0.86	2.01	3.00	
Non-damaged	DHI _{Cum}	1.95	1.20	1.43	2.33	
	DHI _{Var}	0.29	0.14	0.04	0.02	
	DHI _{Min}	0.90	1.29	2.69	2.70	

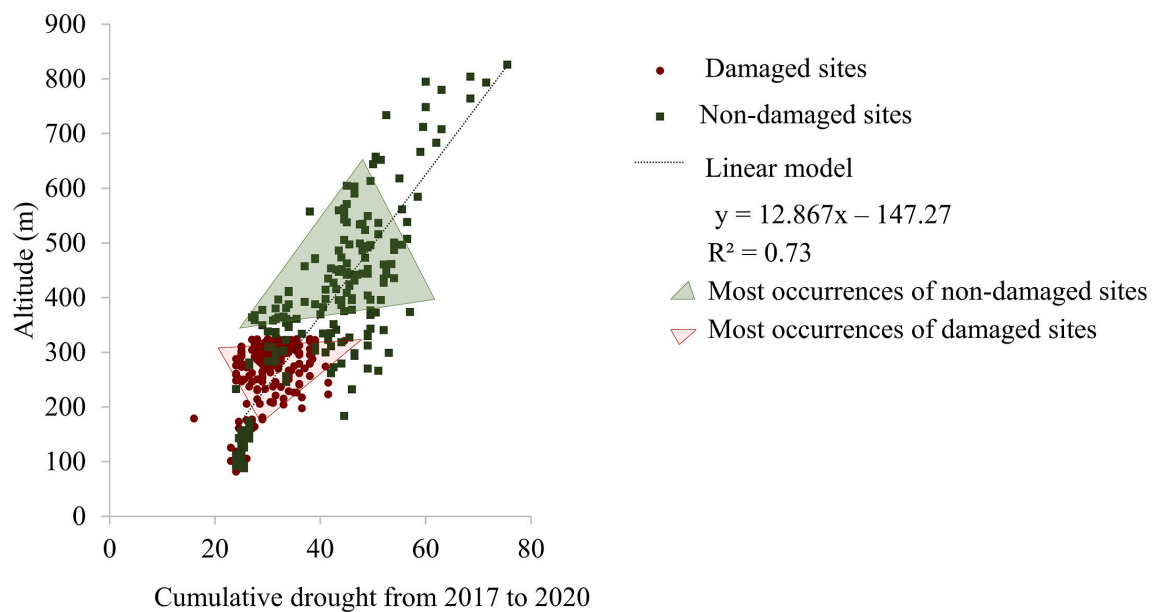


Figure 8: Linear regression between altitude and cumulative drought index (dMI) from 2017 to 2020. Non-damaged sites are displayed in green, and damaged sites are in red. Lower values of cumulative drought indicate stronger drought effects. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Environmental factors affecting health status

Finally, we investigated which environmental factors and which DHI components explained the coniferous health status (Table 3). Out of initially 16 predictors 9 (mainly climatic variables) were removed due to high correlation >0.8 and high collinearity >5 , and 7 remained in the final model. Among them were all DHI components (Table 3).

Logistic regression analysis revealed that the most important factors explaining the health status were the variation in temperature, annual productivity (DHI_{Cum}), altitude, minimum coverage (DHI_{Min}), cumulative drought, and minimum sunshine duration (Table 3, Fig. 9). Seasonality (DHI_{Var}) was among the most important predictors (Fig. 9), but it was not significant (Table 3). McFadden's R^2 value of 0.44 indicated that the GLM model with a binomial family fit the environmental data very well [68], and the results of variable importance matched up with the p-values from the model (Table 3 and Fig. 9). Thus, in addition to environmental parameters, DHI components were among the most important predictors of the distinction between degraded and non-degraded coniferous.

Table 3: Shows the Logistic regression model coefficients and p-values. DHI_{Cum}: DHI Annual Productivity. DHI_{Var}: DHI Seasonality. DHI_{Min}: DHI minimum vegetation cover. Temp_{Var}: Variation in the monthly averaged minimum daily air temperature Sun_{Min}: Minimum monthly sunshine duration. Dry_{Cum}: Cumulative monthly drought index. DEM: Digital elevation model.

Coefficients:	Estimate	Std. Error	z value	Pr(> z)	Significant ^a
(Intercept)	-54.20	5.33	-10.16	<0.0000002	***
DHI _{Cum}	1.27	0.16	7.68	1.55E-14	***
DHI _{Min}	-5.59	2.11	-2.64	0.00821	**
DHI _{Var}	-49.42	26.13	-1.89	0.05856	.
Sun _{Min}	-0.047	0.021	-2.17	0.02931	*
Temp _{Var}	0.007	0.0006	11.18	<0.000002	***
Dry _{Cum}	0.044	0.017	2.54	0.01105	*
DEM	-0.007	0.001	-6.28	3.32E-10	***

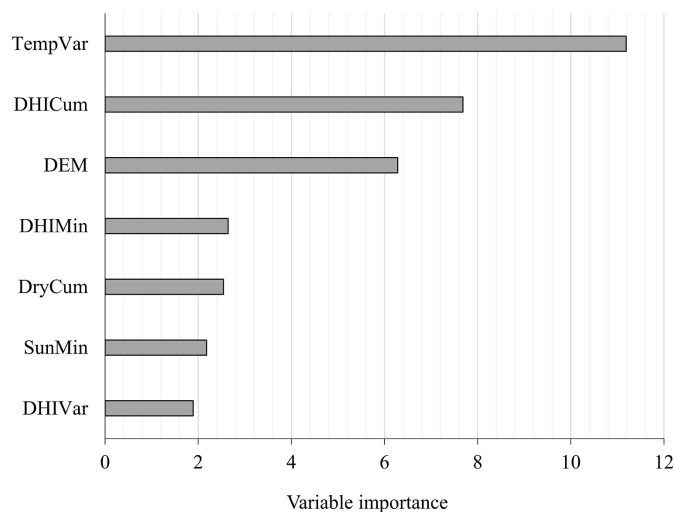


Figure 9: The importance of each predictor variable in the model. Higher values indicate more importance. DHI_{Cum}: DHI Annual Productivity. DHI_{Var}: DHI Seasonality. DHI_{Min}: DHI minimum vegetation cover. Temp_{Var}: Variation in the monthly averaged minimum daily air temperature Sun_{Min}: Minimum monthly sunshine duration. Dry_{Cum}: Cumulative monthly drought index. DEM: Digital elevation model.

Discussion

In this study we show how vegetation information derived from satellite time series in the form of Dynamic Habitat Indices (DHI) can be used as indicators and diagnostic tools to assess forest damages caused by drought. All three components of the DHI (annual productivity, minimum cover, and seasonality) were able to capture the response of the coniferous forest to drought, but overall temporal trends differed. We highlight that the drought effect is clearly altitude dependent, but that DHI components are important in addition to climatic variables to distinguish non-damaged from damaged sites.

The potential of the Dynamic Habitat Index to capture the effect of drought on coniferous forest health DHI was developed as an integrated remote sensing metric to track dynamics of vegetative productivity [53], and to relate these dynamics to biodiversity patterns [69]. As it is based on spaceborne NDVI time series data, it informs on the dynamics of vegetation greenness [53]. The 2018 drought event had a strong negative impact on forest health [46], including coniferous species such as Spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*) [1,70]. We found that the DHI based on dense NDVI time series data proved to be a promising diagnostic tool to capture the dynamic changes and drought assessment [71] including forest dieback in the health status of central European coniferous forests as a consequence of the severe drought events.

While surrogates of single components of the DHI such as seasonality [72] or vegetation productivity [73], or minimum NDVI [74] have been used to assess effects of droughts on vegetation, their combination as DHI as rarely used although they combination allows new insights. In this study, each of three DHI components provided useful information to assess forest health status. Coniferous forests generally have high vegetation productivity [75], making both the DHI_{Cum} and DHI_{Min} suitable health indicators for these ecosystems. For example, coniferous forests with high minimum vegetation cover (DHI_{Min}) remained healthier in 2018. The lowest values and the largest value ranges of DHI_{Min} occurred in 2020 after two years of drought stress, which could indicate a partial or complete canopy dieback [70] together with a legacy effect [76]. Importantly, not only damaged but also non-damaged sites suffered after two years of drought events. At the same time, partial recovery after the drought year 2018, e.g., related to minimum cover, also occurred, so both positive and negative could be mapped using DHI. However, such increases in NDVI might at least partly be the result of herbaceous vegetation resprouting after partial or complete forest die-off [77], so the forest type might have changed. An indicator for strong drought effects might be the altered

vegetation (see Ref. [73]). Here, non-damaged sites showed the least amount of variation (DHI_{var}) compared to the damaged sites. The marked differences for all DHI components value between non-damaged and damaged sites underpin their potential as warning indicators of forest degradation.

Advantages of remote sensing metrics based on times series data

Multiple-year and extended droughts have additive effects on the response of trees in terms of e.g. leaf area [78] and vegetation productivity [79]. So, analysis of temporal changes using time series provides more detailed information about the effects of global change events such as severe droughts on vegetation health compared to a single NDVI tile [80]. We demonstrated that each of the three DHIs components can be useful in terms of drought assessment and showed that Hessian coniferous forests did not fully recover to pre-drought conditions yet. Recovery time as one important component of ecosystem stability is particularly relevant if the frequency and intensities of droughts increase [81]. Ecosystems with longer drought recovery times are more likely to experience a new drought event before fully recovering which leads to increased plant mortality and a potential transition to a new state [82]. These legacy effects are often characterized by ecological responses to water availability and temperature [83]. Therefore, extended droughts affect the recovery time associated with canopy mortality and may push forests beyond a tipping point [46] and ultimately lead to changes in LULC [84]. Our results showed that the time series of NDVIs expressed as DHI indices are helpful for recognizing where damages are considerable and can thus be used as a potential early indicator of forest damage. For example, March 2018 was the start of the drought period that never showed complete recovery by the end of 2020. Similar to our results [46], reported that mean precipitation in April-August 2018 for the growing season was less than half of the normal amount (450-500 mm) in Bavaria in central European forests, and in our study the de Martonne aridity index showed a summer with arid to semi-arid climate (Fig. S. 3 and Fig. S. 4). Decreasing NDVI has been linked to tipping points of *P. sylvestris* forests in Southwest Germany, where the coniferous forest is changing towards a broadleaf forest [16]. Thus, DHI analysis including spatial trends could be used to characterize forest die-off and subsequent recovery. So, changes in DHI might serve as early indicators of forest damage and could be used together with remotely sensed data on tree species identity to explore if there shift towards alternative states such as broadleaf forests or open ecosystems with distinct DHI signatures.

Environmental factors together with the DHIs explain coniferous health status

Severe droughts and heatwaves cause forest die-off in the Anthropocene [76,85] and mortality of coniferous tree species is increasing [2,7,9,70,86,87]. Here, in addition to environmental parameters, DHI components were among most important predictors to distinguish non-damaged from damaged coniferous forests, which emphasizes their usefulness in assessing forest drought. An advantage of DHIs derived from satellite data collections (e.g. Ref. [26]) over other climatic datasets (such as precipitation, drought and, temperature) could be that the latter are derived from interpolation techniques and can suffer from potential biases [25]. Nevertheless, variation in temperature was the most important factor to predict health status in our study. Indeed, tree mortality in Europe is triggered by global-change-type drought [88]. Temperature stress and drought could limit the capability of plants to refill cavitated xylem to support metabolism and therefore disable recoverability from drought [82]. It also has a negative impact on wood formation of coniferous forest species [89]. Such drought-affected growth processes are species-specific, show seasonal dynamics and might be altitude dependant [89]. Altitude is also an important factor concerning the magnitude of potential post-drought legacy effects [90]. We found that the drought was particularly severe (cumulative dMI<28) at lower altitude where the area of coniferous forests is relatively small. For coniferous forests, less drought effects occurred at higher altitudes with higher precipitation and lower temperature, which indicated more suitable habitat conditions. In the lower altitudes, the magnitude of the damages to the coniferous on the DHI components increased as precipitation decreased, and coniferous forests were not able to recover in these very dry regions. Thus, the patterns of coniferous forest damage generally followed the altitudinal patterns of drought (Fig. 9). This highlights the importance of considering both the meteorological and other environmental condition particularly to identify cumulative drought effects of a series of dry and vulnerability of coniferous to drought due to the legacy effect possibly persists for a few years after a drought event [76], and DHIs based on dense time series data could play an important role in analysing such legacy effects.

Future directions

Our findings clearly show that the use of DHIs is a promising and straightforward approach to monitor the health status of coniferous forests at larger spatial scales that

could contribute additional spatio-temporal information about global change effects such as drought. Previous studies on DHIs were performed at a 1 km spatial resolution on a global scale [55]. Latest DHI developments emphasized the combination of the DHIs, climate, and human-related variables in modelling approaches related to the abundance patterns due to high explanatory power [69]. While we were interested in exploiting the globally available NDVI from the Copernicus program [26,91] whose spatial resolution corresponds to earlier DHI studies [21,25] as well as to the climate data set used here, future studies should explore the potential of high to very high spatial resolution NDVI products based on for example PlanetScope, Sentinel-2 or Landsat data [35]. Further, combination of DHIs with ecophysiological measurements [14] and sensory networks [92] together with high-resolution bioclimatic data sets [93] and synthetic aperture radar (SAR)-based maps on soil moisture [94] and forest drought [95] that potentially identify tree damage even before visible evidence [96] could create new insights into forest-die off due to drought events. While the binary forest damage mask based on freely available Sentinel-2 and a random forest model [47] could be further improved using public aerial imagery and methods of deep learning [97], composite remote sensing indices such as the DHI can be computed at high spatial resolution [98], and could provide a continuous metric to assess forest damage, e.g. to map decreasing annual productivity or stagnation at low level after disturbance. Adding structural data and canopy height information from LiDAR data [99] supported by automated field measurements for calibration [100] would be the next step to improve the identification of tipping points and regime shifts to other types of (forest) ecosystems. A long-term networked monitoring system with relatively high-frequency data is needed to understand the underlying forest dynamics (see Ref. [101]). Depending on the availability of the satellite data and acquisitions date, there are numerous existing images with coarser spatial resolutions at the global scale or finer resolutions at the regional or local scale. Dense NDVI times series can be derived from publicly available Landsat and Sentinel-2 imagery at 30 m [102] or even 10 m resolution [15], and vegetation information can be further scaled down to 3 m resolution using PlanetScope imagery [103]. In addition to NDVI-based information, indices that also include the shortwave infrared spectral bands and that are sensitive to vegetation moisture content can be derived from Landsat imagery and bear high potential to assess climate change effects [104]. So, if the annual DHI profiles of healthy and damaged forests are known and calibrated against ecophysiological field data and if the effects of abiotic factors on DHI profiles are explored (e.g. Ref. [27]) and computational

challenges are met, then such time-series based information could contribute to an automated warning system, e.g., by indicating deviations from healthy forest DHI profiles in a spatially explicit way.

Conclusion

Progress in earth technology facilitates its application in ecosystem studies, e.g., to quantify landscape dynamics and capture changes due to extreme droughts, particularly when using time series of remotely sensed and freely accessible data. The DHI based on the multiyear NDVI time series clearly illustrated the strong effect of the drought year 2018 on coniferous forests, so it could support monitoring health status in central European coniferous forest ecosystems or further LULC types. Comparing the values of three DHI components across non-damaged and damaged sites could help to develop early warning indicators of ecosystem degradation and changes in ecosystem functioning. This study also highlighted the importance of considering meteorological and environmental conditions to interpret the remote sensing-based assessment of ecosystem condition. Therefore, we suggest testing this approach across different LULCs types or to assess potential additive effects of multiple extreme events. Future avenues include the use of very high-resolution optical time series data as well as the integration of other data types such as LiDAR to map changes in vegetation structure, or SAR time series data to explore, e.g., changes in vegetation structure and soil moisture especially in areas where the use of optical data is limited.

Availability of data

Data available on request from the authors.

CRedit authorship contribution statement

Mojdeh Safaei: Writing - review & editing, Writing - original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. Till Kleinebecker: Writing - review & editing, Supervision, Methodology, Conceptualization. Manuel Weis: Writing - review & editing, Methodology, Data curation. Andre' Große-Stoltenberg: Writing - review & editing, Validation, Supervision, Resources, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Chapter 11

Potential of the satellite-based Dynamic Habitat Index (DHI) to capture changes in soil properties and drought conditions across Land Use/Land Cover types in a Central European landscape

Mojdeh Safaei^{1,}, Till Kleinebecker^{1,2}, André Große-Stoltenberg^{1,2,**}*

¹Division of Landscape Ecology and Landscape Planning, Institute of Landscape Ecology and Resource Management, IFZ Research Centre for Biosystems, Land Use and Nutrition, Justus Liebig University Giessen, Heinrich-Buff Ring 26-32, 35392, Giessen, Germany

²Center for International Development and Environmental Research (ZEU), Senckenbergstrasse 3, 35390, Giessen, Germany

^{*}, ^{**} Corresponding authors

Abstract

This study evaluates the sensitivity of the Dynamic Habitat Index (DHI), utilizing multitemporal Normalized Difference Vegetation Index (NDVI) data, to changing environmental conditions across Land Use/Land Cover (LULC) types in a central European landscape (2017-2020). We observed distinct DHI characteristics for all LULC types, and the DHI responded to an extreme drought year in 2018 with no return to pre-drought conditions except for deciduous forests. The DHI also effectively captured spatio-temporal variability of pedo-climatic conditions. Thus, integrated with ancillary geodata, the DHI enhances traditional categorical LULC maps, offering applications in biodiversity and ecosystem research. Such integrated products could serve as valuable tools for decision makers to formulate sustainable land management strategies and contribute to Sustainable Development Goal indicators related to land degradation, e.g. by identifying deviations from typical, context-specific DHI profiles as a response to disturbance and environmental stress.

Keywords

Land use/land cover; vegetation productivity; dynamic habitat index; usable field capacity

Introduction

Land Use/Land Cover (LULC) maps provide essential information on landscape structure, functions and dynamics (Belay et al. 2022). Changes in LULC have a crucial impact on ecosystem services (Sharma et al. 2019; Belay et al. 2022; Sharma et al. 2023) and biodiversity assessments (Sharma et al. 2018; Akodéwou et al. 2020; Musetsho et al. 2021) by affecting ecosystem patterns (Gashaw et al. 2018; Safaei et al. 2023) as well as hydrological processes (Wagner et al. 2016; Aghsaei et al. 2020; Yonaba, Biao, et al. 2021). Methods of remote sensing are widely applied to produce and update LULC maps (Chaves et al. 2020; Talukdar et al. 2020) with the aim to identify ecosystem degradation and to guide sustainable land management (Aghsaei et al. 2020; Yonaba, Koita, et al. 2021; Safaei et al. 2023). Consequently, LULC maps are continuously produced by public agencies, eg in Europe within the frame of the Copernicus Land Monitoring Service (CLC 2018), and global products are being developed using novel methods such as deep-learning (Karra et al. 2021). However, these maps are mostly static and categorical representations of LULC. There have been various discussions about moving towards dynamic LULC models that are quantitative and continuous to account for the dynamics of habitat or ecosystem conditions (Coops and Wulder 2019; Le et al. 2022). Quantitative approaches to assess the LULC dynamics are important to understand and manage the landscape variability (Mas et al. 2017; Talukdar et al. 2020). These variabilities have impacts on both environment and human livelihood such as increased flood probability (Avand et al. 2021), drought vulnerability (Fathi-Taperasht et al. 2023), loss of ecosystem services (Belay et al. 2022), soil quality (Safaei et al. 2019) as well as habitat suitability and future species distribution (Marshall et al. 2018). The increasing availability of earth observation data with high temporal resolution allows for exploring ecosystem properties based on time series data in a spatially and temporally continuous way (Ramirez-Reyes et al. 2019; Runge et al. 2019). This includes mapping of LULC based on patterns of vegetation productivity (Gemitzi et al. 2019; Le et al. 2022) for ecosystem service assessments (Kooistra et al. 2023). Consequently, there has been an increasing interest in composite remote sensing indices such as Dynamic Habitat Indices (DHIs), which offer new opportunities to assess the dynamics of habitats related to vegetation productivity (Coops et al. 2008; Hobi et al. 2017; Razenkova et al. 2020). DHIs summarize three measures of vegetative productivity and include the annual productivity and minimum cover as well as seasonality (Coops et al. 2008). The DHI approach showed great potential in biodiversity assessments using a

range of satellite data products such as Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), Gross Primary Production (GPP) and fraction of Photosynthetically Active Radiation (fPAR) at 1 km spatial resolution in Australia (Mackey et al. 2004), Canada (Coops et al. 2008), the United States (US) (Hobi et al. 2017), Russia (Razenkova et al. 2020; Razenkova et al. 2023), Thailand (Suttidate et al. 2019), global scale (Coops et al. 2018) and recently at 3 and 5 m spatial resolutions in the US (Silveira et al. 2023). However, the application of the DHI is mainly restricted to biodiversity aspects. Integration of the DHI with drivers of vegetation productivity such as precipitation regimes (Zeng et al. 2022) as well as soil conditions (Zhang W et al. 2022) in the context of LULC analysis needs to be explored further. Combining the DHI with additional spatial information on ecosystem properties could enhance the understanding of ecosystem dynamics at the landscape scale (Michaud et al. 2012), which in turn would be relevant for applications of the DHI in biodiversity studies.

To our knowledge, a comprehensive assessment of how the DHI changes for different LULC types across different environmental conditions related to precipitation and soil conditions has not yet been studied. Information on the usable field capacity of the soil is essential to understand plant growth particularly in dry years as the response of different LULC types will depend on soil physical and chemical properties (Safaei et al. 2019; Zhang Y et al. 2021). The integration of DHI with explanatory spatial data sets (Michaud et al. 2012) such as soil texture and field capacity under different LULCs and drought conditions would provide more details into drivers of productivity dynamics and underpin the relevance of DHIs to evaluate ecosystem dynamics.

Therefore, the main goal of this study is to investigate if DHIs are sensitive to changing environmental conditions across LULC types. In this case, it will highlight potential to use DHIs in ecosystem studies and could provide further added information to static LULC maps. Our study area is a central European landscape, which experienced a strong drought in 2018 (Senf and Seidl 2021; Thonfeld et al. 2022; Haberstroh et al. 2022). We investigated the effect of soil-related factors such as usable Field Capacity (uFC) and climatic factors on the DHIs of different LULC types such as coniferous forest, deciduous forest, mixed forest, pasture, croplands and built-up areas in the light of the aforementioned drought. Our specific research questions were: (1) Do LULC types have distinct DHI profiles? (2) Do LULC types and their respective DHIs differ specifically regarding their response to the extreme drought in 2018? (3) Do LULC types and their respective DHIs differ in general regarding climatic and soil conditions? Such insights are

expected to be particularly valuable for monitoring activities, management decisions and landscape protection.

Material and methods

Study area

The state of Hesse is located in the centre of the Federal Republic of Germany. It has about 6.3 Million inhabitants, 2.4 Million people living in the Frankfurt-Rhine/Main region in the southern part of the federal state (Kallert et al., 2021). Outside the urbanized areas, the landscape is characterized by a high proportion of forests (ca. 42%), particularly in the northeast and east with forest cover up to 50% (HMUKLV 2023), but also intensively used agricultural regions, eg in the Wetterau north of Frankfurt (Jauker et al. 2009) where forest cover drops down to 15% (HMUKLV 2023), or non-intensively used grasslands in the Lahn-Dill (Reger et al. 2009) or Rhön region (Klinger et al. 2019). In eastern Hesse, the highest mountain with almost 950 m a.s.l is in the Rhön, and the largest continuous basalt area in Europe is the Vogelsberg area (Leßmann et al. 2000). Hesse's geological features include the crystalline Odenwald in the South, the expanse of the Rhenish Slate Mountains in the West, the extensive deposits from the Triassic period (Buntsandstein, Muschelkalk, Keuper) in the North, areas with volcanic rocks, like the above-mentioned Vogelsberg, and the regions where Tertiary and Quaternary sedimentary rocks are distributed, eg the upper Rhine valley in the South (Becker and Reischmann 2021). Small-scale farming is still widespread and cultivated land lies on the limestone uplands and on the loess soils of the river lowlands. Wheat is the most widely grown crop, followed by potatoes and sugar beets. Poultry, pigs and cattle are the main livestock (HLNUG 2023). Figure 1 shows the location of the federal state of Hessen in Germany and a CORINE Land Cover map from 2018 with a spatial resolution of 100 m (CLC 2018) taken from the Copernicus land portal to show different LULC types across Hesse. CORINE land cover maps can be considered a standard for land monitoring in Europe (Feranec et al. 2016).

The climate of Hesse has rather continental features. The average rainfall is between 600 and 800 mm per year ranging from approximately 500 mm in the Upper Rhine Valley to as high as 1400 mm in elevated regions such as the Vogelsberg or the Rhön (HLNUG 2022a). The average annual temperature for the period 1981-2010 stands at 8.8 °C. This marks an increase from the previous period, 1951-1980, during which it was at 8.2 °C (HLNUG 2022a), and the trend shows that it continues to rise, i.e. up to 10.4 °C in 2020

(HLNUG 2020). Considerable variations in annual temperature can be observed, primarily oriented along a North-South axis (HLNUG 2022a, 2022b; Huebener et al. 2022).

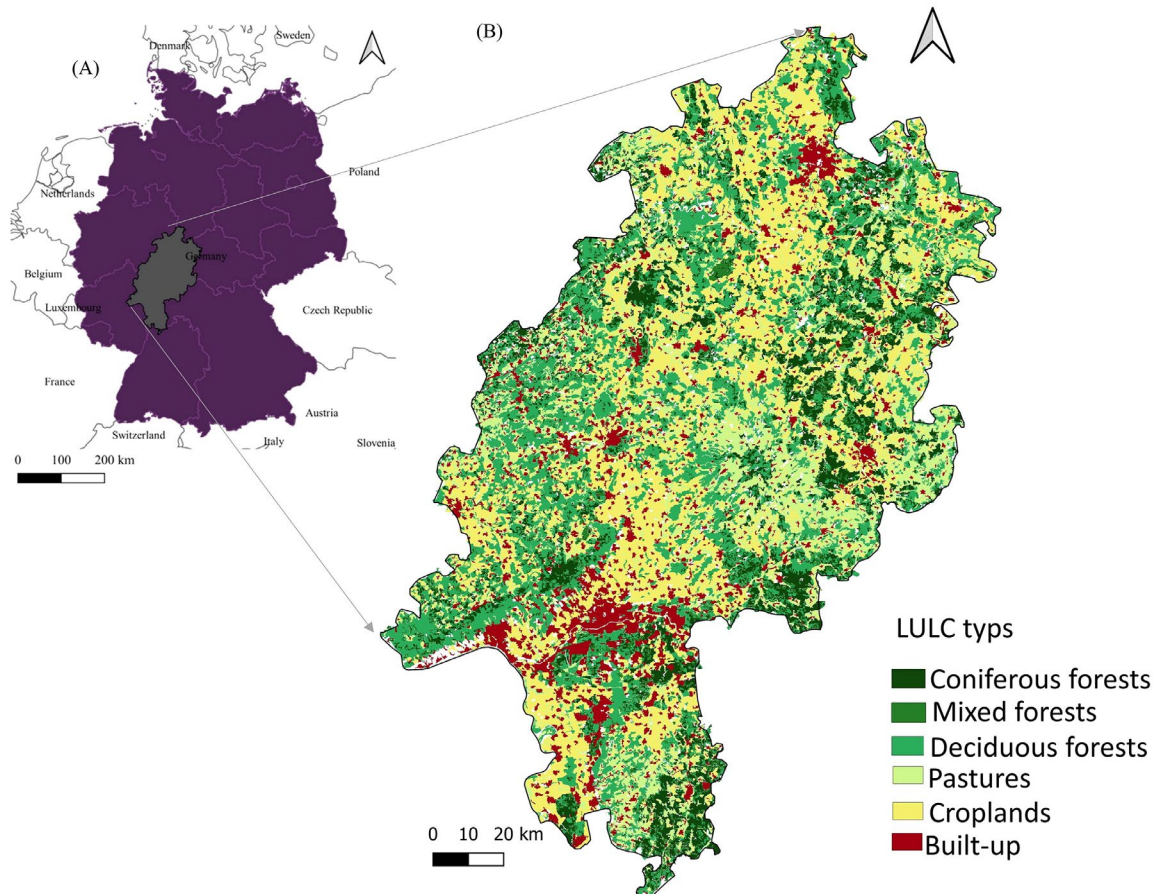


Figure 1: (A) Location of the federal state of Hesse in Central Germany and (B) the CORINE Land cover map from 2018 (CLC 2018).

These variations range from minimal temperature changes in the northern regions to a notable 1.4 °C increase in the South (HLNUG 2022a). In addition, clear differences between urban (hot spots) and rural regions (cold spots) exist (HLNUG 2022b). The annual precipitation levels have also experienced a modest uptick, progressing from 735 mm (1901-1930) to 807 mm (1981-2010). According to the Climate Protection Scenario in Hesse, it is anticipated that average temperatures will continue to rise, leading to an increase in the number of particularly warm days with temperatures exceeding 30 °C (HLNUG 2022a). Nonetheless, there remains a possibility of occasional cold spells in winter and spring, including late frosts. Furthermore, precipitation maxima are expected to shift from summer to winter, with a greater likelihood of rain as opposed to snow during the winter season. Alongside changes in mean temperatures and precipitation, there is a projected increase in the probability and intensity of heavy precipitation events and droughts in the future (HLNUG 2018). In 2018, large parts of

Europe including Hesse were affected by an extreme drought (Senf and Seidl 2021; Thonfeld et al. 2022; Beloiu et al. 2022). Such unprecedented hot droughts in Central Europe are expected to have strong effects, for example, on forest disturbance regimes (Senf and Seidl 2021). Furthermore, nine priority habitat types as defined by the European Habitats Directive (92/43/EEC) occur in Hesse, and seven of them are a likely to be negatively affected by climate change (Schwenkmezger 2019). According to the monthly drought index after de Martonne (CDC 2022), the year 2018 had the highest amount of variation of monthly drought from 2014 to 2021 in Hesse (Figure 2).

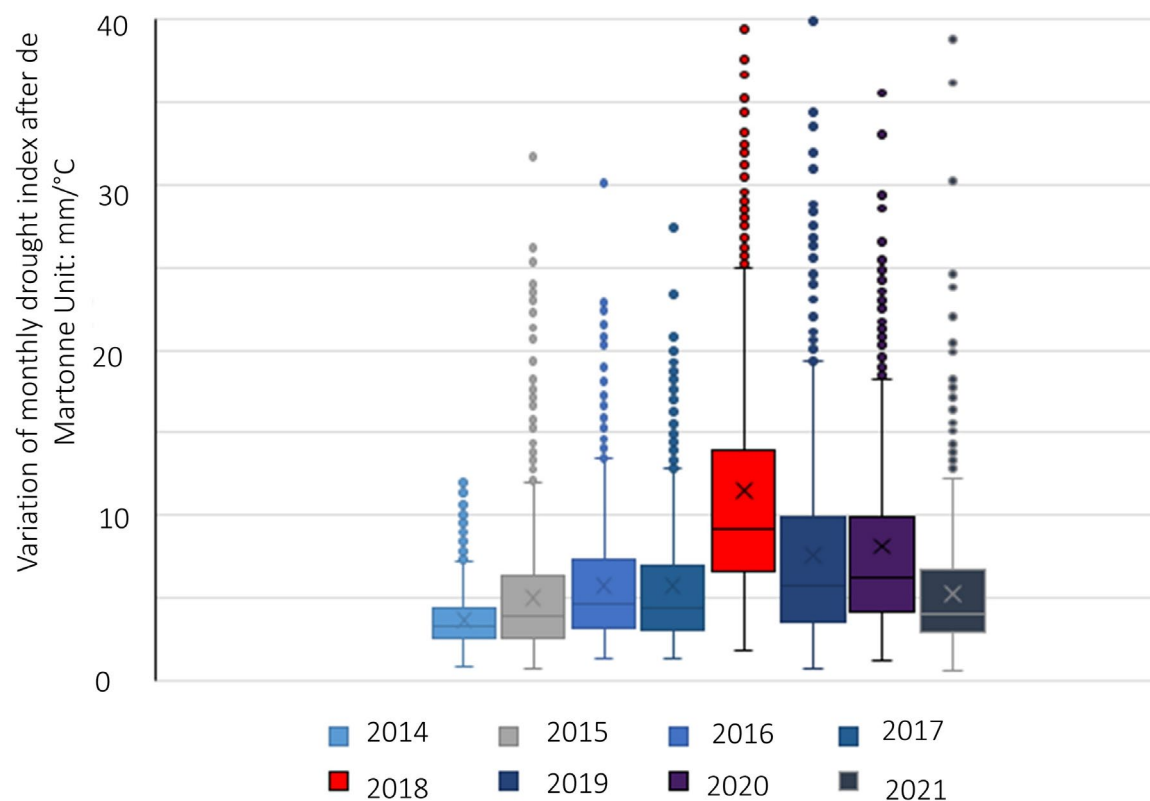


Figure 2: Variation of monthly drought index after de Martonne from 2014 to 2021 in Hesse / Germany (CDC 2022).

Data and analysis

Dynamic Habitat Index (DHI)

The flowchart in Figure 3 shows the conceptual framework of this study. The NDVI products of the Copernicus Global Land Service (Copernicus 2022) that are derived from top-of-canopy PROBA-V satellite data with 300 m spatial resolution (Copernicus 2022) were the basis to compute the three components of the DHI related to vegetation productivity. For this study, we used NDVI data from 01 January 2017 until 31 December 2020 with an interval of 10 days, which totalled up to 144 tiles for the full four-year

dataset. For each year, the three DHI components were computed: cumulative DHI ($DHI_{cum} = \sum p_t$) indicating annual cumulative productivity, minimum DHI ($DHI_{min} = \min(p_t)$) indicating minimum cover and seasonality ($DHI_{var} = \frac{\sigma(p_t)}{\mu(p_t)}$) based on the coefficient of variation using the standard deviation and the mean (p represents vegetation productivity at different periods (t)). The DHI_{Total} was generated from the composite of these three components. All details on DHI calculation are described by Coops et al. (2008), Hobi et al. (2017), Michaud et al. (2012) and Razenkova et al. (2020).

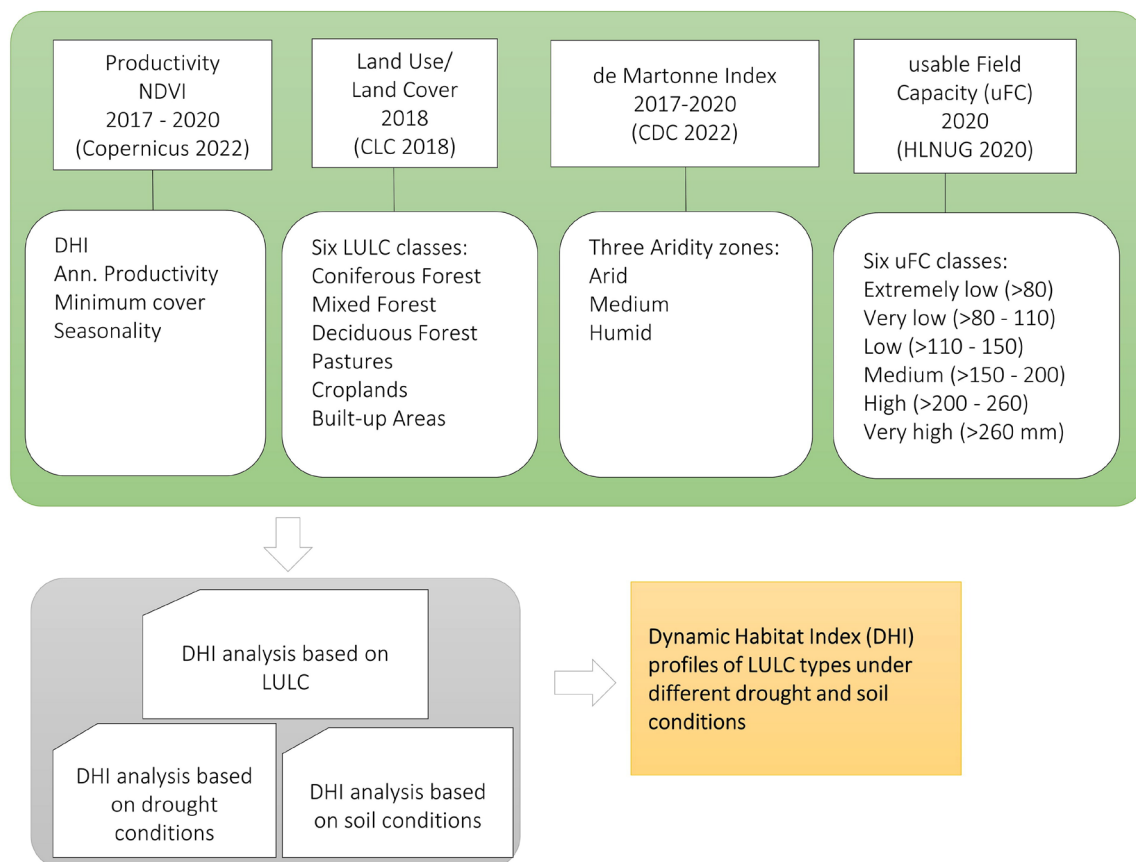


Figure 3: Conceptual framework of the study. The green box contains all input data and their categories. The grey boxes show the methodological steps and analysis to reach the target in the yellow box.

Land use/Land cover (LULC)

The 2018 CORINE Land Cover data set was used to extract six major LULC types in Hesse: coniferous, mixed and deciduous forests, pastures, croplands and built-up areas and a spatial resolution of 100 m (CLC 2018) using ‘Raster’ and ‘SF’ packages in R statistical software version 4 (R Core Team 2021) for raster and vector analysis. To visually control each LULC, the LULC maps and digital orthophotos (DOP) with 20 cm spatial resolution

were overlaid (Geoportal Hessen 2022) in QGIS ver. 3.22 LTR Białowieża (QGIS Development Team 2021) (Figure 1(C)).

Precipitation conditions: de Martonne Index (dMI)

The de Martonne Index (dMI) is based on the relationship of precipitation and temperature for a given area ($dMI = \frac{P}{T+10}$ where T refers to the temperature in degrees Celsius and P refers to the precipitation in mm (de Martonne 1942). Low dMI values indicate aridity while increased values indicate humidity. Thus, the dMI provides information on the drought level at a given site and reflect the aridity of regional climate zones (Bhuyan et al. 2017) and has been used before in Central Germany to describe the extreme drought conditions in summer 2018 (Beloïu et al. 2022). We used monthly grids of the dMI from 01.01.2017 until 31.12.2020 provided by the German Climate Data centre (CDC 2022) to generate regional aridity zones map at 1 km spatial resolution based on a total of 48 tiles for the full four-year dataset (CDC 2022). To do so, we defined three aridity zones (arid, medium, humid) based on cumulative drought in the study area (dMI_{Cum}) for four years using the equation $dMI_{Cum} = \sum dMI_t$, where It refers to the cumulative drought for period t. We used the ‘Raster’ package to calculate the dMI_{Cum} in R statistical software version 4 (R Core Team 2021). We then used natural break (Jenks), which accounts for non-uniform distributions and gives an unequal class width with varying frequency of observations per class, to identify the aridity zones.

Soil conditions: usable field capacity (uFC)

Spatial data on usable Field Capacity (uFC) data was used to study the variation of the DHI across different soil conditions (Table 1). The term field capacity is interchangeably used with the term water holding capacity and refers to the amount of water content held in soil after drainage of excess water (Rai et al. 2017). The uFC of a soil or a horizon describes the available part of the field capacity for vegetation. It thus includes the amount of water that a soil can retain against gravity. The data at a scale of 1:50 000 and a reference depth of 1 m were provided as vector data by Hessian State Agency for Nature Conservation, Environment and Geology (HLNUG_BFD50 2020). There are six main groups of uFC in Hessen ranging from very low to (0-80 mm) to very high (>260 mm) (Table 1). The highest coverage mainly belonged to low uFC (>110-150 mm) with almost 38% of the area, followed by medium uFC (>150-200 mm) with 26% and high uFC (>200-260 mm) with 16.5% of the area.

Table 1: Overview of the different usable field capacity (uFC) categories and the proportional areas in Hesse based on data by HLNUG_BFD(50 2020).

Usable field capacity categories	Level	Area (m ²)	Proportional area in Hesse
Extremely low	0-80 mm	567,495,992	2.99
Very low	>80-110 mm	2,831,954,494	14.95
Low	>110-150 mm	7,199,682,409	38.00
Medium	>150-200 mm	4,885,629,371	25.79
High	>200-260 mm	3,125,752,490	16.50
Very high	>260 mm	3,337,636,467	1.76

To answer the question whether the DHIs are susceptible to changes in soil conditions, we extracted the DHI component values across the six uFC categories for each LULC type in QGIS. When extracting the raster data including the DHIs based on vector categories such as uFC and LULC, pixels smaller than the native DHI pixel size (300 m) at the border of each vector were excluded. For each zone and LULC type the values for the three DHI components were extracted to explore whether the DHI is sensitive towards changing precipitation regimes across LULC types.

We also examined whether yearly DHI components from 2017 to 2020 differed across LULCs and whether they returned to their previous state after the severe drought in 2018. To test it, one-way analysis of variance (ANOVA) and post hoc Tukey test (p value <.05) was employed using the ‘car’ package (R Core Team 2021). Normality of data was checked using the Shapiro-Wilk test and the Q-Q plot of residuals, and Bartlett’s Test was used to check the equality of variances (Zuur et al. 2009).

Results

All LULC revealed distinct DHI profiles (Figure 4) in terms of annual productivity, minimum cover and seasonality. In the map, the colour patterns refer to different amounts of productivity and we could differentiate LULCs visually using digital orthophotos with 20 cm spatial resolution (Geoportal Hessen 2022). For example, blue colour indicates the built-up areas with low annual productivity, low minimum cover and high seasonality. The yellow areas are coniferous forests that are characterized by high annual productivity and minimum cover, but low seasonality. On the other hand, pastures with purple colour have intermediate annual productivity and minimum cover, but low seasonality (Figure 4(A,B)). The three-dimensional scatterplot indicates that

the areas with high seasonality have lower annual productivity and minimum cover than the areas with low seasonality (Figure 4(C)).

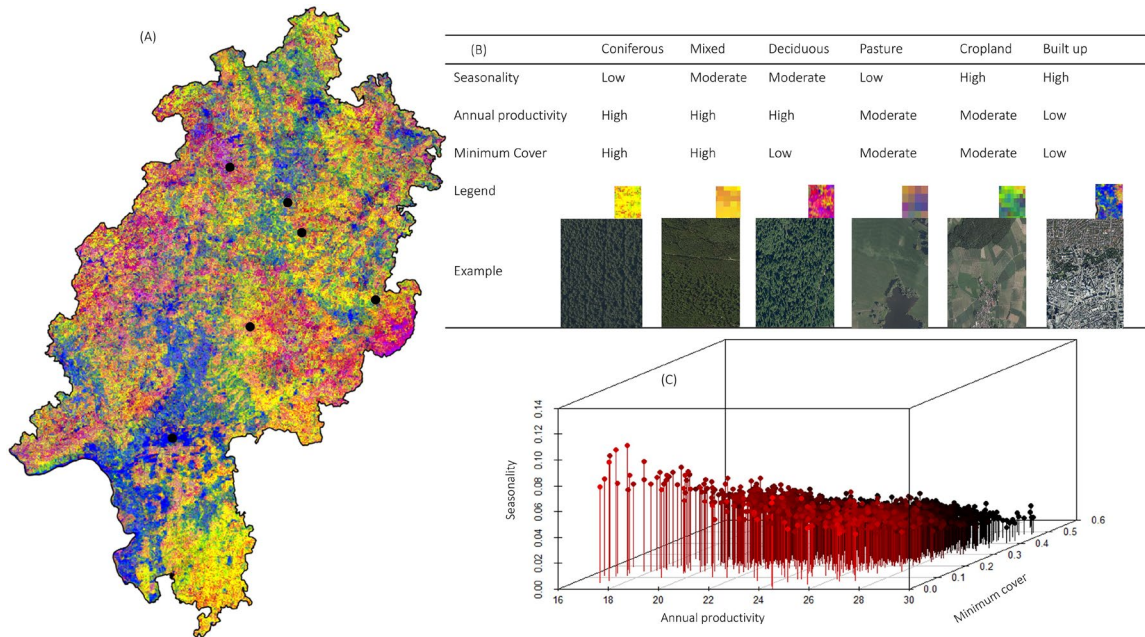


Figure 4: The combined components of the dynamic habitat index derived from 2017 to 2020 (a). this composite image was developed by assigning the annual productivity to the red band, the minimum cover to the green band and the seasonality to the blue band. Blue areas have low annual productivity, low minimum cover and high seasonal variability. Thus, blue areas indicate the locations of the built-up areas. Bright yellow areas have a high annual productivity, a high minimum cover and low variability and represent locations with coniferous forests that were consistently green throughout the year. Purple areas or pastures indicate landscapes with medium annual productivity, medium minimum cover and low variability. Green areas or croplands indicate moderate landscape greenness that varies throughout the year. Red areas or deciduous forest have high annual production, moderate minimum cover and high seasonality. Black points on the map refer to the example areas (B) the three-dimensional scatterplot indicates three components of the DHI. The areas with high seasonality have lower annual productivity and minimum cover than the areas with low seasonality.

Response of the DHI to drought across LULC types

From 2017 to 2020, the annual productivity (DHI_{Cum}) for all LULCs had their maximum in 2017 (Figure 5). In 2018 and 2019, the annual productivity decreased for all LULC types and then started to recover. Except for deciduous forests, none of the other LULCs had fully returned to the pre-drought conditions in 2017. The highest values of annual productivity belonged to forests and pastures (range from 28 to 30) and built-up areas revealed the lowest annual productivity (range from 23 to 25).

Minimum cover increased from 2018 to 2019 for all LULC types, and, in general, the highest values of DHI_{Min} belonged to the forest types (Figure 6). The highest values of minimum cover occurred in the drought year, which contrasts the output of DHI_{Cum}.

Forests and pastures showed less seasonality than croplands and built-up areas (Figure 7). After the drought 2018, the seasonality of the forest LULC types increased. In pastures and croplands, most variation occurred in 2018. In the built-up areas, seasonality was almost constant over the years.

Annual productivity

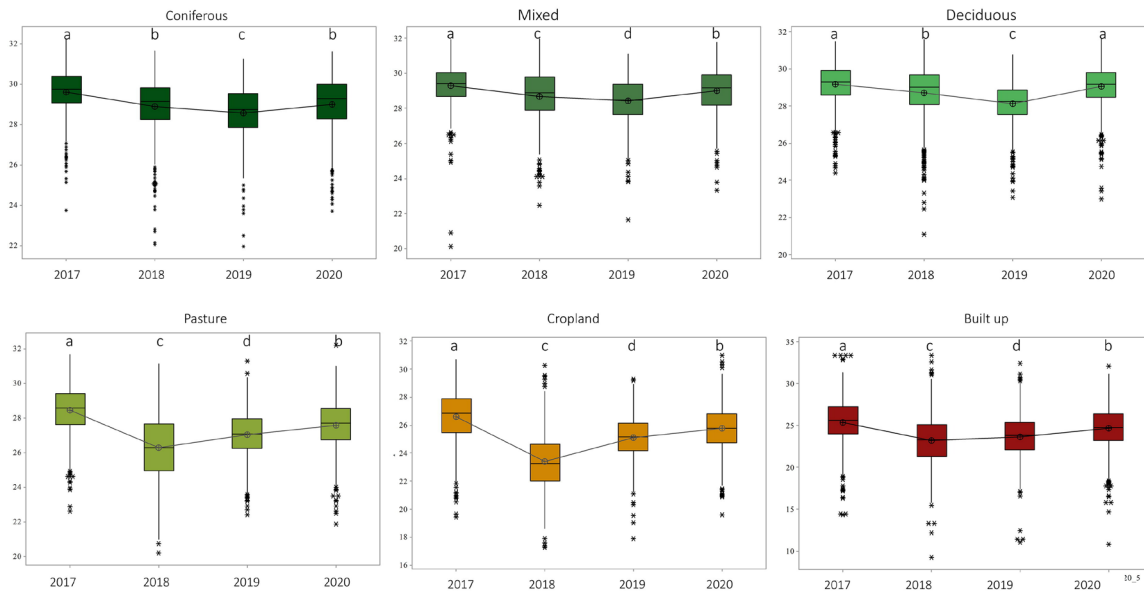


Figure 5: Cumulative annual productivity (DHI_{Cum}) from 2017 to 2020 including the severe drought year 2018 for the six main Land use/Land Cover types in Hesse, Germany, namely, coniferous, mixed and deciduous forests, pastures, croplands and built-up areas. The black line connects the median of annual productivity. Small letters on the columns indicate significant differences in values based on one-way analysis of variance (ANOVA) and the Tukey post hoc test.

Minimum cover

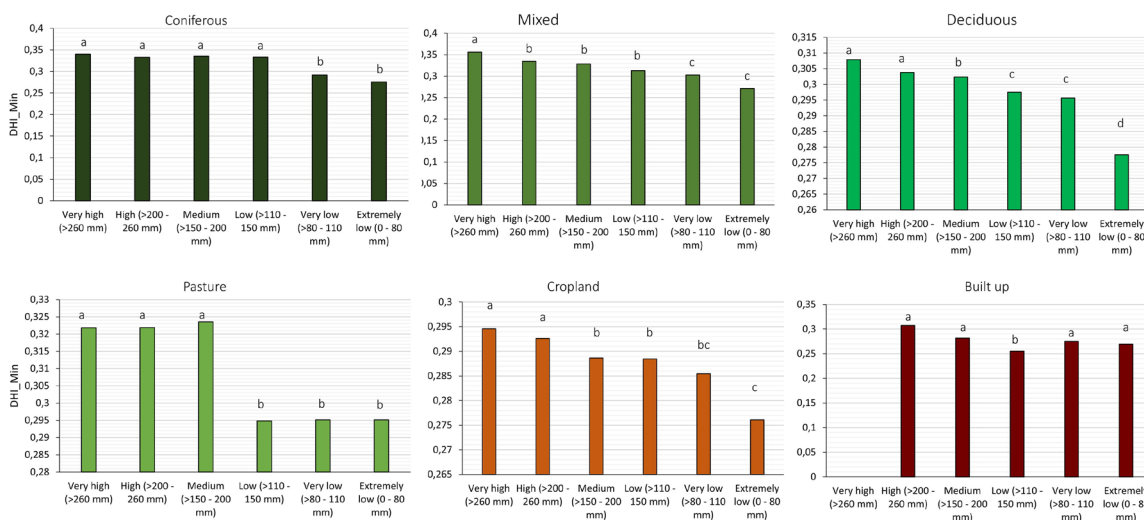


Figure 6: Minimum cover (DHI_{Min}) from 2017 to 2020 including the severe drought year 2018 for the six main Land use/Land Cover types in Hesse, Germany, namely, coniferous, mixed and deciduous forests, pastures, croplands and built-up areas. The black line connects the medians of minimum cover. Small letters on the columns indicate significant differences in values based on one-way analysis of variance (ANOVA) and the Tukey post hoc test.

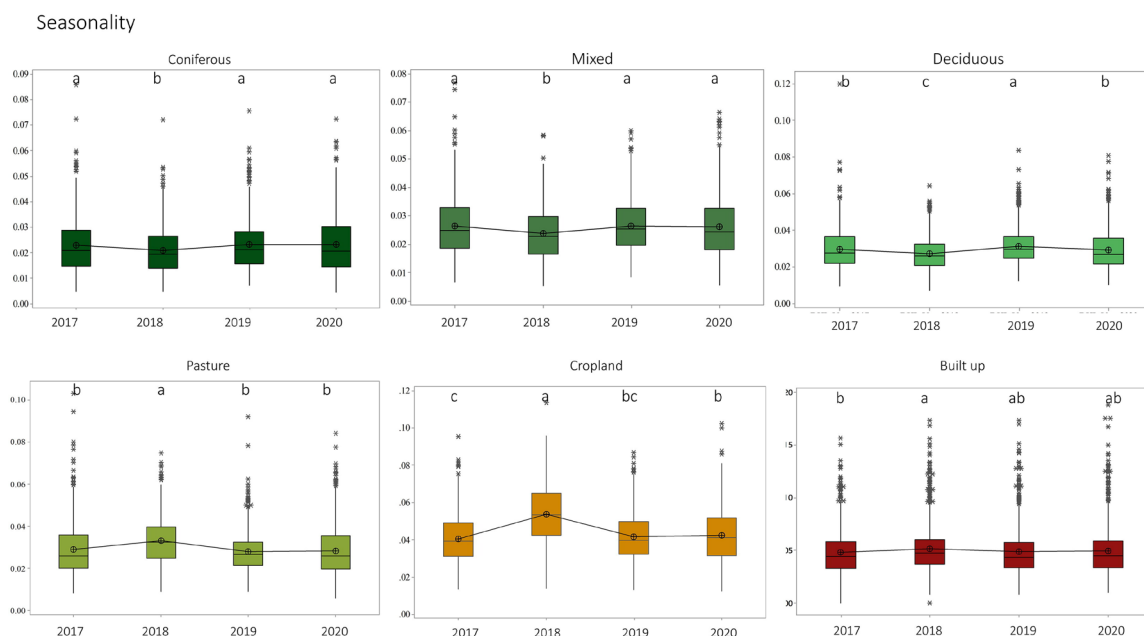


Figure 7: Seasonality (DHIVar) from 2017 to 2020 including the severe drought year 2018 for the six main Land use/Land Cover types in Hesse, Germany, namely, coniferous, mixed and deciduous forests, pastures, croplands and built-up areas. The black line connects the medians of seasonality. Small letters on the columns indicate significant differences in values based on one-way analysis of variance (ANOVA) and the Tukey post hoc test.

Effect of aridity zones on DHI components across LULC types

In general, for all LULC types, annual productivity and minimum cover were significantly higher than in the humid zone than in the medium and arid zone (Figure 8(A,B), $p < .05$). On the other hand, seasonality in arid zones was significantly higher compared to the other two zones (Figure 8(C), $p < .05$). More precisely, the annual productivity in the three forest types, pasture and built-up areas was significantly higher in the humid zone, but there is no significant difference between the medium and arid zone of coniferous and mixed forests and built-up areas (Figure 8(A)). In terms of minimum cover, again the highest values for all LULC types were observed in the humid zone (Figure 8(B)). The maximum seasonality mainly occurred in the arid zone in all LULCs (Figure 8(C)) and the seasonality in forest LULC types was less pronounced than that of pastures, croplands and built-up areas.

Effect of uFC on DHI components across LULC types

With decreasing uFC, annual productivity decreased in all LULC types except built-up areas (Figure 9(A)). In forest types, pasture and croplands lowest annual productivity

was obtained for extremely low (0-80 mm) and very low (>80-110 mm) uFC, whereas maximum annual productivity values were obtained for high (>200-260 mm) and very high (>260 mm) uFC. In built-up areas, annual productivity was not affected by uFC (Figure 9(A)).

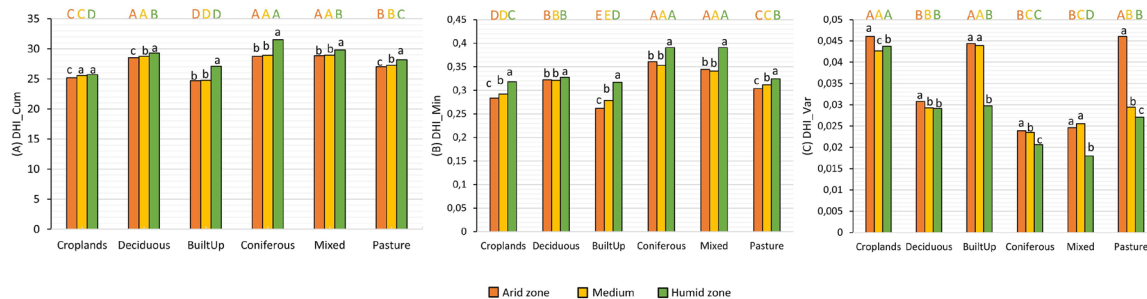
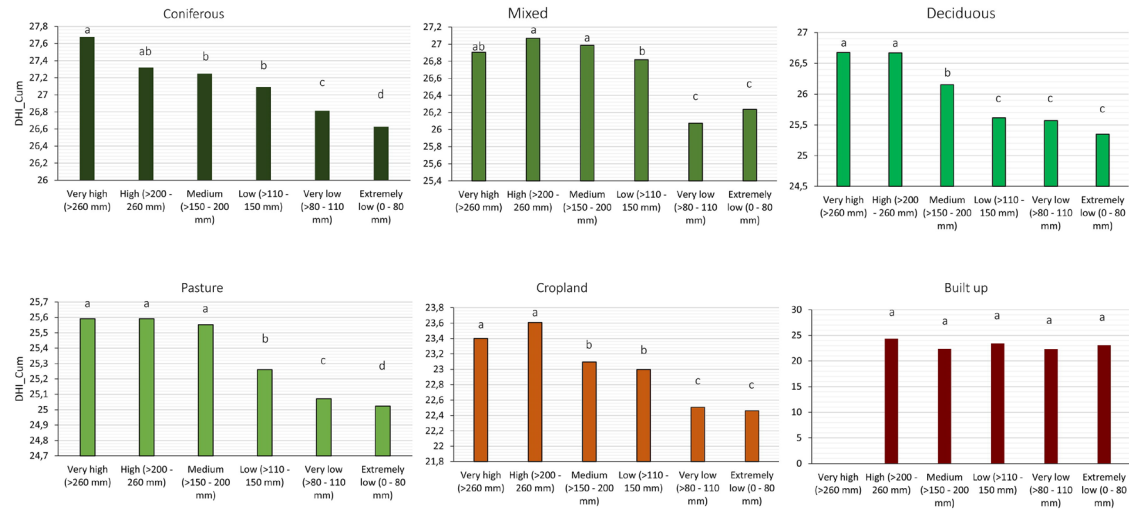


Figure 8: The three components of the Dynamic Habitat Index (DHI), namely (A) DHI_Cum (annual productivity), (B) DHI_Min (minimum cover) and (C) DHI_Var (seasonality) based on NDVI data from 2017 to 2020 are shown for six LULC types (coniferous, mixed and deciduous forests, pastures, croplands and built-up areas) and three aridity zones. The orange columns represent the arid zone, the yellow columns represent the medium zone, and the green columns represent the humid zone. The capital letter above the graph indicates the significance of the comparisons within each aridity zone separately, and the small letters inside the graph indicate the significance of the comparisons within each LULC type (p value < .05).

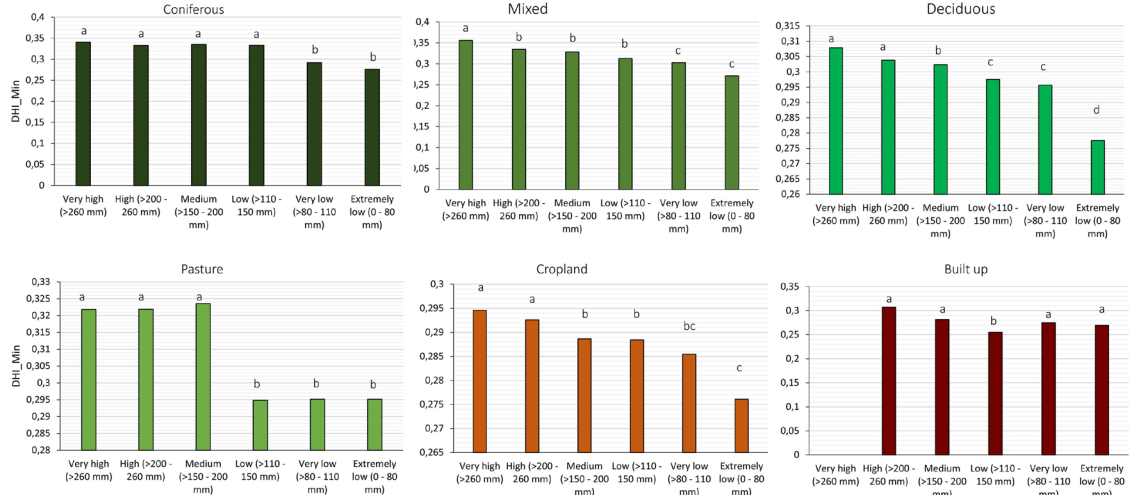
In terms of minimum cover, except of built-up areas, a decreasing trend was observed with decreasing uFC (Figure 9(B)). In forest types, pasture and croplands, the maximum values of minimum cover occurred in the areas with highest uFC.

Seasonality showed a trend opposite to the previous two DHI components. Thus, in forests and pastures lowest seasonality occurred where the uFC was the highest (>260 mm) and seasonality increased when uFC decreased (Figure 9(C)). Cropland and built-up areas showed different trends. For croplands, seasonality was higher in areas with very high uFC (>260 mm), while for built-up areas the changes were not in a particular order.

(A) Annual productivity



(B) Minimum cover



(C) Seasonality

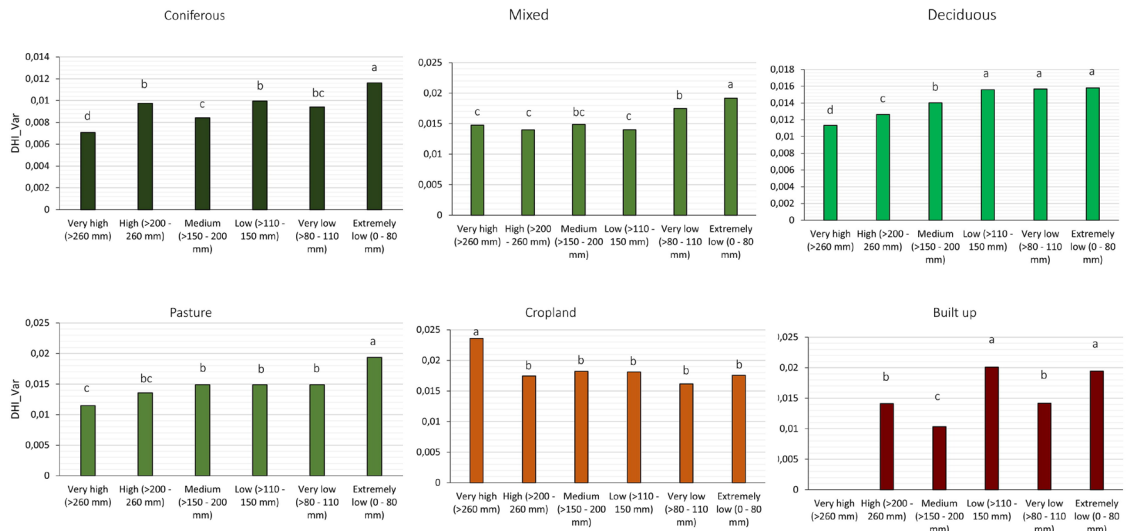


Figure 9: (A) Annual productivity (DHI_Cum), (B) minimum cover (DHI_min) and (C) seasonality (DHI_Var) of each LULC type (namely, coniferous, mixed and deciduous forests, pastures, croplands and built-up areas) depending on the usable field capacity (uFC). Small letters on the columns indicate significant differences between uFC classes (p value < .05).

Discussion

We found that all LULC types had distinct and plausible DHI profiles (eg high productivity and minimum cover, but low intra-seasonal variability for all forest LULC types) that differed due to regional environmental changes related to soil and drought conditions. Annual productivity and seasonality clearly captured the response of the LULC types to different uFC classes and aridity zones, but minimum cover had different temporal trends. Indeed, heat stress and disturbances associated with droughts affect water availability in soil and reduce vegetation productivity (Xu et al. 2019), which is in line with the response of the DHI components to changing climatic and soil conditions. Therefore, the DHI provided a continuous measure to characterize LULC types which could provide more direct connections to ecosystem functions and health than purely static classifications (Coops and Wulder 2019). So, we see potential for composite vegetation indices or other land surface phenological products derived from satellite time-series data to complement common LULC maps to allow for a more detailed analysis of links between LULC and ecosystem functioning and services.

The DHI components responded to the severe drought year 2018. The DHI_{Cum} showed that apart from the deciduous forest none of the LULC types had returned to their original level after the drought event, which could be a sign of weakened resilience and vegetation degradation (Lloret et al. 2022; Manrique-Alba et al. 2022). Indeed, forests are facing several drought events with different intensities and magnitudes during their lifetime and therefore resilience to dry conditions may be critical to long-term survival (DeSoto et al. 2020). Understanding forest productivity and its variation under different environmental conditions is important especially when climate change is likely to strongly affect the productivity of temperate European forests (Morin et al. 2018). Capturing the effect of current droughts based on DHI in the forests can be a promising proxy to assess future tree mortality risk (eg by identifying DHI profiles of forests typical for die-off), especially when producing the DHI using high-resolution optical data like Planet Scopes or Rapid eye images (Silveira et al. 2023). However, the computation of the DHI with a relatively large pixel size comparable to the initial study by Coops et al. (2008) allows retrospective studies, for example using MODIS satellite data. In cases where the use of the NDVI might be limited, for example in semi-arid regions where vegetation cover is low or in the Tropics where the NDVI tends to saturate, other vegetation indices that can partially overcome these limitations such as the Enhanced Vegetation Index or the Soil Adjusted Vegetation Index (Pettoirelli et al. 2005) could be

tested. Another alternative could be a biophysical parameter such as the LAI, which has been used in combination with precipitation indices for vegetation drought monitoring (Kim et al. 2017) and which has been computed in DHI studies (Hobi et al. 2017). A further limitation of using vegetation indices derived from passive optical remote sensing data might be the presence of clouds (Pettorelli et al. 2005). Latest development in forest drought monitoring includes the use of freely available SAR data (Kaiser et al. 2022; Schellenberg et al. 2023), so further potential exists to improve the power of DHI to detect and interpret changes or ecosystem degradation using high-temporal resolution active remote sensing data.

The integration of the DHI with spatial environmental information provides a more comprehensive understanding of ecosystem dynamics at the landscape scale (Michaud et al. 2012), which is extremely valuable for biodiversity assessments (Razenkova et al. 2023; Silveira et al. 2023). In addition, NDVI-based measurements from space have the potential to identify site-specific and climate-induced degradation of vegetation health (Margalef-Marrase et al. 2020), but productivity related effects might show time lags of one to two years (Ogle et al. 2015), so combining the DHI with abiotic factors has the potential to provide insight into ecosystem degradation. Such integrated products could help decision makers to develop sustainable land management strategies and contribute to Sustainable Development Goal (SDG) indicators such as SDG 15.3.1 that is related to land degradation (Sims et al. 2021), eg by identifying deviations of a LULC type from its typical DHI profile within its environmental context as a response to disturbance and environmental stress. Here, examining uFC for different LULCs revealed decreasing annual productivity with decreasing water holding capacity of the soil for all LULCs except built-up areas. The DHI was also able to clearly capture forest and pasture productivity depending on the uFC. Availability of more water is essential for forest growth and thus production, particularly in the context of global change and increased probabilities of severe droughts (Piedallu et al. 2011). In croplands, uFC can have a significant impact on the efficiency of crop productivity under given climate conditions (Fang and Su 2019; He and Wang 2019), and in this study, the DHIs were able to capture such variation. Due to management in croplands (ploughing) and intensive human activities in built-up areas (sealing) the seasonality was higher, and annual productivity was lower compared to forests and pastures. A reason for almost no differences in the built-up area could be the relatively large pixel size as fine urban landscape structures might require spectral unmixing approaches to map urban vegetation greenness even from Landsat time series data (Czekajlo et al. 2020), or the use of very high-resolution

Planet Scope imagery (Silveira et al. 2023). On the other hand, the seasonality of urban heat islands has been mapped using a MODIS-based data product (Sismanidis et al. 2022). Quantifying sealed surfaces and their effect on productivity has been emphasized since it is important in a wide range of strategies to reduce impervious surfaces and their impacts on water resources and vegetation cover for site-level planning and land use regulation (Arnold and Gibbons 1996). Thus, future avenues of research particularly for urban areas could include the combination of the DHI based on the NDVI (or similar parameters) with high temporal thermal remote sensing data.

Conclusion

We show that composite remote sensing indices such as the DHI based on NDVI time series data are useful to characterize LULC types including their variation due to changing soil and drought conditions including effects of severe drought years in Central European landscapes. We argue that DHIs are an appropriate metric to complement or even replace discrete and static LULC maps especially for biodiversity and ecosystem research and application, for example within the frame of Sustainable Development Goals related to sustainable use of terrestrial ecosystems and ongoing land degradation such as SDG 15. Limitations due to coarse spatial resolution could be solved in the future due the availability of free high resolution optical satellite data, and the integration with high temporal resolution thermal and SAR satellite data is to our knowledge still underexplored. The methodological approach was based on publicly available data as well as free and opensource software, so we see potential for further studies in the field of monitoring impacts of climate change, landscape planning and management of ecosystems.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Data are available on request from the authors.

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Chapter 12

The role of small woody landscape features and agroforestry systems for national carbon budgeting in Germany

Karolina Golicz^{1,}, Gohar Ghazaryan², Wiebke Niether³, Ariani C. Wartenberg^{2,4}, Lutz Breuer^{1,5}, Andreas Gattinger^{3,5}, Suzanne R. Jacobs^{1,5}, Till Kleinebecker^{5,6}, Philipp Weckenbrock³ and André Große-Stoltenberg^{5,6}*

¹Institute for Landscape Ecology and Resources Management (ILR), Research Centre for BioSystems, Land Use and Nutrition (iFZ), Justus Liebig University Giessen, Heinrich-Buff-Ring 26, 35392 Giessen, Germany

²Leibniz Centre for Agricultural Landscape Research (ZALF), Eberswalder Straße 84, 15374 Müncheberg, Germany

³Department of Agronomy and Plant Breeding II, Organic Farming, Justus Liebig University Giessen, Karl-Glöckner-Str. 21 C, 35394 Giessen, Germany

⁴Department of Environmental Science, Policy and Management, University of California, Berkeley, CA 94720, USA

⁵Centre for International Development and Environmental Research (ZEU), Justus Liebig University Giessen, Senckenbergstrasse 3, 35390 Giessen, Germany

⁶Division of Landscape Ecology and Landscape Planning, Institute of Landscape Ecology and Resource Management (ILR), Research Centre for Biosystems, Land Use and Nutrition (iFZ), Justus Liebig University Giessen, Heinrich-Buff Ring 26, 35392 Giessen, Germany

* Corresponding author

Land 10: 1028 (2021), doi: 10.3390/land10101028

Supplementary data to this article can be found online at <https://doi.org/10.3390/land10101028>

Abstract

The intensification of food production systems has resulted in landscape simplification, with trees and hedges disappearing from agricultural land, principally in industrialized countries. However, more recently, the potential of agroforestry systems and small woody landscape features (SWFs), e.g., hedgerows, woodlots, and scattered groups of trees, to sequester carbon was highlighted as one of the strategies to combat global climate change. Our study was aimed to assess the extent of SWFs embedded within agricultural landscapes in Germany, estimate their carbon stocks, and investigate the potential for increasing agroforestry cover to offset agricultural greenhouse gas (GHG) emissions. We analyzed open-source geospatial datasets and identified over 900,000 hectares of SWFs on agricultural land, equivalent to 4.6% of the total farmland. The carbon storage of SWFs was estimated at 111 ± 52 SD teragrams of carbon (Tg C), which was previously unaccounted for in GHG inventories and could play a role in mitigating the emissions. Furthermore, we found cropland to have the lowest SWF density and thus the highest potential to benefit from the implementation of agroforestry, which could sequester between 0.2 and 2 Tg of carbon per year. Our study highlights that country-specific data are urgently needed to refine C stock estimates, improve GHG inventories and inform the large-scale implementation of agroforestry in Germany.

Keywords

CORINE; Copernicus land monitoring service; carbon sequestration; biomass carbon stock; agroforestry

Introduction

Globally, the contribution of the land sector (i.e., Agriculture, Forestry, and Other Land Uses, or AFOLU) is estimated to account for 25% (10–12 Pg) of the net anthropogenic greenhouse gas (GHG) emissions, with approximately 50% arising directly from agriculture [1]. Unless these are substantially reduced, the world will fail to meet the Paris Agreement’s target of limiting the increase in average global temperatures to less than 2 °C, relative to pre-industrial levels [2].

The Federal Republic of Germany was one of the first countries to develop a long-term action plan for a low carbon economy and is considered a pioneer in this transition [3]. In their updated Climate Change Act from 2021 [4], the German government stated the ambitious goals of reducing 65% of GHG emissions by 2030, reducing 80% of GHG emissions by 2040, and achieving GHG neutrality by 2045. In 2019, farming contributed 61.8 Tg of carbon dioxide equivalents [5], or 8% of the total GHG emissions in Germany [6]. To address this challenge, new plans for AFOLU sectors include the support for carbon sinks in soils and forestry-related ecosystem services [7]. Germany completed its first agricultural topsoil inventory in 2018 and estimated the mean SOC stocks for croplands ($61 \pm 25 \text{ Mg ha}^{-1}$), grasslands ($88 \pm 32 \text{ Mg ha}^{-1}$), and plantation crops, i.e., orchards and vineyards ($62 \pm 25 \text{ Mg ha}^{-1}$) [8]. Other than these main land use types, we have limited information on the carbon storage potential of emerging land use systems such as agroforestry and interspersed landscape components such as hedges and small woody patches. Increasing recognition by the international community of their potential to contribute to climate change mitigation has led to increased efforts by researchers to quantify their C sequestration potential. However, this remains difficult due to multiple methodological challenges associated with the large-scale assessment of biomass-associated C stocks across heterogeneous landscapes (e.g., [9]).

Farmland including tree biomass (broadly defined as agroforestry) was quantified for the first time by Zomer et al. (2009) [10] and resulted in a major revision to estimates of the C storage potential of agricultural landscapes. This initial approach was subsequently refined in [11], resulting in the global farmland carbon pool estimates of 45.3 and 47.4 Pg C for the years 2000 and 2010, respectively, which were significantly higher than the baseline (11.1 Pg C) stipulated by the Intergovernmental Panel on Climate Change (IPCC). The estimates of Zomer et al. (2016) [11] were based on broad assumptions (e.g., a linear increase in C stock with increasing percentage of tree cover),

but they successfully highlighted the importance of accounting for farmland trees and agroforestry systems.

In Europe, the intensification of food production has resulted in trees disappearing from agricultural landscapes [12,13]. Traditional agroforestry systems such as ‘knicks’ (shelterbelts of Northern Germany), ‘pré-vergers’ (French orchard intercropping), and ‘dehesas’ (Spanish oak-dominated grazed woodlands) were modified to a large extent to accommodate forms of agricultural management that draw on mechanization and low landscape complexity to remain profitable [12]. Several recent meta-analyses have found significantly higher levels of soil carbon under agroforestry compared to agricultural systems without trees [14–17]. This highlights the potential for additional carbon sequestration through agroforestry, particularly when land area is considered. Agricultural land accounts for 39% of the total European Union’s land area, whereas less than 10% is under forestry [18,19]. The remaining small woody landscape features (SWFs), or agroforests as defined by Plieninger (2011) [20]—i.e., hedgerows, isolated trees, riparian woodlands, scattered fruit trees, tree rows, and woodlots—were identified as providing numerous ecosystem functions and services, including C sequestration. Both SWFs and actively managed agroforestry systems play roles in GHG budgeting [21,22]. However, fundamental information regarding their extent and C dynamics is lacking [20].

Factors such as local climate and soil conditions [23], land use history [24], tree density and species, and farm management practices (e.g., frequency of harvesting and pruning) [25] influence the rate and extent to which trees on farms contribute to the sequestration and storage of above-ground and below-ground C. In order to better account for some of these factors, Cardinael et al. (2018) [26] carried out a rigorous literature review to develop coefficients for land use conversion and biomass increments across different climatic regions and agroforestry classes. These coefficients served to refine Tier 1 IPCC Good Practice Guidance [27] on inventorying and reporting GHG emissions but have yet to be widely adopted in practice.

Since no previous assessment of the total contribution of SWF to the carbon storage of German agricultural landscapes was carried out, we propose a novel methodology based on publicly accessible datasets. The methodology can be easily reproduced and replicated, thus constituting a valuable tool to improve current assessments at the pan-European scale and to monitor the development of carbon storage in SWFs over time. This paper was aimed to (1) carry out a national level assessment of the extent and C stock of small woody landscape features (trees and shrubs present on agricultural land)

across Germany and (2) apply the updated IPCC coefficients [26] to estimate the carbon sequestration potential of the increased adoption of agroforestry across the country. We used datasets produced by Copernicus Land Monitoring Service [28] such as the novel Copernicus Small Woody Features 2015 dataset [29], as well as the CORINE Land Cover produced by the Federal Agency for Cartography and Geodesy (BKG), to (i) estimate the extent of small woody landscape features embedded in the agricultural landscape mosaic, (ii) improve estimates of carbon storage of agricultural landscapes by accounting for and quantifying C stocks of small woody landscape features, and (iii) create scenarios to estimate the potential of agroforestry systems to sequester C using the updated IPCC guidelines [26].

Materials and Methods

Conceptual Approach

In this work, we adopted the IPCC Tier 1 approach with default carbon storage values for given land cover types where country-specific biomass data and emission/removal factors were not available [27] to estimate carbon stocks in German SWFs and quantify the carbon sequestration potential of the widespread implementation of agroforestry, i.e., hedgerows (shelterbelts), silvoarable systems, and silvopastoral systems. The steps comprised (1) defining the extent of SWFs across Germany; (2) deriving national-level biomass C estimates through a literature review; (3) estimating the C stocks in above-ground biomass, below-ground biomass, and SOC in accordance with the IPCC methodology; and (4) estimating the potential contribution of agroforestry implementation to agricultural C budget in countrywide land use scenarios.

Data Collection and Geoprocessing

Two publicly available datasets were integrated to map tree and shrub extent over large scales in agricultural areas in Germany. First tree and shrub cover were extracted from the satellite-based Copernicus Small Woody Features 2015 dataset [29], which delineates SWF structures based on the following specifications: a maximum width of 30 m and a minimum length of 50 m for linear features and a minimum and maximum area of 200 and 5000 m², respectively, for patches and additional features. Second, agricultural areas were extracted from the CORINE Land Cover 5 ha CLC5 (2015) product

by the German Federal Agency for Cartography and Geodesy [30]. We only accounted for SWFs on agricultural land, excluding urban areas or other open vegetation.

Our estimates were based on detailed vector layers, which distinguish small woody features into three distinct land cover classes based on geometric characteristics (linear, patchy, and additional; Figure 1) whereas the publicly available raster-based product only separates between two classes (linear and patchy). After visual inspection of the dataset and comparison with a high-resolution base map, the additional woody feature class was also included in the framework. This class includes woody elements that were identified by the pre-classification but did not satisfy all geometric requirements. The additional woody feature class is still connected to a valid SWF or have an area higher than 1500 m² [20]. As the class represents meaningful features that are neither linear nor patchy, it was included to avoid the underestimation of the carbon stocks. Our vector layers were rasterized and overlaid with relevant CORINE land cover classes, i.e., non-irrigated arable land (in ‘Cropland’, CORINE Code 211); pastures, meadows, and other permanent grasslands under agricultural use (‘Grassland’, Code 231); vineyards (Code 221); and fruit tree and berry plantations (‘Orchard’, Code 222) [30].

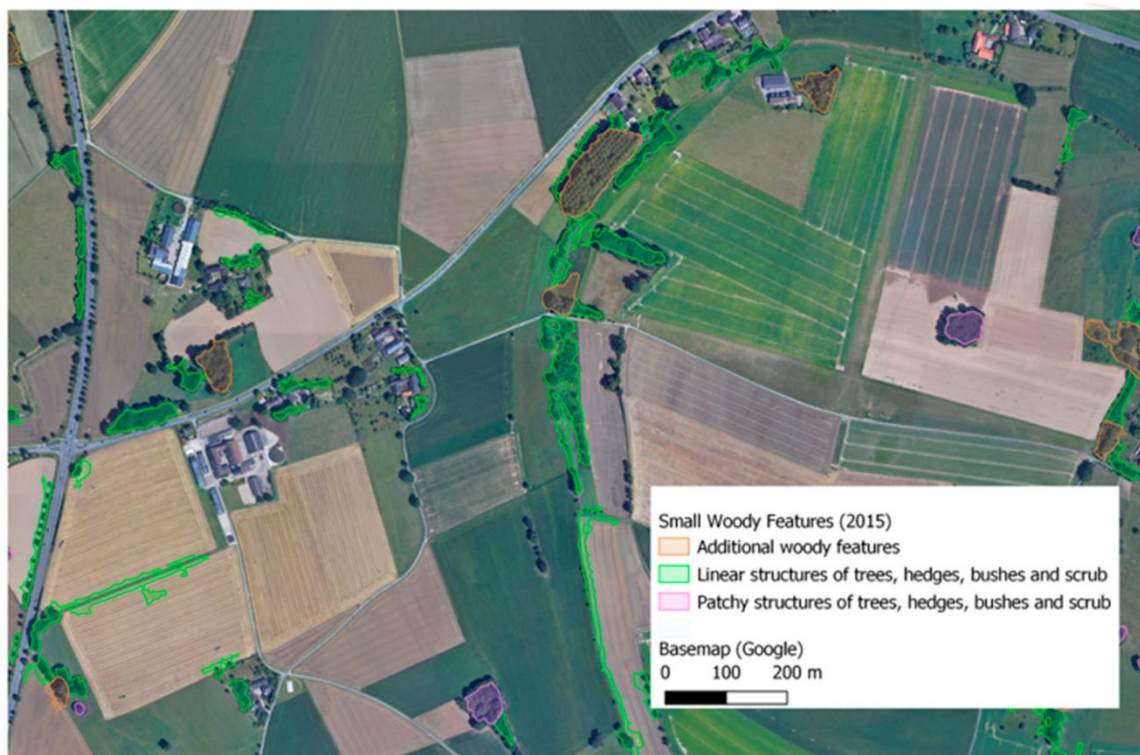


Figure 1: Three classes of small woody landscape features, i.e., linear, patchy, and additional, embedded within agricultural landscapes.

Prior to the analysis, all datasets were reprojected to EPSG 25832 and resampled to a 5 m resolution. Total land cover area and/or hedgerow length were estimated for 16 distinct land use classes, which were based on the combination of the four CORINE land cover classes and the four woody landscape feature classes (three SWF classes and the ‘no SWF’ class) that were identified within each of the CORINE class. We used the raster calculator in QGIS 3.6 [31], and the data were tabulated using the rasterDT package (Ver. 0.3.1) [32] using R Statistical Software (Ver. 4.1) [33]. To assess the spatial patterns of SWFs, the CORINE 2015 dataset was compared against the CORINE 2015 dataset with the SWF dataset using command ‘lsp_compare’ of the R package ‘motif’ (Ver. 0.4.3) [34]. The window size was 500 m, and the distance function was ‘Jensen-Shannon’ with dissimilarity ranging between 0 (low change) and 1 (high change). We analyzed the datasets at the scale of pedoclimatic regions (BKR: Boden-Klima-Räume [35]) of Germany to understand the spatial patterns and abundance of existing SWFs.

Calculations of Biomass Carbon Stocks

To estimate carbon stored in SWF biomass, we referred to the Framework for Data Deficient Areas formulated by Willcock et al. (2012) [36], and we used regionally appropriate carbon estimates derived from the literature (Table 1). The literature search was limited to central Europe, with focus on Germany. The hedgerow biomass was adapted from Drexler et al. (2021) [37] as a proxy for all linear SWFs, values for orchards were adapted from Strohbach and Haase, (2012) [38] and values for vineyards were adapted from the IPCC report (2019) [27]. The steps taken to estimate total biomass carbon (TBC) in non-linear (patchy and additional) SWF structures in cropland and grassland landscape matrices were as follows:

- Identify the above-ground (ABG) C stock in German temperate forests based on information from the National Forest Inventory (C stock equal to 103 Mg C ha⁻¹ [39]).
- Adopt the IPCC (2006) assumption used to develop the GLC2000 Class 17: Forest/Cropland Mosaic [40] and assume an ABG C stock loss equal to 50% of the total ABG C stock of German temperate forests [41].
- Assume further losses due to disturbance and/or harvest equal to 50% of the maximum ABG C in accordance with the IPCC Tier 1 assumption for agroforestry systems [27].
- Calculate carbon in below-ground (BLG) biomass as a fraction ($0.23 \pm 75\%$) of the mean ABG carbon [37].
- Sum up ABG C stock and BLG C stock to obtain TBC stock [37].

Table 1: Biomass carbon stock estimates (mean $\pm$ SD) established for SWFs and agricultural systems including cropland, grassland, and permanent crops (vineyards and orchards). ABG—above-ground, BLG—below-ground, TBC—total biomass carbon. ¹For linear features, the mean ABG and BLG were available from literature, with an expected 50% loss of biomass applied in accordance with the IPCC Tier 1 assumption for the agroforestry systems [27].

SWF Structure/Agricultural System	Maximum ABG C Stock	Mean ABG C Stock	Mean BLG C Stock	Mean TBC Stock	Literature
	Mg C ha ⁻¹				
Linear ¹	-	24.0 $\pm$ 15.0	22.0 $\pm$ 14.0	46.0 $\pm$ 29.0	[37]
Patchy and additional	52.0 $\pm$ 37.0	26.0 $\pm$ 19.0	6.0 $\pm$ 4.0	32.0 $\pm$ 23.0	Own estimation
Cropland	-	-	-	5.0	[42]
Grassland	-	-	-	7.0	[42]
Vineyard	5.5 $\pm$ 0.99	2.8 $\pm$ 0.5	0.6 $\pm$ 0.5	3.4 $\pm$ 0.7	[27]
Orchard	16.0 $\pm$ 3.6	8.0 $\pm$ 1.8	1.8 $\pm$ 1.5	9.8 $\pm$ 2.3	[38]

Calculations of the Soil Carbon Stocks

The SOC (soil depth of 0-30 cm) for linear SWFs was adopted from Drexler et al. (2021) [37], based on findings by Axe et al. (2017) [43]. The SOC (0-30 cm) for patchy and additional SWFs on cropland was estimated by applying the same TBC-to-SOC (21:4) ratio established by Drexler et al. (2021) [37]. The empirically derived SOC data (0-30 cm) for cropland, grassland, orchard, and vineyard systems were adapted from the Thünen Report 64 [8]. The SWF SOC stocks were assumed to be 17 $\pm$ 12 Mg C ha⁻¹ (linear SWFs) [24] and 10 $\pm$ 8 Mg C ha⁻¹ (patchy and additional SWFs) higher relative to the SOC stocks established for cropland, orchard, and vineyard systems. No change in SOC for SWFs on grassland was assumed based on findings by Drexler et al. (2021) [37] and Cardinael et al. (2018) [26]. For a detailed breakdown of values, see Appendix A (Table A1).

Agroforestry Scenarios

In addition to the assessment of the current extent of SWF cover present on farmland and the estimation of their biomass carbon stock, we estimated the potential increase in carbon sequestered by the widespread uptake of agroforestry practices due to the inclusion of trees and shrubs in agricultural land. The potential C sequestration (in ABG, BLG, and SOC) was estimated for three scenarios under which (i) 1%, (ii) 5%, and (iii)

10% of the total amount of croplands, grasslands, vineyards, and orchards in Germany were converted into agroforestry. To develop the land use scenarios, we followed the updated IPCC report (2019) which differentiates between 5 temperate agroforestry systems:

- Hedgerows: linear plantation around fields, including shelterbelts, windbreaks, boundary plantings, and live fences (tree density = 816 stems km⁻¹).
- Silvoarable systems: woody species planted in parallel tree rows to allow for mechanization and intercropped with an annual crop; usually used for timber; low tree density per hectare (tree density = 202 stems ha⁻¹).
- Silvopastoral systems: woody species planted on permanent grasslands, often grazed (tree density = 854 stems ha⁻¹).
- Orchard systems: land planted with woody vegetation, often fruit trees. Understory vegetation is usually mowed or grazed (tree density = N/A).
- Vineyard systems: a plantation of vines, typically producing grapes used for wine-making, but also kiwifruit or passionfruit (tree density = N/A).

The IPCC (2019) agroforestry system definitions and coefficients, alongside their confidence intervals for silvoarable and silvopastoral systems, were used to estimate the potential for C sequestration in ABG biomass, BLG biomass, and SOC (Table A2). The C sequestration rate (ABG biomass, BLG biomass, and SOC) for hedgerows was adapted from the work of Drexler et al. (2021) [37] to reflect country-specific and land-use-specific conditions.

Results

Estimation of the Extent of SWFs

Small woody landscape features in Germany were found to cover 906,243 ha (2.5% of the total land area) across four agricultural systems (Table 2). Grassland systems contributed the greatest acreage of SWFs (517,619 ha or 57% of the total SWF area). Cropland systems had the lowest SWF cover relative to their size (366,678 ha or 2.8% of the total arable area), and orchard systems had the highest (17,528 ha or 9.0% of the total orchard system area). The vineyard systems contributed an SWF cover of 4423 ha (3.5% of the total vineyard area).

The distribution of SWFs and the distribution of the four agricultural systems, i.e., cropland, grassland, and permanent crops (vineyards and orchards) were found to differ between 50 pedo-climatic regions in Germany (Figure 2). Linear SWFs were the most

abundant (520,204 ha), followed by additional (356,164 ha) and patchy SWFs (29,875 ha). The spatial configuration of linear > additional > patchy SWFs was identified for every agricultural system.

Table 2: Total area (ha), agricultural area without SWF (small woody landscape feature) cover (ha), SWF area (ha), and proportion of SWF cover (%) of four agricultural systems across Germany (including CORINE codes).

Agricultural System	Total Area (ha)	Area (No SWFs) (ha)	SWF Area (ha)	SWF Cover (%)
Cropland (211)	12,880,136	12,513,463	366,672	2.8
Grassland (231)	6,433,403	5,915,784	517,619	8.0
Vineyard (221)	127,033	122,610	4423	3.5
Orchard (222)	195,770	178,241	17,528	9.0
Total	19,636,342	18,730,098	906,243	4.6

The pedoclimatic regions in the south and north-east had the lowest SWF cover (0-3%) (Figure 3A). These regions were dominated by cropland (Figure 2). The pedoclimatic regions in the northwest dominated by grasslands had the highest SWF cover (7-8%) (Figure 3A). Landscape structural change, i.e., increasing structural complexity arising from variable SWF cover, was primarily observed in the south, south-west, and central-east, i.e., the areas south of Berlin and north of Leipzig and Dresden, of the country (Figure 3B).

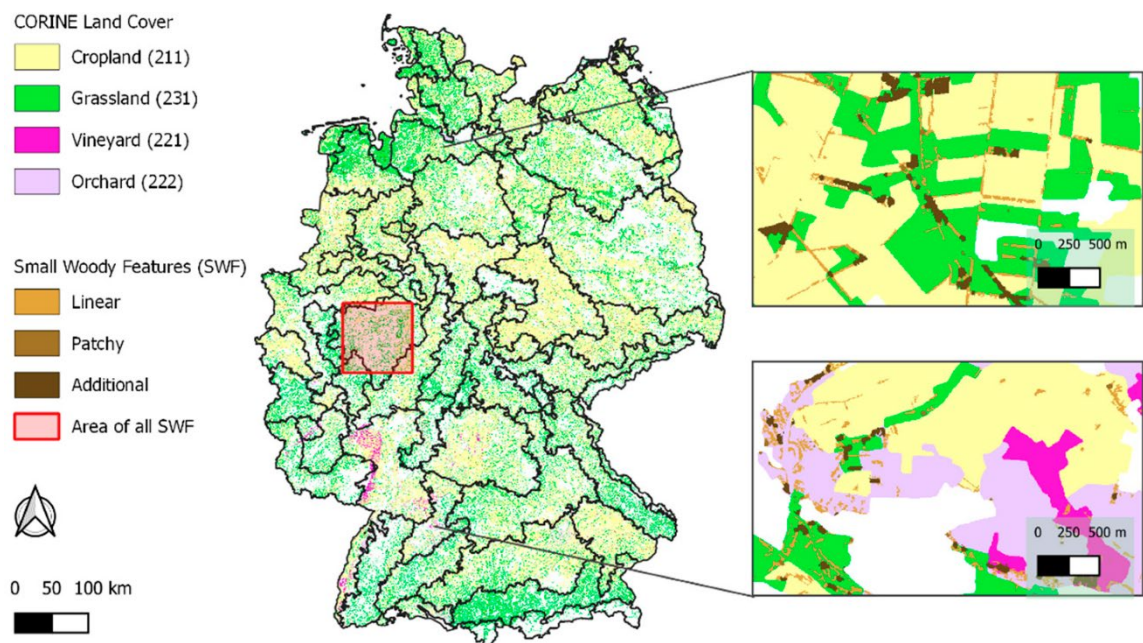


Figure 2: Distribution of SWFs (small woody features) across four agricultural systems. Linear SWFs covered the largest area, and patchy SWFs covered the least. The virtually superimposed red square denotes the total area covered by SWFs relative to the size of Germany. BKR = Boden-Klima-Räume (pedo-climatic regions). Data sources: GeoBasis-DE/BKG (Bundesamt für Kartographie und Geodäsie) CORINE Land Cover 5 ha CLC5 (2015), 2021; Copernicus Land Monitoring Service—High Resolution Layer Small Woody Features—2015 reference year, 2021.

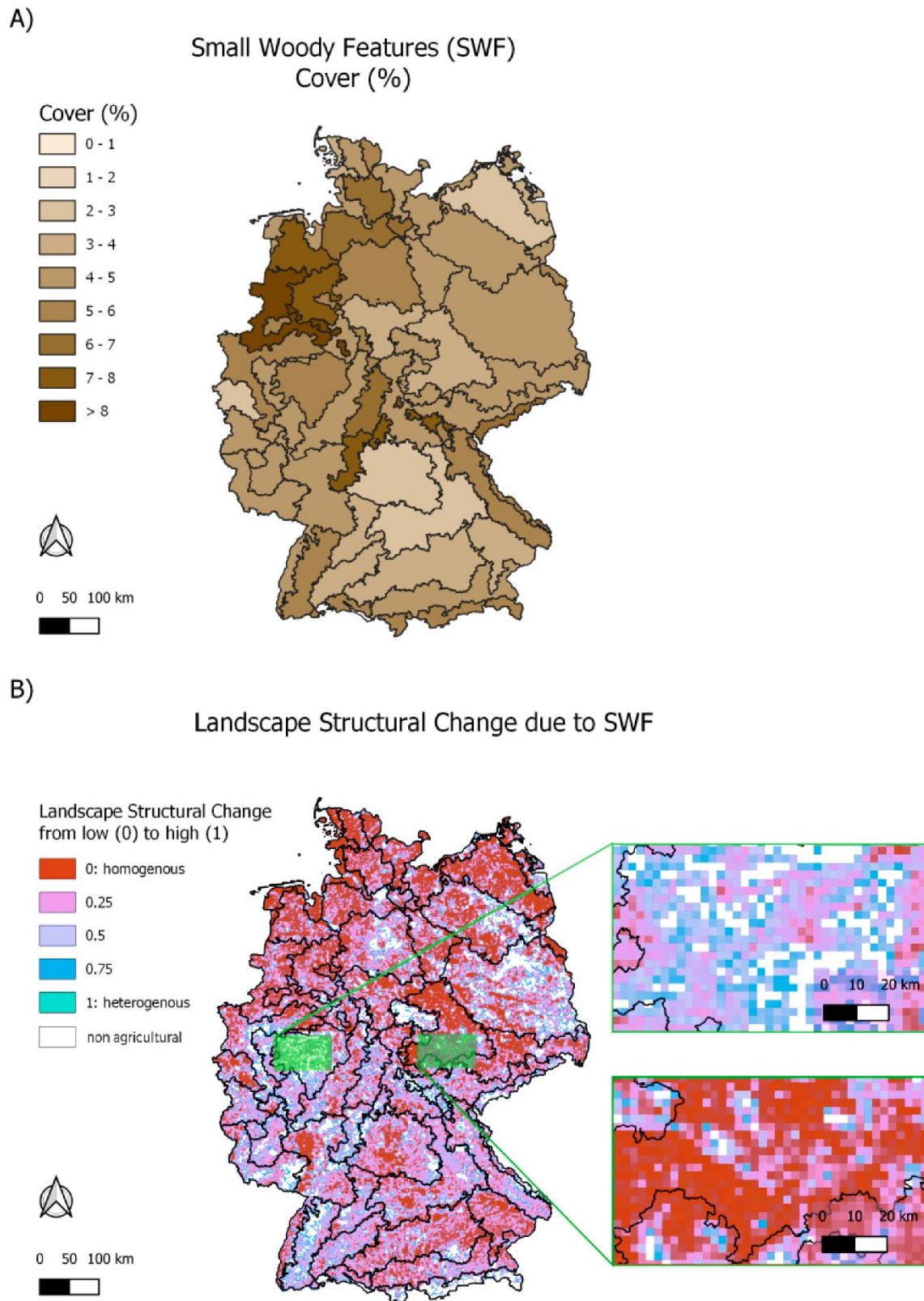


Figure 3: Density of SWFs (small woody landscape features) across 50 growing regions (BKR = Boden-Klima-Räume) (A). Landscape structural change arising from inclusion of small woody features (linear, patchy, and additional) into agricultural land use maps (CORINE) (B). Data sources: GeoBasis-DE/BKG (Bundesamt für Kartographie und Geodäsie). CORINE Land Cover 5 ha CLC5 (2015), 2021; Copernicus Land Monitoring Service—High Resolution Layer Small Woody Features—2015 reference year, 2021.

Quantification of C Stocks of Small Woody Landscape Features

The total C stock of SWFs across Germany was estimated at 111.1 ± 52.5 Tg, with a TBC of 36.3 ± 22.2 Tg and an SOC of 74.8 ± 30.3 Tg. The total SWF C stock constituted 7.9% of the total C stock of agricultural landscapes (Table 3). The SWF TBC was equal to 24% of the estimated annual biomass carbon in cropland systems and half of the herbaceous TBC of grassland systems. The absolute SWFs' TBC was the highest for grassland systems at 20.6 ± 11.9 Tg and second highest (after orchard systems) when considered as a share of all carbon pools combined (SWF TBC = 3% and SWF SOC = 7%) (Figure 4). In cropland and vineyard systems, the SWFs TBC stock constituted 2% of their overall carbon pool and SOC constituted 3% and 4%, respectively.

Table 3: Revised carbon stocks ($\pm$ SD; in Tg C) in Germany after the inclusion of the total biomass carbon stock (TBC, in Tg C) of herbaceous vegetation (including crops), perennial crops, and SWFs. SOC—soil organic carbon, SWF—small woody landscape feature. Numbers refer to CORINE codes. ¹Herbaceous biomass C stocks: 5 Mg C ha^{-1} and 7 Mg C ha^{-1} for cropland and grassland systems, respectively; perennial crop C stocks: 3.4 Mg C ha^{-1} and 9.8 Mg C ha^{-1} for vineyards and orchards, respectively.

Agricultural System	SOC	Other TBC ¹	SWF TBC	SWF SOC	Revised C Stocks
Tg C					
Cropland (211)	763.3 ± 312.8	62.6 ± 46.9	14.8 ± 9.7	27.6 ± 13.0	868.3 ± 382.5
Grassland (231)	520.6 ± 189.3	41.4 ± 31.1	20.6 ± 11.9	45.6 ± 16.6	628.1 ± 248.8
Vineyard (221)	7.6 ± 3.1	0.4 ± 0.1	0.2 ± 0.1	0.3 ± 0.2	8.5 ± 3.4
Orchard (222)	11.1 ± 4.5	1.7 ± 0.4	0.7 ± 0.4	1.3 ± 0.6	14.8 ± 5.9
Total (Tg C)	1302.6 ± 510	106.1 ± 78.5	36.3 ± 22.2	74.8 ± 30.3	1519.8 ± 640.6

The regions with the highest total agricultural area had the highest crop and herbaceous TBC and SOC (Figure 4A-C). The TBC of small woody landscape features constituted a substantial input into the living biomass carbon stocks of agricultural landscapes (Figure 4B), whereas the SWF SOC pools were negligible relative to SOC pools of cropland and grassland systems (Figure 4D).

Overall, the inclusion of SWF C stock (TBC and SOC) in agricultural systems (Figure 5) increased the estimated carbon storage of cropland systems by 4.9% (42 Tg C), grassland systems by 10.5% (66 Tg C), orchard systems by 13.7% (2 Tg C), and vineyard systems by 6.0% (1 Tg C). The contribution of Other TBC sources (herbaceous biomass (i.e., crop and grass) and woody biomass (i.e., perennial crops in vineyard and orchard systems)) ranged from 5 to 12%.

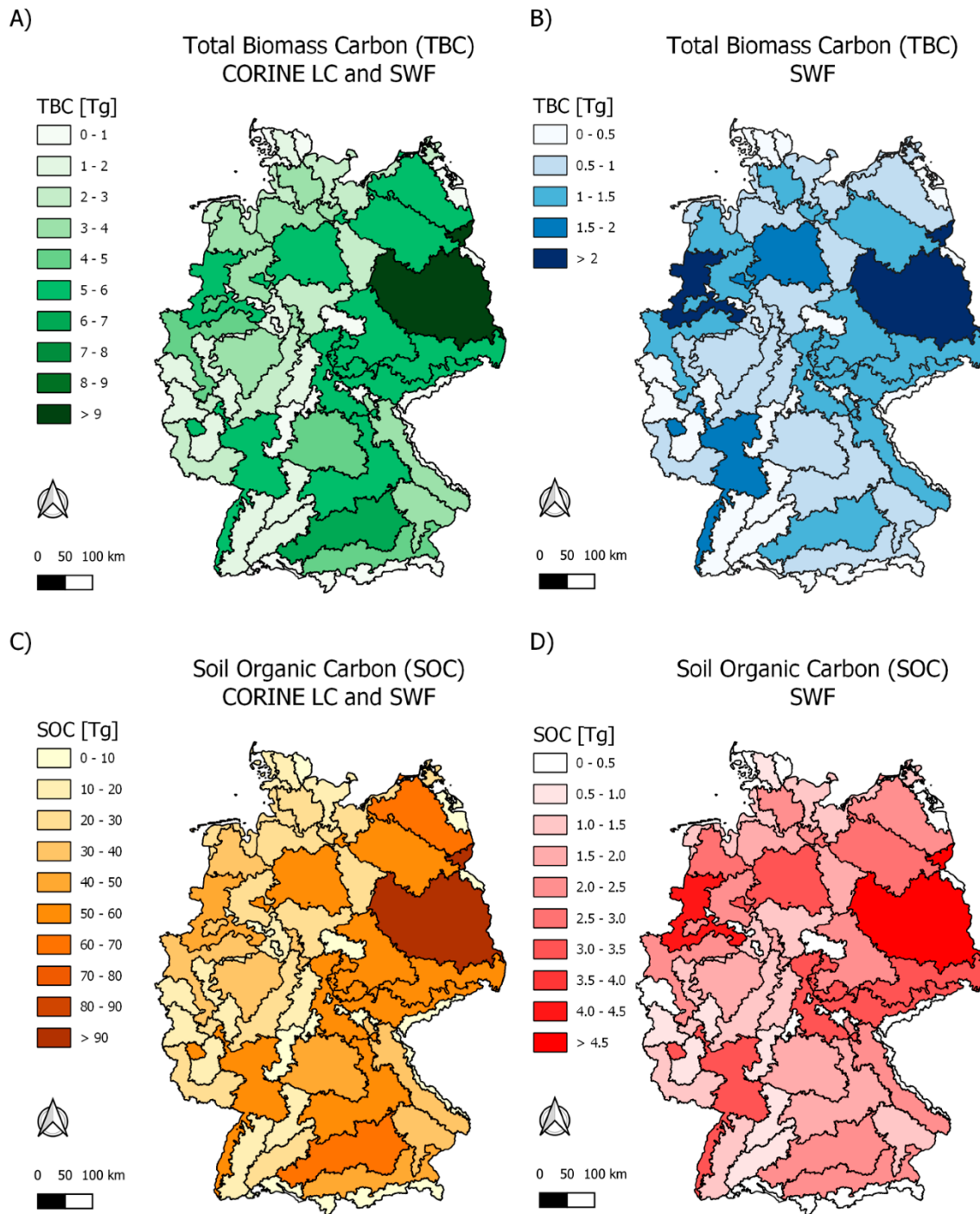


Figure 4: The estimated TBC stock for agricultural land use with SWFs (A) and SWF only (B); the estimated SOC stock for agricultural land use with SWFs (C) and SWF only (D). Data sources: Copernicus Land Monitoring Service—High Resolution Layer Small Woody Features—2015 reference year, 2021.

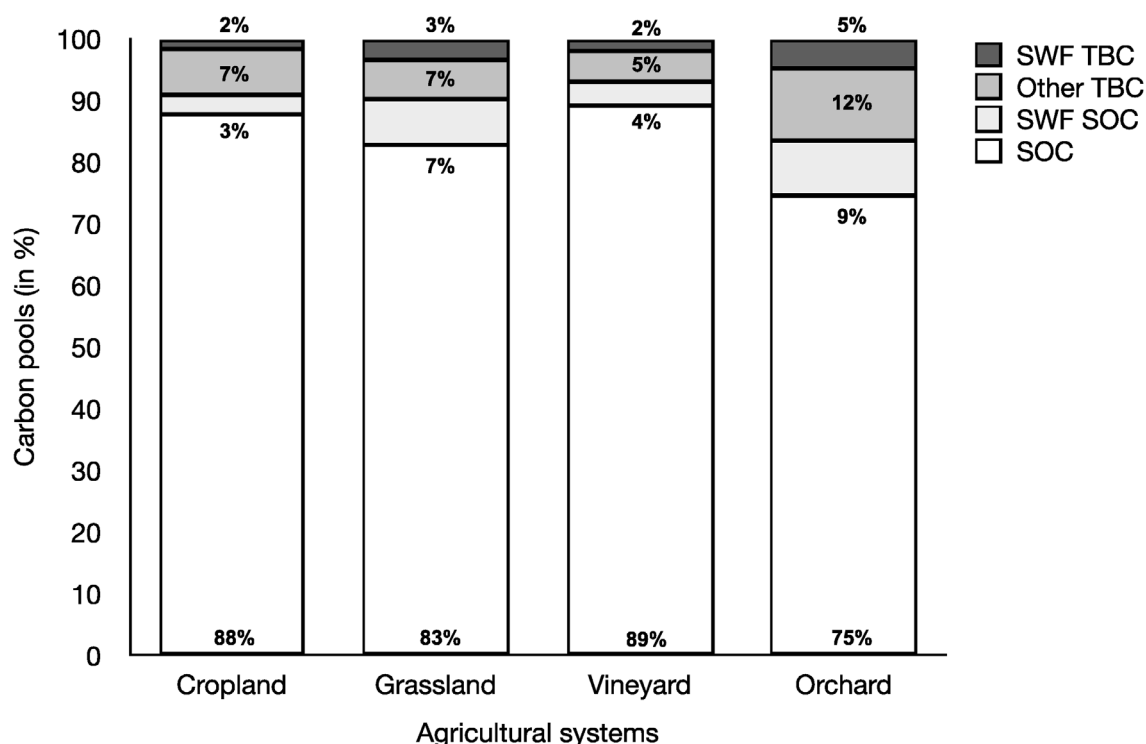


Figure 5: Relative contribution of the components to total carbon pools in four agricultural systems. 'Other TBC' refers to annual crop TBC in arable systems, herbaceous TBC in grassland systems, and woody (not SWF) TBC in vineyard and orchard systems.

The Carbon Benefit of Implementing Agroforestry Practices across Germany

A modest increase (1%) in Germany's cropland converted to either hedgerow or silvoarable systems with an average tree density of 8070-13,931 stems ha⁻¹ [24]; based on [28] or 202 (± 269) stems ha⁻¹ [26], respectively, could result in a maximum C sequestration (in TBC and SOC) ranging from 0.1 to 14.0 Tg C across their expected maturity cycle (30 years) (Table 4). In the 1% land conversion scenario, the installation of hedgerows, i.e., the hypothetical conversion of a full ha of land into hedgerow, were found to be equivalent to the installation of 7,820,915 km of hedgerows with an average width of 4 m. The installation of hedgerows resulted in the highest C gains (14 ± 11 Tg C), followed by the conversion of cropland to silvoarable systems (6.0 ± 3.3 Tg C). The planting of hedgerows on grasslands yielded similar C gains (6.0 ± 5.0 Tg C) to the conversion to silvopastoral systems (5.5 ± 3.1 Tg C). The existing perennial systems, i.e., orchards and vineyards, were found to derive only a minor additional C benefit (0.1 ± 0.1 and 0.2 ± 0.2 Tg C ha⁻¹, respectively) from the installation of hedgerows. In the remaining scenarios, the carbon sequestration potential was found to increase by factors of 5 and 10.

Each land conversion scenario resulted in a positive impact on the carbon sequestration potential of agricultural landscapes across Germany relative to annual carbon emissions estimated at 61.8 Tg C in 2019 (Figure 6).

Table 4: Carbon sequestration potential (in total biomass carbon and soil organic carbon) in Germany for three land conversion scenarios (mean $\pm$ 95% CIs; from [26]). Numbers refer to CORINE codes.

		Land Converted		
Agricultural System	Target Agroforestry System	1%	5%	10%
C Sequestration Potential (Tg C) over 30 Years				
Cropland (211)	Hedgerow	14 ± 11	73 ± 55	143 ± 107
	Silvoarable	6.0 ± 3.3	30.2 ± 16.4	60.4 ± 32.9
Grassland (231)	Hedgerow	6 ± 5	34 ± 25	62 ± 47
	Silvopastoral	5.5 ± 3.1	27.5 ± 15.7	55.0 ± 31.3
Vineyard (221)	Hedgerow	0.1 ± 0.1	0.7 ± 0.5	1.4 ± 1
Orchard (222)	Hedgerow	0.2 ± 0.2	1.1 ± 0.8	2.0 ± 1.5

In the 1% land conversion scenario, the amount of additional land to be converted in each farming system was found to be lower than the amount of land currently covered by SWFs. The potential for C sequestration ranged between 0.005 Tg C (vineyard systems with hedgerows) and 0.5 Tg C yr⁻¹ (cropland systems with hedgerows). The implementation of hedgerows could sequester between 0.5 and 4.8 Tg C yr⁻¹ across three scenarios for cropland systems and between 0.2 and 2 Tg C yr⁻¹ for grassland systems. The conversion of cropland to silvoarable systems could sequester between 0.2 and 2 Tg C yr⁻¹, and the conversion of grassland to silvopastoral systems could sequester between 0.2 and 1.8 Tg C yr⁻¹. Orchard and vineyard systems occupy limited land area, and any increase in C sequestered by hedgerows would be negligible on a national level.

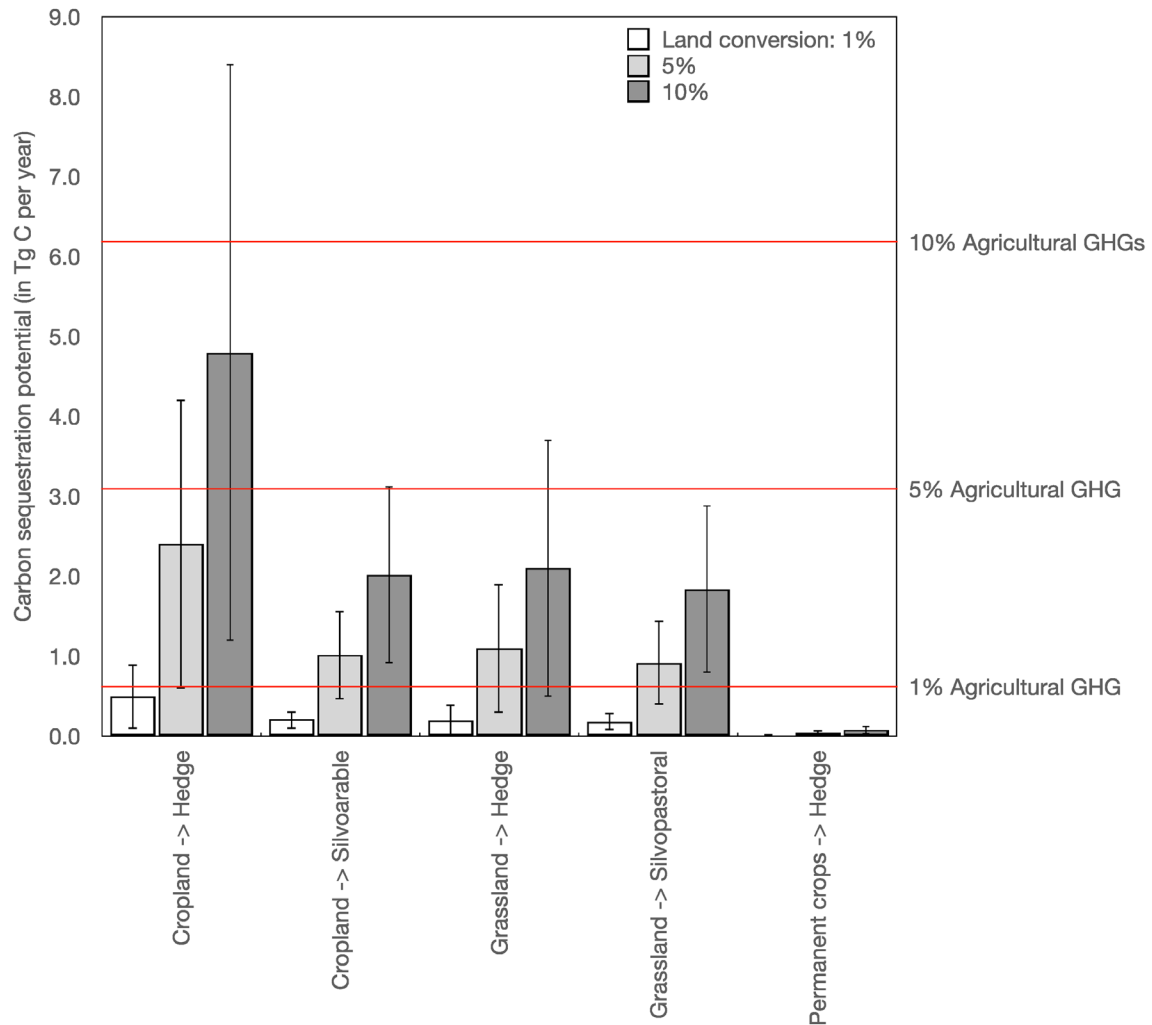


Figure 6: The potential of agroforestry systems to sequester carbon (in Tg yr^{-1}) according to three land conversion scenarios. Red lines denote the percentages of the 2019 agricultural GHG emissions baseline in Germany ($61.8 \text{ Tg C yr}^{-1}$) for comparison purposes [5].

Discussion

The Extent of SWFs in Germany

The nationwide assessment of SWFs resulted in the identification of 906,243 ha of wooded land across German cropland, grassland, vineyards, and orchards. The SWF area was found to be equivalent to 4.6% of the total farmland area, a value three times lower than the European mean tree cover estimates (14.5%) put forward by Zomer et al. (2009) [10]. This difference could be attributed to the used dataset resolution, i.e., the 1 km² used by Zomer et al. (2009), whose calculations were based on 500 m tree cover map by [44] compared to 5 m² in the present study, which was based on the high-resolution SWF Copernicus product [29]. We note the difference in methodological approaches, i.e., tree cover per pixel vs. total SWFs cover derived from accurately delineated

objects. While the work of Zomer et al. (2009) was a benchmark study to show the importance of agroforestry at a global scale, we showed that high-resolution data are required for accurate national monitoring and reporting.

Our findings identified grassland and orchard systems as having the highest SWF cover, which is consistent with previous studies that found European agroforestry to be dominated by grazed woodlands and grasslands with sparse trees [45] and consistent with cropland management practices that favor landscape homogenization [46].

Linear SWFs were the most frequently encountered spatial SWF arrangement, covering over 520,000 ha across the country. In a former assessment, den Herder et al. (2017) [45] estimated their extent across Germany at 73,000 ha. Their estimates were derived from the Land Use and Land Cover (LUCAS) data, and which has been shown to underestimate the hedgerow extent. In the UK, for example, 456,000 ha of hedges was recorded during the Countryside Survey (2007) in England and Wales alone [47], as opposed to the 240,000 ha reported by den Herder et al. (2017) for the entire country [45].

In addition to the linear SWFs, the additional and patchy SWFs, which comprise groups of trees, abandoned farmland encroached by trees and shrubs (including abandoned permanent crop fields), grazed woodlots, and forest fragments, were found to cover close to 390,000 hectares across the agricultural landscape in Germany. These structures are often studied for their contribution to biodiversity conservation [48-51], but no methodology for assessing of their extent across Europe has been developed. We highlight their abundance within German landscapes and note the lack of fundamental information including tree density, stand age, and the contribution of the understory to the carbon storage of SWF structures that warrant further investigation.

The Estimated Carbon Storage Potential of SWFs

We showed that the living biomass and soils of SWFs are important carbon stocks in German agricultural landscapes. Although SWFs cover only 4.6% of the agricultural area, they contribute 7.3% (111 ± 52 SD Tg) to the total agricultural TBC and SOC stocks. In contrast to cropland, the SWF soil carbon stock is not affected by tillage but shows positive sequestration rates in response to the agricultural management (cutting or pruning) of the above-ground biomass [37].

The maintenance of traditional agroforestry practices is supported within the Eco-Schemes of the Common Agricultural Policy (CAP; § 20 3 CAP Direct Payments Act) and at the federal state level [52]. This covers particularly old fruit trees established on

meadows ('Streuobstwiese'). The installation of new agroforestry systems is not recognized as agricultural management at present (2021), but the process to change the legislation is ongoing. In January 2021, the German parliament agreed to subsidize agroforestry [53]. As part of the new national strategic plan of the German government, the planting of trees on cropland and grassland will be supported from 2023 onwards within the new CAP, pending approval in 2022 by the European Commission [54]. Agroforestry is expected to contribute to achieving the EU Green Deal targets, especially through climate change mitigation, water quality improvement, soil degradation limitations, the protection of biodiversity, and pesticide-use reductions [55].

Hedgerow-bordered fields benefit from lower evapotranspiration and thus drought stress, as well as serving as shade dispensers for livestock [56]. The carbon storage potential of hedgerows was recognized early on in Canada [57] and the United Kingdom [43], where hedgerows were found to store between 11 and 105 Mg C km⁻¹ and between 10 and 14 Mg C km⁻¹, respectively. In Germany, the CarboHedge project commenced in 2019 with the goal of quantifying the above-ground and below-ground biomass and SOC sequestration rates typical of German hedgerows; it led to the obtainment of the country-specific information on TBC and SOC sequestration rates [37] that was used in this study. In contrast, the C storage in TBC and soil associated with the remaining SWF structures (patchy and additional) was estimated in accordance with the guidance set out by the IPCC for Tier 1 assessment (with elements of Tier 2 assessment where regional data were available) and the Framework for Data-Deficient Areas formulated by Willcock et al. (2012) [36]. Our estimates broadly corresponded to the values stipulated in the IPCC GL2000 dataset for Forest/Cropland Mosaic (range: 6.8–35.5 Mg ha⁻¹ for the IPCC eco-floristic regions assigned to Germany) and were conservative relative to the C storage estimates of 'Small woodlands' (81 ± 18.0 Mg ha⁻¹), which included successional poplar-dominated and old oak-dominated forest stands investigated in the urban landscape of Leipzig, central Germany [38]. Empirical assessments of the carbon storage potential of non-linear SWFs, particularly, that of their below-ground biomass, are needed in future work to refine the current estimates.

Furthermore, trends in SWF presence and the level of landscape complexity were linked to pedoclimatic regions of Germany. Regions dominated by cropland had the lowest SWF cover, and regions dominated by grassland had the highest SWF cover (7–8%). Understanding the spatial distribution of SWFs could assist with targeting regions

characterized by inherently low SWF cover for the implementation of carbon sequestration-oriented agronomic practices such as agroforestry at a national scale.

The Carbon Sequestration Potential of Agroforestry Systems

We calculated the carbon sequestration potential of agroforestry systems adopted at a conservative level of 1% and moderate levels of 5% and 10% of total agricultural land. This hypothetical land conversion showed a high potential for offsetting GHG emissions, ranging from 0.005 (CIs: 0.002-0.008) to 4.8 (CIs: 1.2-8.4) Tg C per year. Planting hedgerows on 125,135 ha of cropland could result in an annual CO₂ sequestration close to 1% of the GHG emissions from farmland in 2019 [5]. Assuming no future tillage takes place, approximately 20% of the carbon would be permanently stored in the soil [37]. Integrating tree lines in cropland and pastures provides lower carbon sequestration than the installation of hedgerows. This can be explained by the structure of hedges, which have a high stem density of 81,368 stems ha⁻¹ per hedge [43] or 125-816 stems ha⁻¹ in hedgerow agroforestry systems [26], and the regrowth capacity after regular trimming that results in high carbon input to SOC through the turnover of litter and dead root material [37]. In contrast, trees in silvoarable agroforestry systems such as alley cropping are planted with greater (15 m) inter-row spacing [12] and lower (99-111 stems ha⁻¹) stem density [26], resulting in lower carbon sequestration.

Whereas hedgerows are traditionally planted as windbreaks with no marketable products besides their biomass for energy production, tree species in agroforestry systems are intentionally selected for their production of fruits, or precious timber, and may therefore offer additional income [58] and increased productivity per area [59]. The concept of successional or dynamic agroforestry, where trees, shrubs, and bushes are planted in spatial proximity and temporal succession [60], adopted for temperate regions may combine the agroecological benefits of hedges with a high biomass production and carbon sequestration, as well as the fruit or timber production of selected tree species among other ecosystem services related to both structures. Finally, installing hedgerows in perennial systems (vineyard and orchard systems) has only a minor effect on the carbon sequestration at a national level, but it could increase other ecosystem services, e.g., biodiversity conservation, and thus lead to pollination success [61].

Farmers are aware of the environmental benefits of agroforestry systems, but the effects on the overall productivity of systems remain uncertain [62]. In addition, a lack of effective policy measures, e.g., at the EU and national levels, currently constitutes a major constraint of the wider adoption of tree-planting measures in agriculture (e.g.,

[13,63]). Therefore, the development of improved legal frameworks and incentive mechanisms, along with the reduction of administrative burdens, is likely to increase the farmer adoption of agroforestry measures, including in highly productive pedoclimatic regions [13,62]. The widespread adoption of agroforestry in Germany and other temperate regions should be considered for the future agricultural mitigation of climate change.

Study Limitations and Data Needs for Future Research

In our study, we applied regional estimates specific to temperate Europe, derived from scientific literature sources, to develop a national assessment of above- and below-ground carbon stocks and sequestration rates for small woody landscape features in Germany. We acknowledge that our approach did not account for high variability in carbon storage and sequestration rates across temperate agroforestry systems driven by species-site-, or management-specific heterogeneity inherent to these systems [14,25,64,65]. Moreover, though we applied a systematic methodology to estimate carbon storage potential at a national scale here, our approach may not have accounted for inconsistencies in individual study measurements used to derive our coefficients [37,64]. Although recent advances have been made to differentiate between climatic conditions and typologies of agroforestry systems [26], accurate assessments remain limited by data availability, particularly in temperate zones.

Given the increasing recognition of the potential of tree-based systems for climate regulation, we reiterate the need for consistent and precise empirical datasets documenting carbon storage and GHG emissions and removals in agroforestry systems at the national or sub-national levels [14,26]. This would be particularly relevant for the patchy features class identified in the Copernicus dataset used here. Such data could be obtained through a combination of standardized long-term field measurements [14,37] and remote-sensing sensing such as airborne LiDAR in combination with digital orthoimagery [66], and they should account for temporal-, spatial-, species-, and management-specific variation. Agroforestry practices have long been associated with a suite of broader agroecological benefits beyond carbon sequestration, including the rehabilitation of degraded land, improved nutrient recycling, soil erosion control, and the diversification of income sources for farmers ([67,68]). Therefore, a coordinated examination of the optimization of SWF and agroforestry benefits for climate in the context of broader socio-economic considerations is needed to guide policies and improve agroforestry implementation amongst farmers (e.g., [69]).

Conclusions

In this work, we successfully estimated the carbon stocks in German SWFs and quantified the carbon sequestration potential of the widespread implementation of agroforestry, i.e., hedgerows (shelterbelts), silvoarable systems, and silvopastoral systems. The results highlighted the need to account for SWF extent and carbon stocks for a more accurate assessment of the C storage capacity of agricultural landscapes in Germany. Empirical data for non-linear SWFs are urgently needed to validate the TBC and SOC estimates derived through a literature review and to decrease uncertainties associated with the estimates. Additionally, the current SWF dataset does not include, e.g., scattered trees, which might result in an underestimation of C stocks; in the future, regional datasets could be used for more precise assessments. Furthermore, the widespread implementation of agroforestry was shown to be a promising approach to offset parts of the agricultural GHG emissions. However, the analysis should be refined by, e.g., considering farmer adoption rates as opposed to the total land area to be converted and having regional TBC and SOC data for silvoarable and silvopastoral systems. While we acknowledge the shortcomings of our study, our methodology has the benefit of being reproducible and can be used to inform SWF assessments across Europe.

Author Contributions

Conceptualization, L.B., K.G., A.G.-S. and W.N.; formal analysis, A.G.-S., G.G., A.C.W. and K.G.; writing—original draft preparation, K.G.; writing—review and editing, A.C.W., W.N., L.B., T.K., S.R.J., A.G.-S., P.W. and A.G. All authors have read and agreed to the published version of the manuscript.

Funding

We would like to acknowledge funding of the ‘Agroforstprojekt Gladbacherhof’ (VII 5—80e04-09-04) through the Hessische Ministerium für Umwelt, Klimaschutz, Landwirtschaft und Verbraucherschutz as part of the Hessische Ökoaktionsplan 2020-2025.

Data Availability Statement

Data are available on request from the authors.

Acknowledgments

Many thanks are extended to J. Breslin for proofreading of the article.

Conflicts of Interest

The authors declare no conflict of interest.

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Chapter 13

Once common, long in decline: dynamics of traditional orchards in a Central European landscape

André Große-Stoltenberg^{1,2,}, Andreas Hanzl³, Mojdeh Safaei¹ and Till Kleinebecker^{1,2}*

¹Institute for Landscape Ecology and Resources Management (ILR), Research Centre for BioSystems, Land Use and Nutrition (iFZ), Justus Liebig University Giessen, Heinrich-Buff-Ring 26, 35392 Giessen, Germany

²Centre for International Development and Environmental Research (ZEU), Justus Liebig University Giessen, Senckenbergstrasse 3, 35390 Giessen, Germany

³Earth Observation for Ecosystem Management, School of Life Sciences, Technical University of Munich, 85354 Freising, Germany

* Corresponding author

Land 13: 1639 (2021), doi: 10.3390/land13101639

Supplementary data to this article can be found online at <https://www.mdpi.com/article/10.3390/land13101639>

Abstract

The intensification of food production systems has resulted in landscape simplification, with trees and hedges disappearing from agricultural land, principally in industrialized countries. However, more recently, the potential of agroforestry systems and small woody landscape features (SWFs), e.g., hedgerows, woodlots, and scattered groups of trees, to sequester carbon was highlighted as one of the strategies to combat global climate change. Our study was aimed to assess the extent of SWFs embedded within agricultural landscapes in Germany, estimate their carbon stocks, and investigate the potential for increasing agroforestry cover to offset agricultural greenhouse gas (GHG) emissions. We analyzed open-source geospatial datasets and identified over 900,000 hectares of SWFs on agricultural land, equivalent to 4.6% of the total farmland. The carbon storage of SWFs was estimated at 111 ± 52 SD teragrams of carbon (Tg C), which was previously unaccounted for in GHG inventories and could play a role in mitigating the emissions. Furthermore, we found cropland to have the lowest SWF density and thus the highest potential to benefit from the implementation of agroforestry, which could sequester between 0.2 and 2 Tg of carbon per year. Our study highlights that country-specific data are urgently needed to refine C stock estimates, improve GHG inventories and inform the large-scale implementation of agroforestry in Germany.

Keywords

traditional orchards; orchard meadows; agroforestry; Streuobstwiese; biodiversity; scattered trees; fruit trees; extensively cultivated landscapes

Introduction

Traditional orchards, also known as orchard meadows, are distinctive features of cultural landscapes in Central Europe [1-4]. They are characterised by fruit trees with high trunks, scattered across meadows or pastures that are managed with low intensity. Unlike high-intensity fruit plantations, traditional orchards exhibit a much wider age distribution and typically feature a diverse array of fruit tree species and varieties that were planted at low densities [4].

Covering a wide range of environmental conditions, traditional orchards play a crucial role in preserving biodiversity at both the local and landscape scales [5-8]. The extraordinary biodiversity found in these traditional agroforestry systems derives from the combination of low-intensity fruit production and grassland management, which creates a high level of structural diversity, allowing for many species to co-exist [4,9]. In Germany, traditional orchard meadows (in German Streuobstwiese) provide a habitat for more than 5000 plant and animal species, and they are regarded as a particular hotspot for biodiversity north of the Alps [3]. They are also important in terms of genetic diversity, representing a reservoir for old domestic animal breeds and fruit tree varieties [10].

Beyond their high value for biodiversity conservation, traditional orchards offer numerous essential ecosystem services and functions. Their complex structure, with the unique combination of a tree and an herbaceous stratum, and the minimal to nonexistent use of chemical fertilisers and pesticides support a wide array of provisioning, cultural, supporting, and regulating services [3,11]. Provisioning services include the production of regional fruits and products derived from fruit such as juices or wines, as well as fodder for domestic animals [12]. Culturally, these traditional orchards contribute to recreation, education, tourism, the landscape's aesthetic value, and the regional identity of people [13-15]. Finally, they contribute to essential regulation and support services such as regulation of the microclimate, carbon sequestration, or a reduction in surface run-off and erosion [16-19]. Therefore, such traditional agroforestry systems could play a vital role in agroecological schemes in Europe [20].

Despite their ability to provide multiple ecosystem services at high levels and their substantial ecological value, orchard meadows are an endangered biotope type in Germany. Following the expansion of fruit trees during the 18th and 19th centuries and the peak of traditional orchards in the mid-20th century, both their quantity and the

ecological quality have steadily declined due to the increasingly uneconomical nature of their maintenance [1,3,21]. They have only recently reached protection status at the national level [22]. However, in Germany, no comprehensive spatial data sets exist on the cover and distribution of traditional orchards to estimate the current area or to monitor temporal trends [3]. Although the official data sets available for the country, such as the Digital Landscape Model (DLM) and the Digital Land Cover Model (LBM), include spatially explicit data on traditional orchards, estimates of orchard areas from these sources differ strongly, and many inconsistencies are apparent when compared to external reference maps [3]. While spatial data exist at the federal state level, differences in mapping methodologies often limit their interpretative value [3]. Historical data sets that would enable trend analyses [15,23] are similarly inconsistent [3]. High-quality data sets do exist for twelve so-called model regions in Germany, but these are mostly limited to the district level and cover an area between 10 and 1000 km² [3]. To properly analyse the current situation and historical trends in traditional orchards, large-scale data with high spatial resolution, acquired using consistent methodologies, are required, but these are currently only available locally.

The considerable loss of traditional orchards observed during recent decades can be attributed to a variety of socio-ecological factors. These include topographical and edaphic factors such as slope or soil quality, landscape metrics such as parcel size or perimeter-area ratio, and surrogate measures of socio-economic development such as distance to urban settlements or main roads [23]. For example, the case study of Plieninger et al. [23] on orchards in southwestern Germany revealed that distance to urban settlements was the most important factor determining the observed loss of orchard area and the decrease in average patch size. However, temporal patterns and trends in orchard loss might differ regionally due to different environmental and societal contexts and can be attributed to both the intensification of land use and the abandonment of land [24]. In some regions, the abandonment of traditional orchards and subsequent succession towards shrubby vegetation, as well as conversion into forests, could be explained by the long distance to roads and the low cover of settlements and sealed areas, while orchards persisted in other areas, especially upland and in low mountain regions [7]. Therefore, understanding the socio-ecological drivers behind traditional orchard loss requires a comprehensive approach, considering a wide range of attributes and indicators. To accurately assess regional differences and generalise findings, it is essential to use high-resolution data that cover a large spatial extent.

Here, we selected the federal state of Hesse as the study area. Hesse has the second largest share of traditional orchards in Germany [3]. These orchards are an integral part of the cultural landscape, characteristic of the surroundings of many municipalities [12]. They are designated as a protected habitat type [22], with a state-level protection strategy in place [25]. The main hotspots of traditional orchards are predominantly located in the southern part of the state [12,25]. Politically, their ecological relevance was explicitly acknowledged in the latest coalition treaty in Hesse, where, for example, their preferential use for compensation measures is emphasised [26], making them highly relevant for landscape monitoring and planning.

Comprehensive base data for spatio-temporal analyses of traditional orchard properties in Hesse are available. These include spatial data sets on land use and land cover (LULC) [27], data on soil quality [28,29], and a publicly accessible, high-resolution digital elevation model [30], facilitating detailed topographical analyses. Furthermore, traditional orchards were mapped across the entire state in 2010 via a manual interpretation of public aerial imagery [31]. Georeferenced digitised historical aerial photos covering the time span of 1952-1967 have also been made publicly available, but their potential for detailed trend analyses of traditional orchards at a broad spatial extent has yet to be fully utilised (e.g., [32]).

Therefore, the main objectives of this study were to (1) quantify long-term orchard dynamics, (2) compare orchard characteristics from historic and recent datasets in terms of their topographical, ecological, and socioeconomic factors, and (3) identify the key drivers of orchard loss from the local to regional levels for the entire state of Hesse. This information is crucial for the timely development of effective policies to prevent orchard loss and protect ecosystem services.

Materials and Methods

Study Area

The federal state of Hesse is located in Central Germany and has a total area of ca. 21,116 km² [33] (Figure 1). Hesse is subdivided into three government districts, namely Kassel (ca. 8291 km²) in the north, Gießen (ca. 5381 km²) in the centre, and Darmstadt (ca. 7444 km²) in the south (referred to as North, Centre, and South, respectively, in the following) (Figure 1). Government districts are major socio-economic regions according to the European Nomenclature of Territorial Units for Statistics (NUTS) and belong to the second NUTS level (NUTS 2) [34]. These government districts are further

subdivided into smaller administrative districts (NUTS 3). The latter include rural (Landkreise in German) and urban districts (Kreisfreie Städte). Hesse comprises twenty-one rural and five urban districts. In this study, the government districts are defined at the regional level, while the smaller administrative districts are defined as the local level. The whole state of Hesse has a population of about 6.3 million people, with more than a third living in the Frankfurt-Rhine/Main area in the south of the state [35].

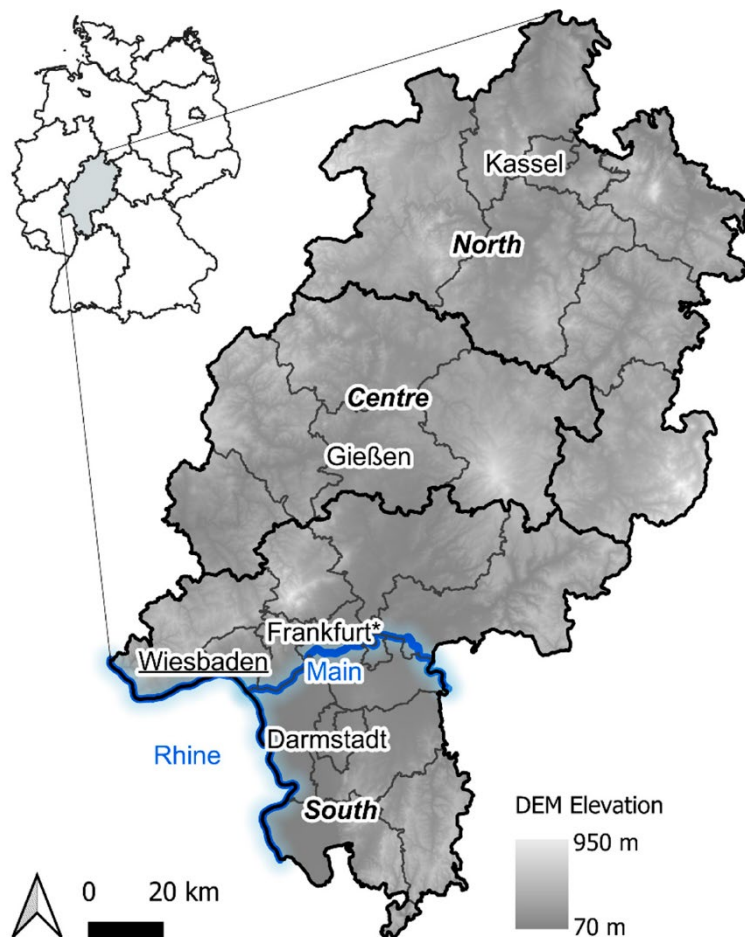


Figure 1: Location of the federal state of Hesse in Central Germany with a digital elevation model (DEM) ranging between 70 and 950 m above sea level in the background. The bold black line delineates the three government districts of Kassel, Gießen, and Darmstadt, which correspond to the regions North, Centre, and South, while the thin black lines delineate the rural and urban districts. The shiny blue lines represent the Rhine and Main rivers, respectively. Wiesbaden (underlined) is the state capital, and Frankfurt (asterisk) is the largest city in Hesse.

Aside from the highly urbanised parts, such as the Frankfurt-Rhine/Main area, Hesse is characterised by a high share of forests (ca. 42%), especially in the northeast and east, where forests cover up to 50% of the landscape [36]. Intensively used agricultural regions are present in the area, e.g., in the Wetterau district north of Frankfurt [37], where forest cover is low (15%, [36]), as well as peripheral areas with large proportions of non-intensively used grasslands, such as the Lahn-Dill district [38]. The highest

mountain, at almost 950 m a.s.l., is located in the Fulda district, west of one of the largest continuous basalt areas (mainly located in the Vogelsberg district [39]).

The climate of Hesse is rather continental. The average annual precipitation ranges between 600 and 800 mm. The lowlands of the Upper Rhine Valley in the south are characterised by an even lower annual rainfall of 500 mm, while at higher elevations, such as in the Vogelsberg district, annual precipitation exceeds 1400 mm [40]. The average annual temperature for the period of 1981-2010 was 8.8 °C [40], showing an increase compared to the time period of 1951-1980, where it was lower, at 8.2 °C [41]. Pronounced variations in annual temperature can be observed, primarily oriented along a north-south gradient, with higher temperatures in the south [40,41]. The Climate Protection Scenario for Hesse predicts that average temperatures will continue to increase, subsequently leading to an increase in exceptionally warm days with temperatures higher than 30 °C [41]. At the same time, the risk of late frost remains, and precipitation patterns are expected to change [42]. In the future, precipitation maxima are more likely to occur in winter than in summer, and the probability of both heavy precipitation and drought events is likely to increase, too [42]. Recent extreme drought events, such as that in 2018, had a noticeable effect on ecosystem conditions across Land Use/Land Cover types in Hesse [43].

Geospatial Data

The geospatial data analysed in this study comprised spatial information on recent and historic traditional orchard distribution, soil quality, road network, Land Use/Land Cover, and topography (Table 1).

Traditional orchards, together with woody features, tree rows, and tree alleys, were mapped via manual image interpretation of aerial orthophotos from 2008 to 2010 by the Hessian Agency for Nature Conservation, Environment and Geology (HLNUG) for the entire Hesse [31]. These data are available in vector format and are referred to as recent data in the following. Ancillary data for this manual interpretation included cadastral information as well as the results of the statewide biotope mapping [31,44]. The landscape elements were distinguished based on structure, texture, spectral information, size, and shape, and were only mapped outside urban areas [44]. In addition, historical digital aerial images covering the years 1952-1967 are available for almost the whole state of Hesse via the Web Map Service, with only a few data gaps in the northeast near the former border between East and West Germany [45]. Due to the high quality of the historical images, we were able to apply the HLNUG mapping key

[44] to also produce maps in vector format via manual image interpretation for traditional orchards in Hesse for the period 1952-1967, referred to in the following as historic data. In addition, the recent and historic vector data were intersected.

Table 1: Overview of the geospatial data and the derived attributes for each traditional orchard.

Geospatial Data	Derived Attribute for Each Traditional Orchard
Administrative Units [57]	Regional level (NUTS 2): Government Districts; Regions North, Centre, South Local level (NUTS 3): Districts
Maps of Traditional Orchards: Recent (2008-2010) [31,44] and Historic (1952-1967) [this study]	Status: Historic, Recent; Gain, Loss, Remain Landscape Ecological Parameters: Area Perimeter Perimeter-Area Ratio Distance Nearest Orchard Shape Complexity Index
Soil Map [28,29]	Soil Quality: Yield Potential
Digital Landscape Model (Basis-DLM) [27]	Socioeconomic Parameters: Nearest Highway Nearest Settlement Land Use/Land Cover (LULC)
Digital Elevation Model (DEM) [30]	Topographical Parameters: Slope Northness Eastness

Therefore, we identified traditional orchards that existed either only in the historic data set and were removed after 1952-1967 (referred to as loss), or only in the recent data set and were established after 1952-1967 (gain), or in both data sets and remained orchards throughout the years (remain) (Table 1). Polygon fragments in the gain, loss, or remain data set resulting from the aforementioned intersection that had a smaller

size than the minimum polygon size of the recent and historic data, i.e., 50 m², were removed.

For all traditional orchards of these five data sets (recent, historic, gain, loss, remain), we computed the following landscape ecological attributes: Area, Perimeter, Perimeter- Area Ratio, Distance Nearest Orchard, and the Shape Complexity Index [46]. In addition, soil quality was extracted from the yield potential map of the HLNUG [28,29]. The yield potential ranges from 1 (very low) to 5 (very high) and combines information on the usable field capacity of the rooting zone, the effects of groundwater, land use, and base saturation [28]. If an orchard polygon was covered by more than one yield class, the final yield potential class for the respective orchard was computed proportionally (i.e., if 750 m² of an orchard was covered by yield potential class 3, and 250 m² by class 2, the resulting yield class was 2.75).

The distances from traditional orchards to urban settlements or main roads (Table 1), as surrogate measures of socio-economic development [23], were computed based on the aforementioned orchard maps and vector data on highways (classes autobahn and bundesstrasse) and urban settlements (class siedlung) extracted from the German Digital Landscape Model of Hesse [27]. To analyse the main drivers of orchard decline, LULC information was extracted for the lost orchards based on the German Digital Landscape Model [27] (class objektart) and recoded based on Table S1, resulting in seven LULC classes: Agricultural Land, Artificial Surfaces, Forest, Other Vegetation, Residential Buildings, Water Bodies, and Woody Features. For further analysis, LULC conversion data were aggregated at the local (district) level.

Finally, the topographical attributes Slope, Northness, and Eastness were computed for each traditional orchard based on the 5 m digital elevation model provided by the Hessian Agency for Land Management and Geoinformation (HVBG) [30].

Data were processed using the packages terra (version 1.7-78) [47], sf [48,49] (1.0-16), exactextractr (0.10.0) [50], dplyr (1.1.4) [51], units (0.8-5) [52], and ngeo (0.4.8) [53], and data were tabulated using the packages gtsummary (2.0.1) [54] and gt (0.11.0) [55], in R statistical software (4.4.0) [56]. The Shape Complexity Index was computed using Whitebox Toolbox (2.4.0) [46].

Data Analysis and Modelling

To produce area-based overviews of historic, recent, gained, lost, and remaining traditional orchards independently of administrative regions, hexagonal grid maps [58]

were produced with a cell size of 55.46 km². Orchard density per hexagon was computed as orchard area divided by hexagonal cell area.

To compare the attributes of traditional orchards between the regions and between historic and recent, as well as gained, lost, and remaining orchards, first the normality of the data were assessed using Q-Q plots and the Shapiro-Wilk test [59] and the homogeneity of variances was checked using Bartlett's test [60]. The data set was also controlled for missing data and infinite values, which were subsequently removed. We employed nonparametric tests for our analyses because the data did not follow a normal distribution and exhibited unequal variances. The Mann-Whitney U test ($p\text{-value} \leq 0.05$) was used to compare historical and recent data. For multiple comparisons across different regions (North, Centre, and South) and across different status categories (gain, loss, and remain), we applied the Kruskal-Wallis (KW) test [61] ($p\text{-value} \leq 0.05$), followed by the Benjamani-Hochberg (BH) correction test [62].

To analyse if differences regarding orchard attributes at the regional level enable the regions to be distinguished in a semi-automated way using machine learning, Random Forest classification models [63] were applied using the orchard attributes as predictors and the three regions as response variables for both historic and recent data. Random Forest is also a powerful machine learning algorithm [64] for ecological applications [65]. To account for potential differences between orchards in the South, an orchard hotspot [12], compared to the other regions, a three-class model with the original response classes and a two-class model, where Centre and North were merged, were calculated for each data set. The data were split into 75% training and 25% test data, preserving class distributions. Models were trained using 10-fold cross-validation with five repeats and the parameter *mtry* was optimised for overall accuracy using a search grid ranging from one to eleven while the parameter *ntree* was set to 1000. Model quality was evaluated based on test set data and several accuracy metrics, including Overall Accuracy, Kappa, Sensitivity, Specificity, Positive Predicted Value, Negative Predicted Value, and F1, considering, if applicable, the Prevalence of the data as well as Precision and Recall [66]. In case of a two class-model, accuracy was evaluated based on a confusion matrix of the test set data, as in Table 2. For the three class-model, each class was compared to all other classes in a similar manner, using a “one versus all” approach [66].

Based on the confusion matrix in Table 2, the accuracy metrics were calculated as follows, based on [66]:

$$\text{Overall Accuracy} = \frac{A + D}{(A + B + C + D)}, \quad (1)$$

$$\text{Kappa} = \frac{O - E}{1 - E}, \quad (2)$$

where O is the observed accuracy and E is the expected accuracy,

$$\text{Sensitivity} = \frac{A}{(A + C)}, \quad (3)$$

$$\text{Specificity} = \frac{D}{(B + D)}, \quad (4)$$

$$\text{Prevalence} = \frac{(A + C)}{(A + B + C + D)}, \quad (5)$$

$$\text{Positive Predicted Value} = \frac{\text{sensitivity} \times \text{prevalence}}{((\text{sensitivity} \times \text{prevalence}) + ((1 - \text{specificity}) \times (1 - \text{prevalence})))}, \quad (6)$$

$$\text{Negative Predicted Value} = \frac{(\text{specificity} \times (1 - \text{prevalence}))}{((1 - \text{sensitivity}) \times \text{prevalence}) + ((\text{specificity} \times (1 - \text{prevalence})))}, \quad (7)$$

$$\text{Precision} = \frac{A}{(A + B)}, \quad (8)$$

$$\text{Recall} = \frac{A}{(A + C)}, \quad (9)$$

$$\text{F1} = \frac{2 \times \text{precision} \times \text{recall}}{(\text{precision} + \text{recall})}. \quad (10)$$

The loss rate of traditional orchards between 1952-1967 and 2008-2010 at the local level was calculated as in [23], following [67]:

$$r = \left(\frac{1}{2009 - 1959.5} \right) * \ln \left(\frac{\text{Area } 2009}{\text{Area } 1959.5} \right) \quad (11)$$

Table 2: Confusion matrix of the test set data as a basis for the calculation of the accuracy metrics for the two class-model with the class South and the merged class Centre_North.

Predicted	Reference	
	South	Centre_North
South	A	B
Centre_North	C	D

To examine a potential north-south gradient regarding the drivers of orchard loss at the local level, the y-coordinate of each district centre was extracted and correlated against the percentage/area of each LULC class using the Spearman-Rank correlation [68].

Data analysis and modelling was performed using R statistical software (see above) including the packages car (3.1.2) [69] and multcompView (1.4-25) [70]. Violin plots with embedded box plots to examine the orchard attributes were produced using the

packages ggplot2 (3.4.2) [71], gridExtra (2.3) [72], ggbreak (0.1.2) [73], and cowplot (1.1.1) [74]. Random Forest modelling was performed using the packages caret (6.0.-94) [66], randomForest (4.7-1.1) [75], doParallel (1.0.17) [76], and corrplot (0.92) [77]. All maps were created in QGIS, version 3.34 “Prizren” LTR [78], and the coordinate reference system for all data was EPSG: 25832—ETRS89/UTM zone 32N.

Results

Long-Term Dynamics of Traditional Orchards at the State Level

At the state level, the density of traditional orchards has strongly decreased over the past 50 to 60 years (Figure 2a,b). Historically, these orchards were concentrated in the South near the Main River and towards the southern border of the state, as well as in the North near the town of Kassel. By 2010, only the southern hotspots remained noticeable, albeit at much lower levels (Figure 2b). These comparably high densities in 2010 were historically common throughout the state (Figure 2a,b). Consequently, both the number and the total area of traditional orchards decreased dramatically, from 66,602 orchards covering 504 km² historically (Table S2) to 21,544 orchards covering 117 km² in recent times (Table S3). In fact, the number of traditional orchards at the state level in 2010 was almost equivalent to the number of traditional orchards found in the Centre region alone in 1952-1967 (21,568 orchards, Tables S2 and S3). This strong decrease in absolute numbers is actually even higher than that recorded, as the northeastern part of the study area was not covered by the historic imagery (Figure 2a). The proportional loss in the number and the area of traditional orchards varied among regions. Statewide, the number of traditional orchards dropped to 32% of historic levels with an even sharper decrease in area, which fell to 23% (Tables S2 and S3). The South mirrored these trends, with reductions to 35% in number and 22% in area (Tables S2 and S3). The North exhibited the lowest proportional decreases, with numbers falling to 46% and area to 33%, while the Centre experienced the most significant losses, with both number and area declining to 23% of historic levels (Tables S2 and S3).

However, there were also slight increases in traditional orchard density, reflecting the establishment of new orchards in locations that historically had different land uses. These gains were primarily observed in the South around two hotspots (Figure 2c), with the largest gains in parts of the main area and near the border of the Centre region, where most of the remaining orchards were located (Figure 2e). Slight increases were also observed in the Centre (Figure 2c). The areas with the largest losses of traditional

orchards corresponded to the historical hotspots in both the North and South (Figure 2a,d).

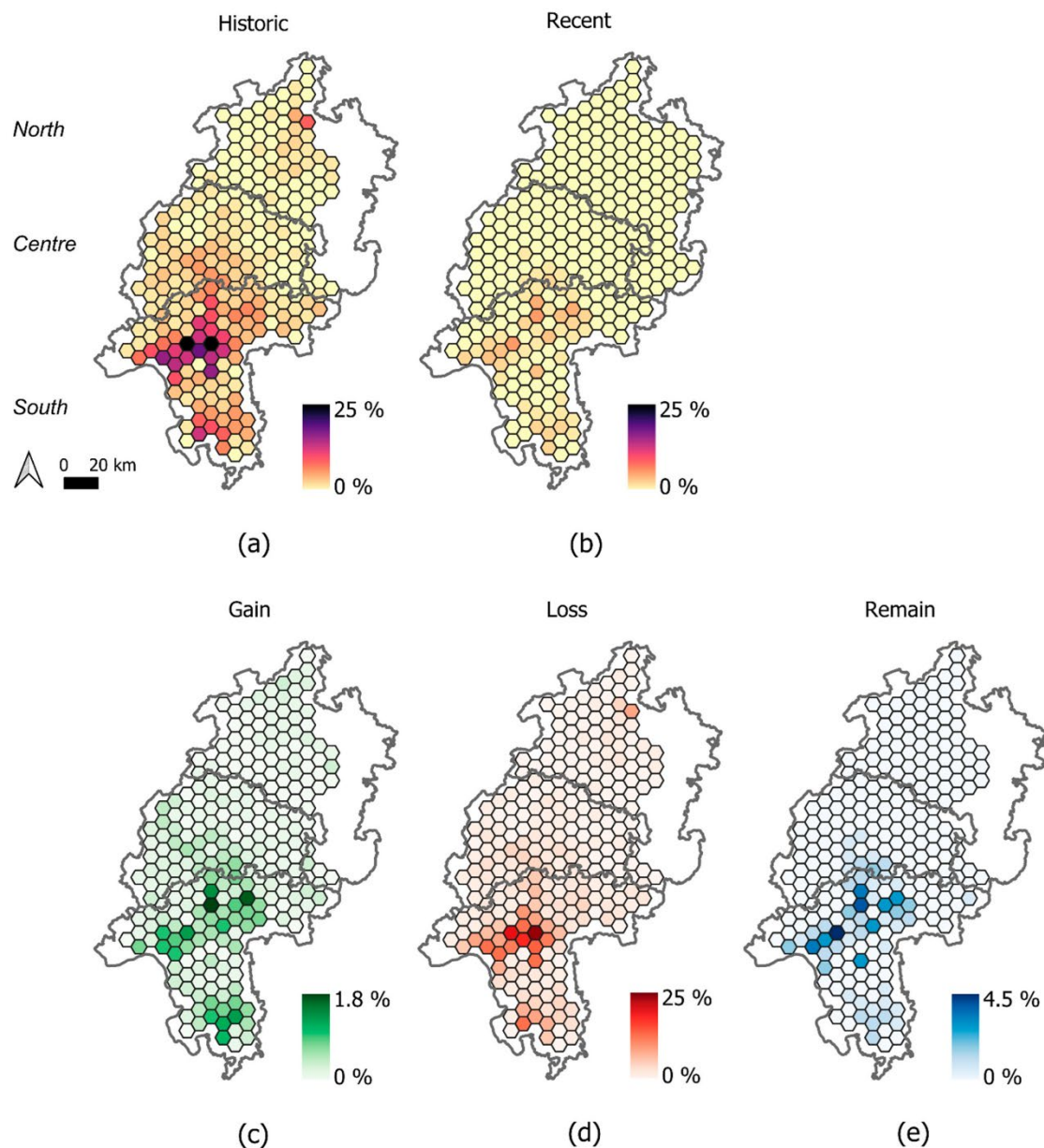


Figure 2: Hexagonal grids of traditional orchard density in Hesse for (a) historical (1952-1967), (b) recent (2008-2010), (c) gained, (d) lost, and (e) remaining orchards. Grey lines delineate government districts, which define the regional level in this study.

In summary, the loss of traditional orchards occurred all over the state, though the patterns of decline varied by region. Pronounced losses occurred near historical hotspots, with only the South retaining some of these historic hotspots in recent imagery, due to a relatively high number of remaining and newly established traditional orchards. Meanwhile, the North showed generally low densities. The locations of hotspots have shifted slightly, particularly in the South towards the Centre region, where a relatively high proportion of historical orchards persisted. In addition to the

hotspot in the South, slight gains were also observed in large parts of the Centre, highlighting the regional differences in orchard dynamics.

Characteristics of Traditional Orchards at Regional Level

The attributes of orchards differed significantly between regions, with the exception of the exposition-related parameters Northness and Eastness, where no significant differences were observed between Centre and South, and North and Centre, respectively (Figure 3). In all regions, historic traditional orchards differed significantly from recent ones across all 12 tested parameters, although the direction of these changes varied between the regions (Figure 3, Tables S2 and S3). For instance, all ecological landscape attributes, namely Area, Perimeter, Perimeter-Area Ratio, and Shape Complexity Index, were generally lower in recent orchards compared with historic ones across nearly all regions (Figure 3, Tables S2 and S3). The only exceptions were an increase in Perimeter in the North, and a rise in median Area from 2223 m² to 2655 m² in the Centre (Tables S2 and S3). In contrast, all distance-related attributes, namely Distance Nearest Orchard, Distance Settlement, and Distance Highway, along with the topographical attributes Slope and Elevation, increased (Tables S2 and S3). Thus, in 2010, traditional orchards were located, on average, at higher elevations and on steeper slopes compared to 1952-1967 (Figure 3, Tables S2 and S3). The exposition-related attributes showed diverging trends: while exposition shifted slightly towards the northeast in the North and South, it shifted towards the southwest in the Centre (Tables S2 and S3). Soil quality remained relatively stable, with a slight decline observed in the South, suggesting that recent orchards are, on average, located on less fertile soils compared to 1952-1967 (Tables S2 and S3).

The comparisons of attributes among newly established (Gain), lost (Loss), and remaining (Remain) orchards revealed a consistent pattern (Figure 4, Tables S4-S6). All attributes showed significant differences, except for the exposition-related parameters. Specifically, Northness showed significant variation only in the North, while Eastness did not differ at all across regions (Figure 4). All ecological landscape parameters differed significantly between lost orchards and both newly established and remaining orchards (Figure 4, Tables S4-S6). Lost orchards had, on average, a larger Area, higher Perimeter values, and a greater Shape Complexity, while Distance Nearest Orchard and Perimeter-Area Ratio was consistently lower (Figure 4, Tables S4-S6). Additionally, lost orchards tended to be closer to highways, situated on moderately steep slopes, and, with the exception of the South, facing towards the south (Figure 4, Tables S4-S6).

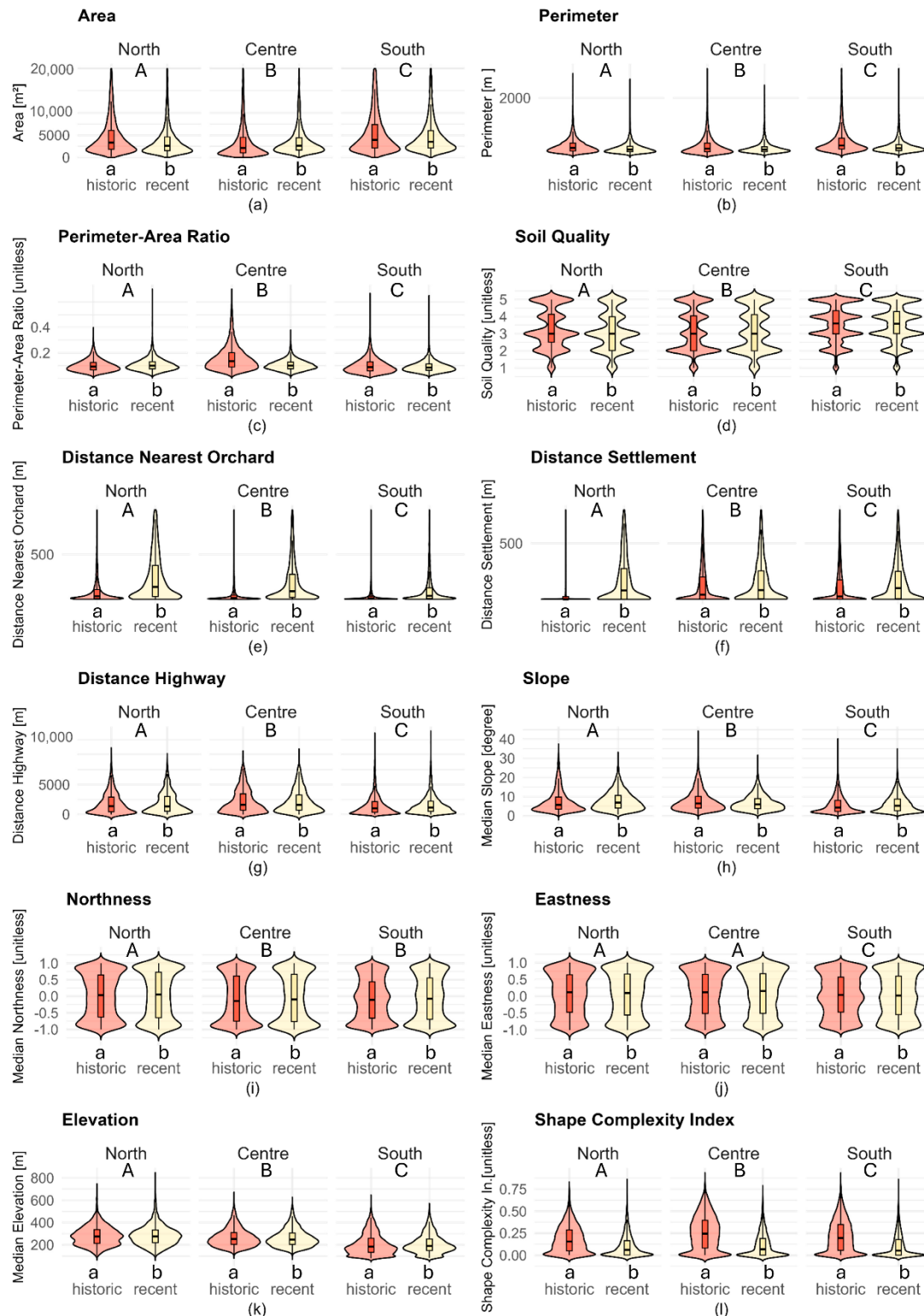


Figure 3: Comparison of the twelve computed traditional orchard attributes between the three regions and between the historical (1952-1967, red) and the recent (2008-2010, yellow) data. The capital letters above the violin plots indicate significant differences in the comparisons between the regions for both historic and recent data, and the small letters below the violin plots indicate significant differences in the comparisons between historic and recent data within each region ($p\text{-value} \leq 0.05$). Orchard attributes include (a) Area, (b) Perimeter, (c) Perimeter-Area-Ratio, (d) Soil Quality, (e) Distance Nearest Orchard, (f) Distance Settlement, (g) Distance Highway, (h) Slope, (i) Northness, (j) Eastness, (k) Elevation, and (l) Shape Complexity Index.

In contrast, newly established orchards were characterised by a relatively high Perimeter- Area Ratio and both a greater Distance Nearest Orchard and Distance Highway (except for the North). These orchards also showed consistently higher Distance Settlement and were slightly more oriented towards the north, with a general trend towards orchards being located at higher elevations (Figure 4, Tables S4-S6). Soil quality was moderate for all orchards, with slightly better soil quality in the South (Figure 4, Tables S4-S6).

Comparing the remaining with the newly established orchards, the most notable differences were related to Area, Distance Nearest Orchards, and Distance Settlement. Newly established orchards were slightly (Centre) or clearly (South) smaller than the older orchards from 1952 to 1967, while in the North they were actually about 10% larger. Similarly, the distances between remaining orchards were, on average, smaller in the Centre and in the South, but clearly larger in the North compared to the distances between the newly established orchards. In contrast, the distance to settlements showed consistent patterns. The remaining orchards in all regions were located closer to settlements than the newly established orchards, with minimum distances for the older orchards occurring in the North and maximum distances occurring in the South (Figure 4, Tables S4-S6).

In addition to the observed regional patterns in traditional orchard dynamics (Figure 2), we also found significant differences in orchard attributes between regions (Figures 3 and 4). However, the RF model using these orchard attributes as predictors to classify orchards as either North, Centre, or South did not reveal such differences in the historic or in the recent data set (Tables S9-S12). The three-class model yielded rather moderate test set accuracies, with an overall accuracy of 0.71 and 0.64, a Kappa value of 0.47 and 0.41, and an F1 ranging between 0.40 and 0.79 and 0.49 and 0.79 for the historic (Table S9) and the recent (Table S10) data set, respectively. The per-class accuracies (Tables S9 and S10) and the confusion matrices (Tables S11 and S12) indicated higher classification accuracies for the South, but lower accuracies for the Centre, and particularly for the North.

In contrast, the two class-model, which discriminated between the South and a merged Centre_North class, resulted in higher test set accuracies, with Kappa values ranging between 0.52 and 0.54 and all other metrics between 0.72 and 0.80 (Table 3). The two-class classification showed a good model fit for both the historic and the recent data set, with F1 scores of 0.78 and 0.79 (Table 3), respectively. This indicated balanced errors (see also the confusion matrices in Tables S7 and S8), despite the high prevalence

of the South class and, thus, imbalanced data sets. Therefore, traditional orchards in the South differ from those in the Centre and in the North in both the historic and recent years.

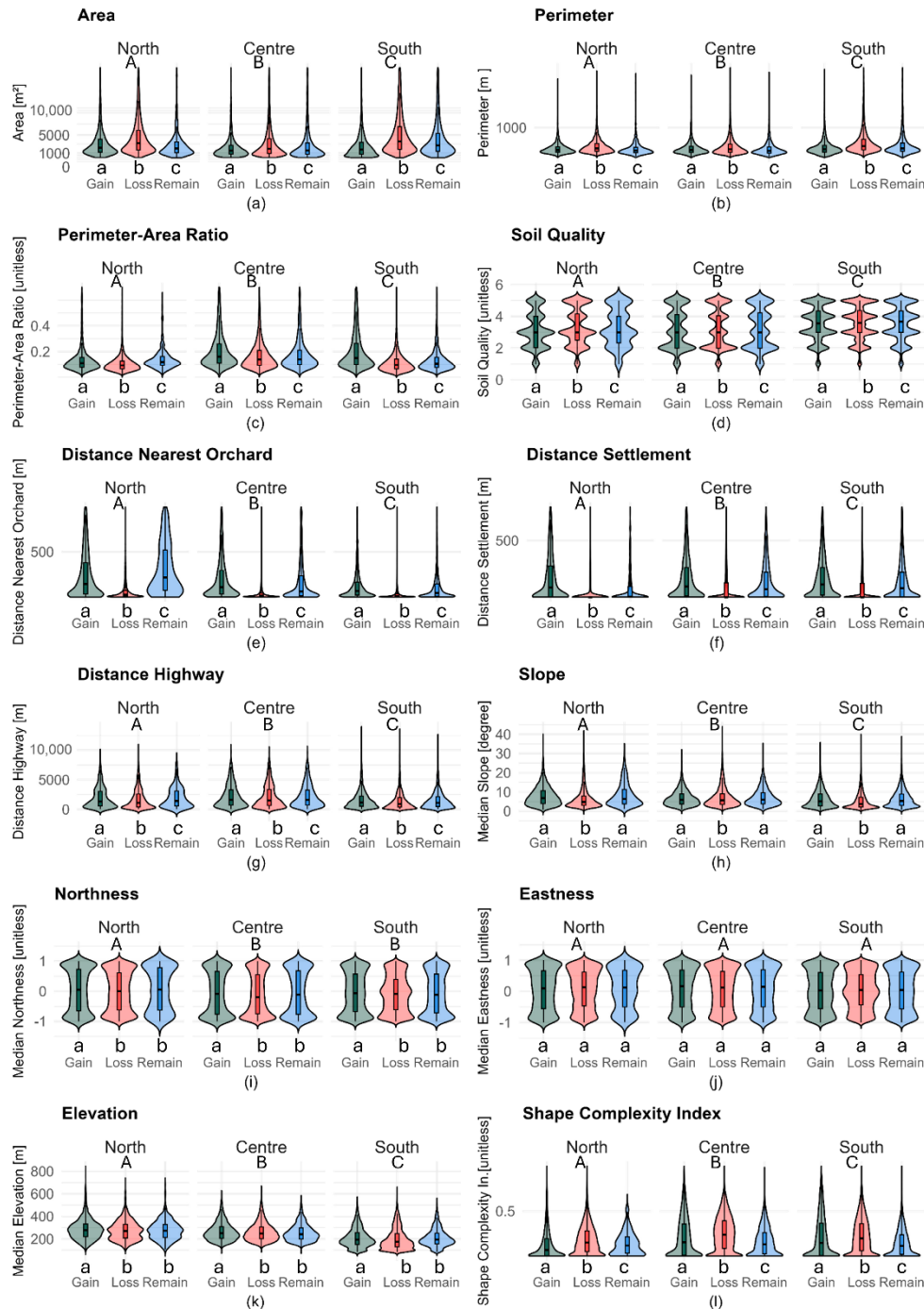


Figure 4: Comparison of the twelve computed traditional orchard attributes of the three regions and between the newly established or gained (green), lost (red), and remaining (blue) traditional orchards for the time spans 1952-1967 and 2008-2010. The capital letters above the violin plots indicate the significant differences in the comparisons between the regions of gained, lost, and remaining orchards, and the small letters below the violin plots indicate significant differences in the comparisons between gained, lost, and remaining orchards within each region (p -value ≤ 0.05). Orchard attributes include (a) Area, (b) Perimeter, (c) Perimeter-Area-Ratio, (d) Soil Quality, (e) Distance Nearest Orchard, (f) Distance Settlement, (g) Distance Highway, (h) Slope, (i) Northness, (j) Eastness, (k) Elevation, and (l) Shape Complexity Index.

Table 3: Accuracy metrics of the two-class Random Forest classification model comparing traditional orchards in the South with those in the North and Centre for both (a) historic and (b) recent data.

Accuracy Metric	Historic	Recent
Overall Accuracy	0.77	0.77
Kappa	0.54	0.52
Sensitivity	0.76	0.80
Specificity	0.77	0.72
Pos. Pred. Value	0.80	0.78
Neg. Pred. Value	0.73	0.74
F1	0.78	0.79

The RF models were optimised for the mtry parameter and overall accuracy. The optimal mtry value for the RF models based on historical data were lower (4) than those based on recent data (7). Variable importance followed this pattern (Figures 5 and S1), and despite significant differences between almost all attributes (Figure 3, Tables S2 and S3), variable importance differed. In the two-class models, the selected predictors had similar ranks for both the historic and recent datasets. Median Elevation emerged as the most important variable and Median Slope also had high importance. Conversely, the Shape Complexity Index, Median Eastness, and Soil Quality were less important. The importance of other predictors differed between the historic and recent datasets. While Perimeter-Area Ratio and Area were more important in models based on the historical data, all distance-related predictors (Distance Nearest Orchard, Distance Highway, Distance Settlement) were more important in recent years.

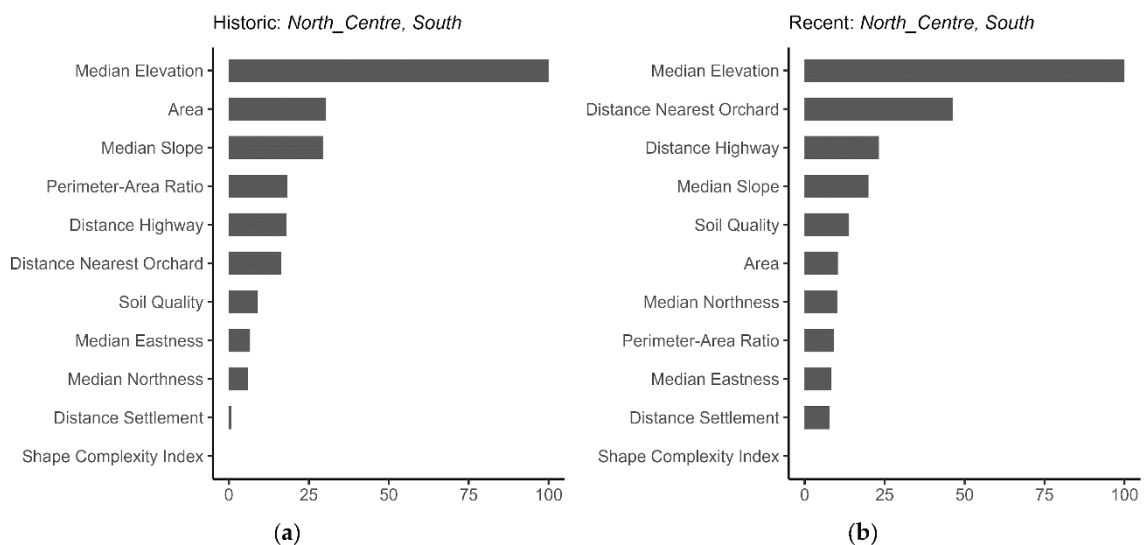


Figure 5: Variable importance of the two-class Random Forest classification model comparing traditional orchards in the South with those in the North and Centre for both (a) historic and (b) recent data.

Key Drivers of Traditional Orchard Loss at the Local Level

The dynamics and drivers of the conversion of traditional orchards to other land use types varied between regions and at the local level (Table 4, Figure 6). The lowest historical area of orchard cover for a rural district was found in the North (Waldeck-Frankenberg, Table 4), while the highest area of historical orchard cover, together with the lowest proportional loss, was located in the South. In the Wetterau district, 41% of the historical 43.13 km² of orchard area remained by 2010, with an annual loss rate of 1.83% (Table 4, Figure 6), accompanied by relatively high densities and slight gains due to newly established traditional orchards (Figure 2). At the same time, the district with the highest proportional loss was also located in the South. In the Rheingau-Taunus district, only 10% of the historical 18.96 km² of orchards remained by 2010, with an annual loss rate of 4.68% (Table 4, Figure 6), the second highest loss rate after the urban district of Kassel (8.22) in the North. The median loss rate for Hesse at the district level was 3.37%, with a standard deviation of 1.31.

The three main drivers of traditional orchard loss, namely conversion to Residential Buildings, Artificial Surfaces, and Agricultural Land, accounted for 81% to 94% of the observed loss. The maximum loss of 94% was found both in the North and the South, although the specific drivers differed. In the North, the urban district of Kassel, located near a former orchard hotspot (Figure 2a), showed the highest proportional conversion to Residential Buildings (Table 4, Figure 6). In contrast, in the South, the districts Bergstraße and Odenwald, which were also former (and are recent) hotspots of traditional orchards (Figure 2a,b), were predominantly characterised by conversion to Agricultural Land (Table 4, Figure 6).

Regarding the third main driver, major conversions to Artificial Surfaces were observed in the urban districts of Frankfurt and Offenbach near the Main River (Table 4, Figure 6), areas that coincide with the third historical hotspot and that have experienced high orchard losses (Figure 2a,b). The conversion to Other Vegetation and Water Bodies was highest in the district of Groß-Gerau in the South, although the area and proportion were low (Table 4). The Centre contained districts with the highest, but proportionally still minor, conversions to Forests and Woody Features in Lahn-Dill and Limburg-Weilburg (Table 4, Figure 6).

In summary, the three historical traditional orchard hotspots (Figure 2) were also areas of major conversions, driven by different factors in each region (Table 4, Figure 6). Accordingly, the three main drivers showed moderate Spearman rank correlations of -0.42 for Agriculture, 0.37 for Artificial Surfaces, and 0.32 for Residential Buildings

along a South-North gradient at the state level, while all other drivers were only weakly correlated (Table 4).

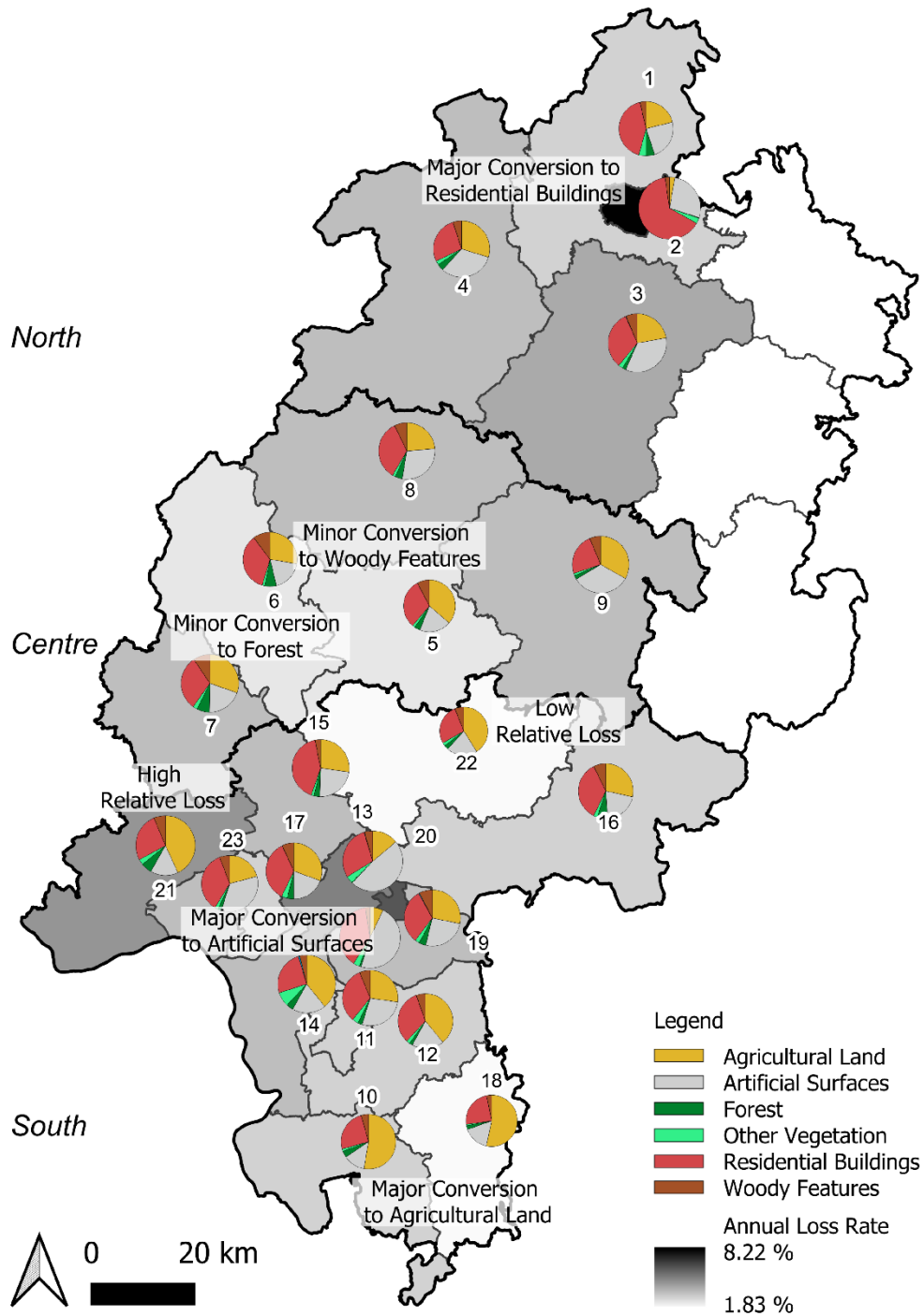


Figure 6: Map of traditional orchard conversion into other Land Use/Land Cover (LULC) types including loss rate per district. The numbers of the districts correspond to the numbers in Table 4.

Table 4: Overview of traditional orchard conversion into other Land Use/Land Cover (LULC) types including loss rate per district ordered by region as well as correlation along a South-North gradient. Urban districts were always specified, rural districts only if they shared the same name with an urban equivalent. The main drivers included Artificial Surfaces (Artif. Surfaces), Residential Buildings (Resid. Build.) and Agricultural Land (Agri. Land). Other Veg. = Other vegetation. Minimum (except Water Bodies) and maximum values (regarding percentages) are in bold and highlighted in grey.

District	Area Traditional Orchards				LULC Conversion [km²] ([%])								Main Drivers [%]
	Historic [km²]	Recent [km²]	Ratio R/H [%]	Loss Rate [%]	Agri. Land	Artif. Surfaces	Forest	Other Veg.	Resid. Build.	Water Bodies	Woody Features		
North													
1 Kassel (rural)	13.81	3.39	25	2.84	2.79 (21)	3.15 (24)	0.68 (5)	0.57 (4)	5.55 (42)	0.01 (0)	0.47 (4)	87	
2 Kassel (urban)	8.99	0.15	2	8.22	0.24 (3)	2.46 (27)	0.03 (0)	0.26 (3)	5.81 (65)	0 (0)	0.21 (2)	94	
3 Schwalm-Eder	16.19	2.11	13	4.12	3.50 (22)	5.39 (34)	0.31 (2)	0.40 (3)	5.08 (32)	0.04 (0)	1 (6)	89	
4 Waldeck-Frankenberg	10.2	1.93	19	3.37	2.88 (30)	3.10 (32)	0.38 (4)	0.22 (2)	2.62 (27)	0.01 (0)	0.47 (5)	89	
Centre													
5 Gießen	26.11	8.15	31	2.35	7.74 (36)	4.18 (20)	0.76 (4)	0.35 (2)	6.58 (31)	0.02 (0)	1.63 (8)	87	
6 Lahn-Dill	20.26	5.04	25	2.81	5.09 (28)	3.41 (19)	1.28 (7)	0.29 (2)	6.45 (35)	0.02 (0)	1.88 (10)	81	
7 Limburg-Weilburg	16.68	2.55	15	3.79	4.82 (30)	3.17 (20)	1.13 (7)	0.39 (2)	4.86 (31)	0.01 (0)	1.48 (9)	81	
8 Marburg-Biedenkopf	14.97	2.78	19	3.40	3.30 (24)	4.03 (29)	0.57 (4)	0.23 (2)	4.79 (34)	0 (0)	0.98 (7)	87	
9 Vogelsberg	12.65	2.21	17	3.52	3.97 (33)	3.98 (33)	0.26 (2)	0.15 (1)	2.85 (24)	0 (0)	0.75 (6)	90	
South													
10 Bergstraße	38.32	8.91	23	2.95	17.93 (53)	4.34 (13)	1.28 (4)	0.47 (1)	8.47 (25)	0.01 (0)	1.48 (4)	90	
11 Darmstadt (urban)	3.50	0.75	21	3.12	0.83 (27)	0.84 (27)	0.08 (3)	0.11 (4)	1.00 (33)	0 (0)	0.19 (6)	88	
12 Darmstadt-Dieburg	21.76	5.03	23	2.96	7.60 (39)	3.69 (19)	0.37 (2)	0.40 (2)	6.34 (33)	0.01 (0)	1.05 (5)	91	
13 Frankfurt a. M. (urban)	37.21	3.03	8	5.07	5.14 (14)	17.64 (48)	0.16 (0)	1.41 (4)	10.62 (29)	0.08 (0)	1.65 (4)	91	
14 Groß-Gerau	19.75	2.97	15	3.83	7.62 (39)	3.66 (19)	0.77 (4)	1.57 (8)	4.90 (25)	0.15 (1)	0.75 (4)	83	
15 Hochtaunus	23.98	4.01	17	3.61	5.84 (27)	5.01 (23)	0.71 (3)	0.32 (2)	8.91 (41)	0 (0)	0.68 (3)	92	
16 Main-Kinzig	38.34	8.78	23	2.98	9.68 (28)	7.02 (21)	2.08 (6)	0.74 (2)	12.09 (35)	0.03 (0)	2.44 (7)	84	
17 Main-Taunus	31.72	6.38	20	3.24	8.60 (31)	5.47 (19)	1.10 (4)	0.95 (3)	10.09 (36)	0.03 (0)	1.91 (7)	86	
18 Odenwald	21.50	6.95	32	2.28	9.57 (53)	2.92 (16)	0.42 (2)	0.14 (1)	4.35 (24)	0 (0)	0.55 (3)	94	
19 Offenbach (rural)	18.63	3.51	19	3.37	4.62 (28)	4.18 (26)	0.65 (4)	0.42 (3)	5.16 (32)	0.07 (0)	1.25 (8)	85	
20 Offenbach (urban)	5.37	0.29	5	5.91	0.37 (7)	2.52 (48)	0.05 (1)	0.17 (3)	2.04 (39)	0 (0)	0.13 (2)	93	
21 Rheingau-Taunus	18.96	1.87	10	4.68	8.16 (43)	2.86 (15)	1.12 (6)	0.57 (3)	5.00 (26)	0.01 (0)	1.21 (6)	85	
22 Wetterau	49.13	19.90	41	1.83	15.05 (41)	7.50 (21)	1.09 (3)	0.79 (2)	9.91 (27)	0.03 (0)	2.21 (6)	89	
23 Wiesbaden (urban)	27.29	5.08	19	3.40	4.93 (21)	8.03 (34)	0.50 (2)	0.44 (2)	8.39 (35)	0 (0)	1.36 (6)	90	
Correlation along south-north gradient					-0.42	0.37	0.17	0.05	0.32	-0.22	0.17	-0.15	

Discussion

Traditional orchards are complex landscape elements. This complexity is reflected by their different characteristics and different spatio-temporal dynamics at the local and regional scales. In this study, we analysed, to the best of our knowledge, the most comprehensive data set for temperate European orchards. Our findings revealed several key insights:

- (a) A decline in traditional orchards: The number and area of traditional orchards have significantly decreased across Hesse, with the pattern of decline varying by region. Notably, major losses occurred near historical hotspots.
- (b) Characteristics of old vs. new orchards: Historically old orchards tended to have larger Areas, higher Shape Complexity, and were located closer to settlements, highways, and neighbouring orchards. In contrast, newly established orchards were often found at higher elevations and on steeper slopes.
- (c) Regional differences: Despite significant differences in orchard attributes, the regions could only be distinguished in a two-class model, with the Centre being merged with the North. This highlights the distinctiveness of the traditional orchards in the South.
- (d) Hotspots of orchard loss: The three historical orchard hotspots also experienced the most notable losses, driven by different factors in each region. In two hotspots, the expansion of Artificial Surfaces and Residential Buildings was the primary driver, while in the southernmost hotspot, conversion to Agricultural Land played a dominant role.

Generalising findings about temporal dynamics and the loss of traditional orchards is a challenging task and requires fine-scale spatial data to broad spatial extents. The median annual loss rate of 3.37% in Hesse is notably high and aligned with and exceeded maximum loss rates reported by case studies in Austria (3.47% [79]) and France (2.80% [80]), as reported by Plieninger et al. [23]. Even in districts with the lowest loss rates and the lowest proportional loss, such as the Wetterau, the losses exceeded those observed in similar studies. For example, the lowest loss rates and highest ratio of recent and historical orchard areas, of 1.83% and 41%, respectively, were more than double those observed in a study in southwest Germany for a similar time span and a slightly smaller area [23]. Therefore, overall orchard loss in Hesse is notably high even in areas where small gains due to newly established orchards were observed and new

hotspots have emerged. Additionally, the strong differences within Hesse compared to southwestern Germany [23] that were found in this study underline the necessity of comprehensive historical data to evaluate the severeness and spatial patterns of traditional orchard loss.

Distance to settlements and main roads were identified as the main drivers of orchard decline in southwestern Germany [23]. In our study, the expansion of Artificial Surfaces and Residential Buildings emerged as the most critical factor contributing to orchard decline in two historic orchard hotspots, which aligns with the model regions for Hesse proposed by Henle et al. [3]. In addition, lost orchards were typically located closer to highways, with both proximity to highways and settlements being important factors that distinguished orchards in the South from those in the Centre and North. In contrast, in the third hotspot located in the South (Bergstraße), orchard decline was primarily driven by conversion to Agricultural Land. In general, the high proportion of conversion to Agricultural Land in Hesse is likely a result of agricultural policy changes in Germany during the 1950s (e.g., Emser Beschluss in 1953) that encouraged and financially supported the conversion of traditional agroforestry systems into grasslands or arable land. Additionally, the European Community's grubbing-up scheme, which continued until 1974, further accelerated this trend [81]. Conversion to Agricultural Land also showed the strongest correlation along the south-north gradient, indicating its significant impact, particularly in the South, where, traditionally, horticulture and special crops played an important role in agricultural production due to the favourable growing conditions, but also to socioeconomic reasons and local agricultural structures [82]. Changes in the latter two were also the main reasons for the decline of orchards, e.g., in the form of conversion to other agricultural uses [82]. Furthermore, orchard decline might also result from abandonment, leading to succession towards dense woody vegetation and forests [7], a trend observed in the Centre region. This trend could have been overlooked if the focus had been solely on model regions and/or historic orchard hotspots. Overall, the drivers of orchard loss and the characteristics of orchards themselves are manifold and vary both regionally and locally. Despite this heterogeneity, the Random Forest-based classification model for the two classes reached good and fairly balanced accuracies for a real-world ecological data set (see, e.g., [83]) underlining the distinctive features of the South compared the rest of the state. However, the feature importance changed between historic and recent data sets, indicating that even though orchards can be discriminated with similar accuracies, the temporal dimension needs to be considered to understand why they can be

distinguished. While Random Forest is one of the most popular algorithms used in landscape ecological studies, novel methods based on Deep Learning are on the horizon, which would enable a deeper analysis of complex data [84]. Such approaches might be able to decipher even local differences across landscapes, but appropriate geospatial data on orchard distribution, orchard attributes, and drivers of loss are required to train and validate such novel algorithms. Therefore, this study highlights the need for data at broad spatial extents to fully understand the dynamics of these small, but important landscape elements.

High-resolution spatial data of traditional orchards, acquired in a standardised way, are essential. Not only could they address data gaps in model regions [3] or correct existing cadastral data products [3,85], these data are crucial for effective conservation planning [4], monitoring compliance with agricultural policies, and guiding landscape planning in the context of compensation measures [12], especially in orchard hotspots such as southern Hesse, where an expansion of Artificial Surfaces and Residential Buildings is to be expected [86]. Moreover, spatial maps of traditional orchards can also be used for computing carbon sequestration potentials [11,16] and other ecosystem services [11], and are also central to biodiversity studies on orchards at the landscape scale [4]. For instance, the area requirements of species within orchards and the importance of habitat connectivity are still poorly understood and it remains an open question whether species that require larger areas can also thrive in landscapes characterised by smaller, but well-connected orchards [4]. A local study in one of the orchard hotspots in southern Hesse by [87] demonstrated that the diversity and number of protected bird species increase with the size and connectivity of orchards, emphasising the conservation priority for such landscape features. Similarly, a study by [88], which compared 30 traditional orchards, found that the effects of habitat isolation can be more important than habitat amount in traditional orchards, with these effects likely being specific to different species groups. Furthermore, the links between orchard size, isolation, and species traits are still underexplored [4]. Given these challenges, multitemporal spatial data sets on traditional orchards, which can also provide insights into orchard age and historical fragmentation, are essential for a wide range of applications, from basic ecological research to the computation of ecosystem services and environmental planning.

While using manual image interpretation to produce maps of traditional orchards is highly accurate, it is also labour-intensive and costly, highlighting the need for automatised approaches. In this context, novel methods from the field of Artificial

Intelligence (AI) could play a transformative role. Deep Learning approaches have already been successfully applied to vegetation mapping [89-91], including the classification of historical imagery [92] and the identification of individual tree canopies [93]. AI models that leverage information from existing, general databases (e.g., [91]), as well as specific reference data on orchards (e.g., [3]) and similar landscape elements such as small woody features [85] from public sources, could enable high-resolution orchard mapping across broad spatial extents. Additionally, these models could enhance the transferability of mapping techniques between regions or states, as traditional orchards are not only diverse landscape features by themselves, but also occur within landscapes of varying complexity [16].

Beyond quantitative parameters, there is also a notable lack of data on orchard quality [3]. This includes spatial information on the number and area of individual trees [3], shrub encroachment, and succession towards forests [3,7,24]. Recent advances in deriving parameters on ecosystem structure from 3D remote sensing data [94] could facilitate the mapping of quality indicators for traditional orchards. For example, the increasing availability of airborne laser scanning (LiDAR) data allows for multitemporal analyses of tree dimensions, ground vegetation growth, and developments towards forest-type vegetation [32]. Therefore, in line with the recently published strategic dialogue on the future of EU agriculture [20], we advocate for the adoption of novel technologies to support the analysis of dynamics of complex landscape features and traditional agroforestry systems such as traditional orchards, promoting landscape monitoring and management in the context of agricultural policies, compensation measures, and nature conservation.

Conclusions

Traditional agroforestry systems in Central Europe, such as orchard meadows, are in decline, and the state of Hesse is no exception. Local annual loss rates are high, and major losses occur near hotspots, but both patterns and drivers vary locally and regionally. Orchards in the traditional hotspot region in the South are characterised by distinctive topographical, ecological, and socioeconomic attributes compared to the rest of the state, but the importance of these attributes changes over time. Newly established orchards are often situated at higher elevations and on steeper slopes, while historically old orchards were located closer to settlements, highways, and neighbouring orchards, and were characterised by comparably larger areas and higher complexity. The most important drivers of loss were expansions of Artificial Areas, Residential

Buildings, and Agricultural Land, while, locally, conversions into Forests or Woody Features also occurred. Comparisons to other study areas are helpful but limited due to the unavailability of spatial data. Therefore, we emphasise the necessity of high-resolution, multitemporal maps of these complex and biodiverse landscape features to enable evaluation of the severity of orchard loss and to facilitate the monitoring of the condition of traditional orchards in terms of quantity and quality. Continuous and long-term geospatial data on traditional orchards could also provide information on orchard age and the dynamics of orchard fragmentation, serving as backbone data for basic ecological research, calculations of ecosystem services, and environmental planning. Recent advances in geospatial technology and analysis have the promising but untapped potential to simplify the retrieval of orchard maps including quality indicators over broad spatio-temporal extents in support of agroecological schemes.

Author Contributions

Conceptualization, A.G.-S. and T.K.; methodology, A.G.-S.; formal analysis, A.G.-S. and M.S.; investigation, A.G.-S.; data curation, A.G.-S.; writing—original draft preparation, A.G.-S.; writing—review and editing, A.G.-S., A.H., M.S. and T.K.; visualisation, A.G.-S., A.H. and M.S.; supervision, A.G.-S. and T.K.; project administration, T.K.; funding acquisition, A.G.-S. and T.K. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by the “Hessischer Biodiversitätsforschungsfonds“ of the Hessian Agency for Nature Conservation, Environment and Geology (HLUNG), project “Entwicklung eines fernerkundungsbasierten Monitoringsystems zur Bewertung der quantitativen und qualitativen Veränderung von Streuobstwiesen in Hessen mit Fokus auf 3D-Laserscanningdaten (MOST3D) (funding number Z1-15 c 02.03).

Data Availability Statement

New raw data created in the study are included in the Supplementary Materials; further inquiries can be directed to the corresponding author.

Acknowledgments

We would like to thank Aykut Aksoy for the manual interpretation of the historical aerial imagery.

Conflicts of Interest

The authors declare no conflicts of interest.

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Chapter 14

Integration of InSAR coherence and SAR backscatter increases accuracy of LULC mapping in tropical high-mountain ecosystems

William Martínez^{1,}, Ivan Lizarazo², André Große-Stoltenberg^{3,4}*

¹Departamento de Geografía, Universidad Nacional de Colombia, Bogotá, Colombia, Carrera 45 No. 26-85, Bogotá, Colombia

²Facultad de Ciencias Agrarias, Universidad Nacional de Colombia, Bogotá, Colombia, Carrera 45 No. 26-85, Bogotá, Colombia

³Institute of Landscape Ecology and Resource Management, IFZ Research Centre for Biosystems, Land Use and Nutrition, Justus Liebig Universität Giessen, 35392 Giessen, Germany

⁴Center for International Development and Environmental Research (ZEU), 35390 Giessen, Germany

* Corresponding author

Abstract

Páramos, neotropical high mountain biomes of the northern Andes, are increasingly threatened by human land use (i.e., potato monoculture, cattle farming, and fires) and climate change. Timely and accurate land use/land cover (LULC) mapping is critical for monitoring these pressures. However, persistent cloud cover in these regions creates substantial challenges for optical satellite imagery. This limitation is shared by many high-altitude ecosystems worldwide, particularly those in inaccessible areas with heavy precipitation. previous studies have utilized dual polarimetric synthetic aperture radar (SAR) data, the potential of advanced interferometric SAR (InSAR) techniques remains uncharted. This study aims to improve LULC mapping accuracy in páramo ecosystems by integrating multitemporal InSAR coherence with traditional backscatter intensities. Specifically, it investigates (1) the ability of multitemporal InSAR coherence to differentiate vegetation types and land use in páramo landscapes and (2) the potential of combining coherence and backscatter to enhance classification accuracy compared to using backscatter alone. A one-year time series of Sentinel-1 images covering about 17,000 hectares of Colombian *páramos* from January to December 2019 was analyzed to map 17 LULC classes. Results demonstrate that combining multitemporal dual-polarimetric backscatter intensity with multitemporal coherence increased F1-Score and overall accuracy (OA) by 9% and 11%, respectively, compared to relying solely on multitemporal SAR backscattering data. This study advances research in two directions. Firstly, it emphasizes the critical role of multitemporal SAR as a primary data source for LULC mapping in *páramos* ecosystems, particularly where cloud cover impedes the use of optical imagery. Secondly, it underscores the utility of cloud-based Earth Observation platforms in overcoming computational barriers and streamlining SAR time-series processing for LULC mapping. This study's approach is valuable for mapping high mountain ecosystems worldwide, especially in inaccessible and heavy precipitation regions.

Keywords

InSAR coherence; polarimetric SAR; high-mountain ecosystems; land use/land cover mapping; multitemporal SAR

Introduction

The Andean *páramos* are neotropical biomes encompassing a variety of unique ecosystems, each characterized by endemic vegetation and wetlands adapted to high-altitude montane environments. (MADS 2018; Rangel 2005). Located between the forest line and the periglacial deserts of the Andean Mountain range and nestled between the tropical zone of the Americas, *páramos* are fundamentally recognized for their contribution to water regulation and regional carbon cycling. (Hofstede 2003). *Páramos* soils comprise quite porous organic matter with a high-water absorption capacity. It has been stated that one cubic meter of *páramos* soil can store up to 500 liters of water (Hofstede 2003). In Colombia, approximately 70% of the nation's population's water demand relies on *páramos* water production (Galvis Hernandez and Ungar Ronderos 2021; Ungar Ronderos 2014). Thanks to their sustained moisture and cool temperatures, these soils play a crucial role in capturing atmospheric CO₂. In fact, on a per-hectare basis, their carbon sequestration can surpass that of tropical forests. (Hofstede 2003; UNEP 2019).

Páramos are fragile ecosystems, and intensive agricultural management may lead to soil carbon loss and increase greenhouse gas emissions, contributing to global warming (Brück, Torres, and de Moraes Polizeli 2023). The level of land use change, including intensification, can be exemplified by monitoring the status of traditional agricultural practices such as cultivating forage grass and potato crops (Estupiñan et al. 2009; Fonseca et al. 2024). For many years, subsistence farming based on potato and livestock production was the primary agricultural activity in most Colombian *páramos*, sustaining family farms (Galvis Hernandez and Ungar Ronderos 2021; Ungar Ronderos 2014). However, the growing demand for these products from urban areas has driven the adoption of more intensive agricultural practices (León Rodríguez 2011), where tilling and NPK-based fertilizers play a significant role, ultimately causing the infiltration of these nutrients into surface waters (Estupiñan et al. 2009; Reay et al. 2012).

The current agricultural practices in these areas are contrary to the principles of the Colombian environmental policy for *páramos* ecosystems (Instituto Alexander von Humboldt 2017; MADS 2018). The misuse of agrochemicals and pesticides, together with extensive soil tillage practices and shortening fallow periods, often linked with capital-intensive potato production, conflict with the objectives of preserving *páramo* biodiversity and protecting water resources (Robineau et al. 2010). Timely and accurate land use/land cover (LULC) maps production could help to monitor land use change and

agricultural management in *páramos*, i.e. providing precise location and state of areas of conservation as well as spatial information on upward expansion of intensive farming practices (see Figure 1).

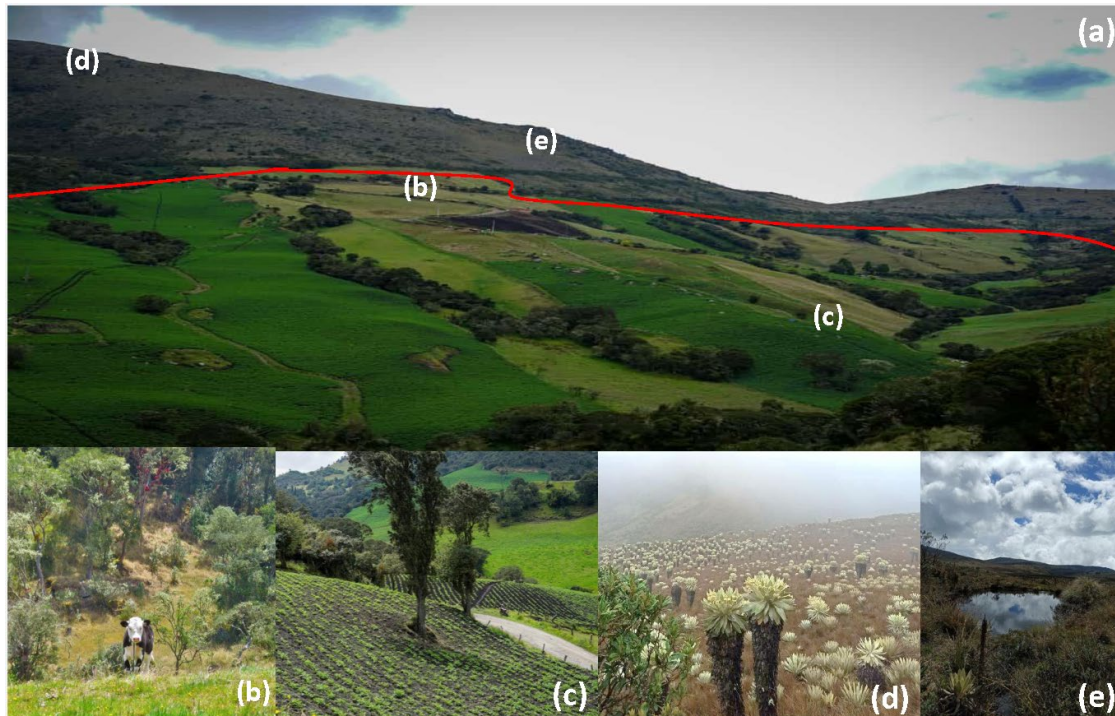


Figure 1: Illustration of land use/land cover types in the *páramo* of Guerrero. (a) Official *páramo* boundaries are shown in red color, (b) Areas of *grazing pastures* (c) Areas of small-scale *potato* farming, (d) Areas of *espeletias*, (e) Areas with small *water bodies*. Photos by William Martínez 2024

In Colombia's *páramo*, LULC mapping is intrinsically challenging due to their extensive spatial coverage (Borrelli et al. 2015), frequent cloudy conditions, and intricate topography. Despite these challenges, collaborative initiatives involving Colombian national agencies, specifically the Regional Autonomous Corporation of Cundinamarca (CAR) and the Agustín Codazzi Geographic Institute (IGAC), have successfully generated national-level LULC maps for *páramos* ecosystems adapting the CORINE Land Cover methodology for Colombia (Instituto Alexander von Humboldt 2018). These maps were produced using visual and digital interpretation techniques to extract information from remote sensing satellite data and aerial photographs. The resulting data products include, for example, detailed maps of the distribution of grasslands at scales of 1:25,000 or 1:10,000, with enhanced accuracy of water body location compared to global reference maps (Gumbrecht et al. 2017). These maps also allow for distinguishing potato crops from other agricultural areas, a challenging task in previous studies (Castiblanco Roza et al. 2015; Cortés-Duque and Sarmiento Pinzón 2013). While their thematic accuracy is high, LULC map production based on visual image interpretation of optical data is a time-consuming and long-lasting. With advancements in remote

sensing technology and open access to satellite imagery, monitoring and management of Andean *páramos* could be improved if thematic maps were produced in a timely manner using advanced image processing and digital analysis techniques.

The increasing availability of earth observation data has facilitated the application of automatic methods in wetland hydrological assessment (Quiñones, Vissers, and Pacheco 2016), ecosystem health (Safaei, Bashari, et al. 2023), and land cover change (Peyre et al. 2021; Poveda-Sotelo, Bermúdez-Cella, and Gil-Leguizamón 2022; Safaei, Kleinebecker, and Große-Stoltenberg 2023; Salomão et al. 2024). Particularly, synthetic aperture radar (SAR) is a promising technology in this context due to its ability to penetrate through the clouds, record surface backscatter data within a short time, and operate in mountainous settings (Chimner et al. 2019; Prudente et al. 2020; Quiñones et al. 2016; White et al. 2015). Besides, SAR is not dependent on sun illumination and can operate in all weather conditions, making it a reliable choice for wetland monitoring (Mahdavi et al. 2018). Unlike optical remote sensing applications in *páramos* ecosystem that rely on structural and spectral properties of objects (Fonseca et al. 2024; León Rodríguez 2011; Peyre et al. 2021; Poveda-Sotelo et al. 2022; Salomão et al. 2024) SAR data can convey information about the structure and moisture content of the ground that may be used to identify LULC changes (Sayedain, Maghsoudi, and Eini-Zinab 2020), with potential applications for *grasslands* and *mountain wetlands* monitoring (Chimner et al. 2019; Mahdavi et al. 2018; Novresiani, Setiyoko, and Arief 2023).

SAR-based mapping techniques, in particular those using dual-polarization backscattered intensity data, can be applied to high-mountain tropical ecosystems (Barrett et al. 2016; Chimner et al. 2019; Prudente et al. 2020; Quiñones et al. 2016). However, the potential of using interferometric SAR (InSAR) coherence as predictors in classification models to produce LULC maps in *páramos*, remains unexplored. Whereas SAR polarimetry provides information about the scattering properties of the observed target in different polarizations, coherence is a measure of the phase stability between two images, offering accurate assessments of land surface changes (Hanssen 2001; Zhang, Ding, and Lu 2011). Coherence can involve multiple comparisons of a pair of SAR images with similar geometric configurations (Nikaein et al. 2021). These comparisons can be captured over varying temporal intervals or baselines, which can be structured into a mathematical representation known as a multitemporal coherence matrix (MCM) (Jacob et al. 2020). MCM is a promising analysis technique for tracking seasonal LULC changes, crop conditions, and agricultural practices like seeding and harvesting over time (Shang et al. 2020; Villarroja-Carpio and Lopez-Sanchez 2023).

Previous studies using InSAR for LULC analysis predominantly relied on European Remote Sensing (ERS) missions for mapping forested regions and built-up areas (Engdahl and Hyypä 2003; Matikainen, Hyypä, and Engdahl 2006; Santoro et al. 2007; Strozzi et al. 2000; Yang et al. 2009). Regarding Sentinel-1 data, multitemporal InSAR coherence has also been applied for LULC mapping (El Kamali et al. 2020), though with less emphasis. For instance, combining coherence and SAR backscattering for wetlands, mountains, and flooded areas resulted in higher accuracy for LULC mapping compared to methods based solely on intensity (Jacob et al. 2020; Vicente-Guijalba et al. 2018). In the context of human-managed land covers, coherence has been critical for discerning diverse responses among various grasslands management practices (Chiboub et al. 2019; Tamm et al. 2016) during mowing events and among crop types during phenological stages such as seeding and harvesting (Shang et al. 2020), exploiting high coherence from small baseline MCM scenarios (pairs of images separated in 6 or 12 days) (Mestre-Quereda et al. 2020). Furthermore, novel LULC mapping approaches based on interferometric polarimetric InSAR coherence resulted in higher classification accuracies using multifrequency, different polarizations and several MCM temporal baselines scenarios (Ni et al. 2022). In this regard, this paper seeks to examine whether a InSAR-based methodological approach, based both on multi-temporal coherence and backscattering techniques can be applied to *páramos* ecosystems to map challenging vegetation types and agricultural practices with high thematic accuracy.

Integrating multitemporal coherence and multitemporal backscatter intensity into a classification process is complex. It involves devising an optimal strategy to integrate, process and analyse SAR time series in a digital classification process (Jacob et al. 2020; Ni et al. 2022; Pandit et al. 2022). The curse of dimensionality, i.e., the challenge of analysing data in high-dimensional spaces, has led either to the development of robust algorithms to reduce the effects of overfitting or to the discovery of effective strategies for feature reduction. For example, Mestre-Quereda et al. (2020) used the shortest baseline interferometry combinations of the MCM (i.e. 6 days). The loss of coherence between pair of images, denoted as temporal decorrelation, proved to classify effectively crops due to their specific growth stages. In addition, Jacob et al. (2020) evaluated multiple strategies to transform and reduce the dimensionality of the MCM and suggested that aggregating coherence can mitigate the effects of the decrease in coherence associated with weather conditions (rain) and changes in vegetation moisture, while improving LULC accuracy. In both studies, accuracy did not improve after the second shortest baselines (12 and 24 days). This article delves into the same

approach of aggregating MCM shortest baselines based on the region's regime of precipitation (e.g. Jacob et al. (2020); Mestre-Quereda et al. (2020)).

Therefore, the primary aim of this study is to evaluate the potential of multitemporal SAR as a key data source for land use/land cover (LULC) mapping in *páramo* ecosystems by integrating dual-polarization backscatter intensity with multitemporal coherence. This integration leverages the complementary strengths of these methods: backscatter intensity provides detailed information on surface roughness and vegetation structure, aiding in the differentiation of vegetation such as shrublands and grasslands, while multitemporal coherence captures temporal stability and variability, which is particularly useful for distinguishing natural vegetation from agricultural fields undergoing periodic changes due to cultivation or harvesting cycles. By combining these techniques, the study seeks to enhance mapping accuracy by capturing temporal patterns among diverse land covers and improving classification across thematic levels. Furthermore, it examines the practical utility of readily accessible SAR data and preprocessing workflows, including polarimetric and interferometric approaches, available on Earth Observation cloud platforms, thereby demonstrating scalable and replicable solutions for LULC mapping in data-limited regions like *páramo* ecosystems.

To address this aims, the paper is organized as follows: Section 2 describes the study area, the data, and methods, including a formal description of InSAR coherence, input data setup, processing, and digital analysis strategies. Section 3 presents exploratory data analysis and LULC classification results using different predictor variables. In Section 4, a discussion of the results obtained is presented. Finally, in Section 5, conclusions and suggestions for future research are provided.

Materials and Methods (Section 2)

Study area

The study area is located at the center of the Colombian Andes region. This 17 km x 17 km area covers the *páramo* of Guerrero, particularly highland areas near San Cayetano municipality (see Figure 2). The altitude varies from 3.210 to 3.790 m above sea level, with a mean of 3.500 m. Slope ranges from 0% to 26%, averaging of 15%. Despite its high ecological value due to water production and provision of multiple ecosystem services, the occupation of land for potato monoculture poses a threat to quality and quantity in

the provision of essential ecosystem services in the area (Morales-Rivas et al. 2007; Triana Gasca, Díaz Ramírez, and Vallejo Quintero 2022).

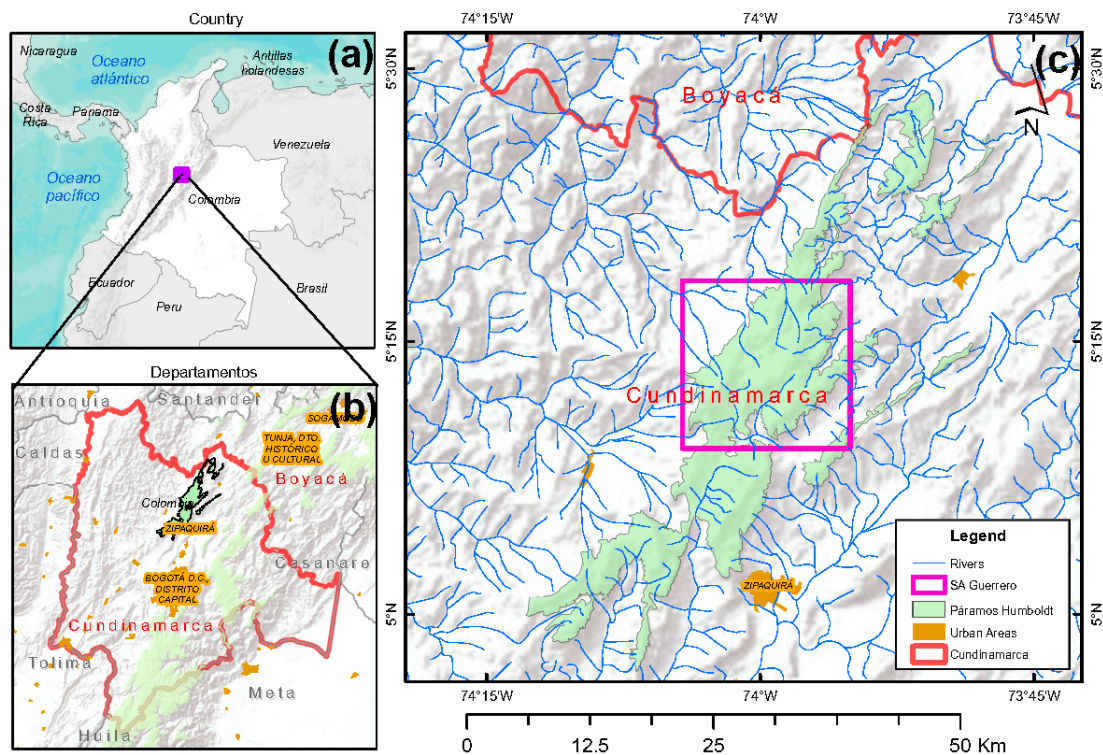


Figure 2: Location of the study area. (a): Geographical location within the country. (b): Location of the study area within the administrative region. (c): Overlapping location with the páramo of Guerrero

Reference data

The official LULC maps of páramo of Guerrero for the years 2011 and 2019 are based on visual interpretation of high-resolution multispectral aerial images captured using Vexcel Ultracam (Vexcel Imaging GmbH, Graz Austria), which provides true color and near infrared bands with a ground sampling distance of 15 cm. Additionally, PlanetScope satellite images (Planet Labs, San Francisco, USA) were utilized, using multispectral data with a spatial resolution of 3 m, including true color and NIR bands. The interpretation was supported by auxiliary insitu information collected during field surveys (IGAC 2022). These maps follow the CORINE land cover system adapted to Colombian ecosystems (e.g. Fagua, Rodríguez-Buriticá, and Jantz 2023; Mancera-Flórez and Lizarazo 2020). This adaptation results in a more detailed legend depicting the spatial distribution of the LULC categories at a 1:10.000 scale (IGAC 2022). Figure 3 illustrates the legend of the official LULC vector map overlaid on the study area, accompanied by a zoomed-in view showcasing a color composition derived from polarizations and the normalized ratio procedure between bands (NRPB) (see Filgueiras

et al. (2019)), as well as high-resolution imagery sourced from Google Earth (Yu and Gong 2012). The color composition helps to differentiate in cyan color some agriculture classes.

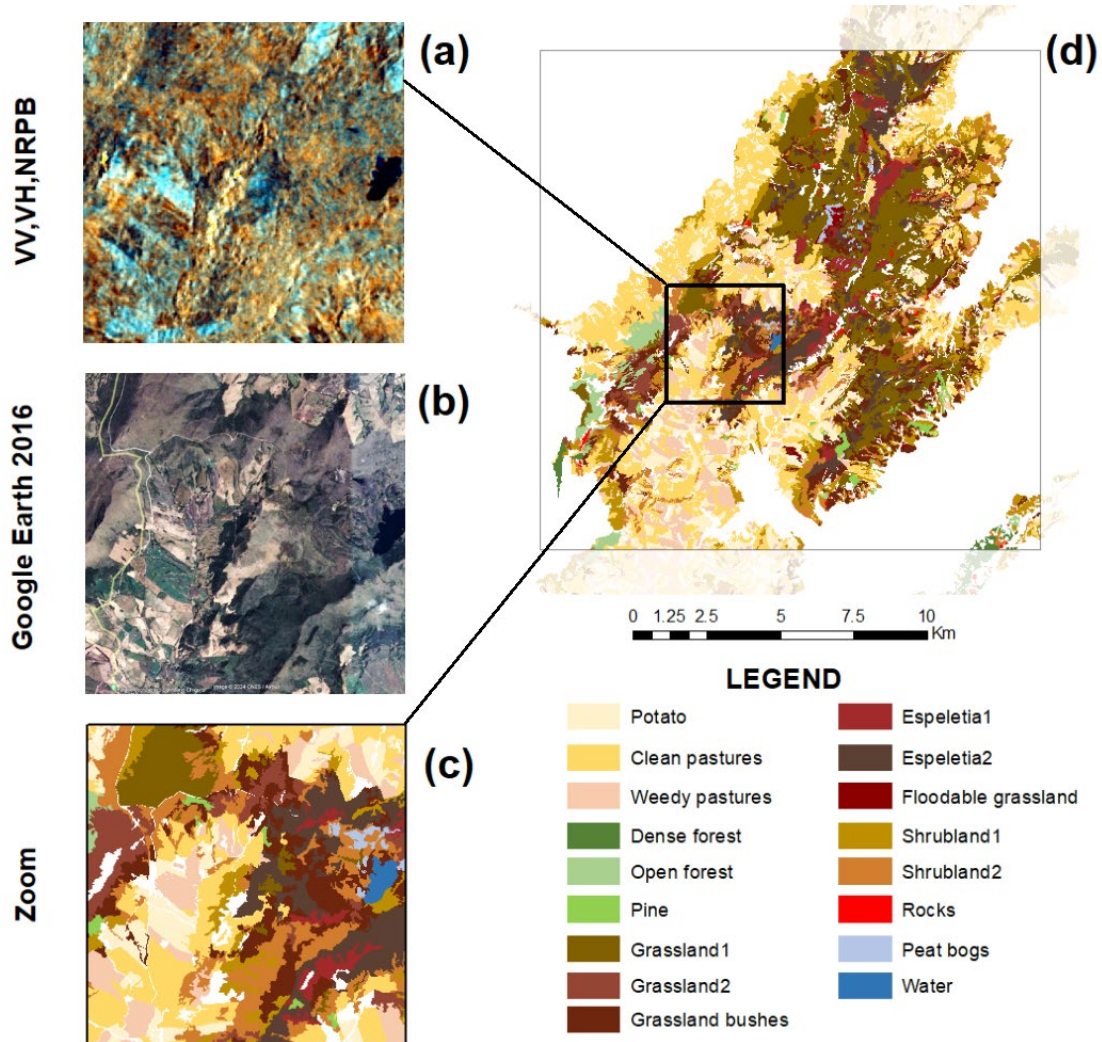


Figure 3: (a) Reference land use/land cover (LULC) map 2019 Source: Agustín Codazzi Geographic Institute. (b) Color composition based on VV, VH and NRPB index Source: Google Earth engine. (c) Google Earth Imagery year 2016, (d) Zoom into the LULC map

The reference map includes a legend of 17 target LULC classes prevalent in *páramos*, such as *grasslands*, *wetlands*, *shrublands*, *clean pastures*, and *potatoes*. These classes are derived from the compression of levels 4 and 7 in the CORINE land cover system (see Table 1). The target classes are disaggregated according to the first three levels of the CORINE land cover system, from coarse (level 1) to very detailed (levels 4-7) LULC classes. Classes like *clean pastures* or *dense forests* fit within the semi-detailed levels (level three). At the same time, classes of *herbaceous* vegetation (also at level three) can be further subdivided into more detailed categories, such as *espeletias* and various types of *grasslands* (ranging from levels 4 to 7).

Table 1: Legend of the reference land use/land cover map: The 17 target classes are derived from levels 4 and 7 compressions in the CORINE land cover system. Each class is disaggregated according to the first three levels of CORINE and includes a description, spatial coverage in hectares (after preprocessing of the vector reference map), and a proportion of the class in relation to the overall study area

	Level 1	Level 2	Level 3	Target classes (L4-L7)	Description	Area (Ha)	% SA
	1. Artificialized areas	1.2. Industrial or commercial areas	x	x		0.63	
		1.3. Mining	x	x		0.66	
1	2. Agriculture	2.1. Transient crops	2.1.1. Other transit crops	x	Areas of small scale farmers and entrepreneur planting potatoes	0.67	
			2.1.5. Potato	2.1.5.1. Potato		702.5	8.4%
2		2.2. Permanent crops	2.2.2 Other permanent shrub crops	x		0.3	
			2.3.1. Clean Pastures	2.3.1. Clean Pastures	Grassland for livestock grazing	2191.2	26.1%
3		2.3. Pastures	2.3.3. Weedy pastures	2.3.3. Weedy pastures	Grassland for livestock grazing with trees taller than 3m and cover less of 50%	537.7	6.4%
			2.4.5 Mosaic of crops with natural spaces	x		30.0	
4		3.1. Forest	3.1.1. Dense forest	3.1.1.2.1. Dense forest	Dense low forest between 5 and 15 m	39.3	0.5%
5			3.1.2. Open forest	3.1.2.2.1. Open forest	Open low forest between 5 and 15 m	185.5	2.2%
6			3.1.4. Gallery or riparian forest	x		12.8	0.2%
7			3.1.5. Forest plantation	3.1.5.1.1. Pine	Plantation of pines	56.6	0.7%
8			3.2.1. Herbaceous	3.2.1.1.1.1. Grassland1	Tall dense grassland of land not wooded	1951.4	23.3%
9				3.2.1.1.1.2. Grassland2	Dense low grassland of land not wooded	176.0	2.1%
10				3.2.1.1.1.3. Grassland bushes	Dense grassland of land with bushes	623.0	7.4%
11				3.2.1.1.4.1. Espeletia1	Espeletias with bushes	228.1	2.7%
12				3.2.1.1.4.2. Espeletia2	Espeletias with not bushes	543.8	6.5%
13				3.2.1.1.2.1. Floodable grassland	Dense floodable grassland without trees	18.5	0.2%
14				3.2.2. Shrubland	Dense mesophyllous shrub of mainland	565.6	6.7%
				3.2.2.2.1. Shrubland2	Open mesophyllous shrub of mainland	423.2	5.0%
			3.2.3. Secondary or transition vegetation	x		46.8	0.6%
15		3.3. Open areas, with little or no vegetation	3.3.2. Rock outcrops	3.3.2.1. Rocks	Masive rock outcrops	8.2	0.1%
16	4. Wetlands	4.1. Continental humid areas	4.1.2. Peat bogs	4.1.2. Peat bogs	Dense wetlands filled with partially decayed vegetation	27.8	0.3%
17	5. Water bodies	5.1. Inland waters	5.1.2 Lagoons, lakes, and natural swamps	5.1.2 Water	Lagoons, lakes, and natural swamps	11.2	0.1%

We conducted a geometric intersection of the 2011 and 2019 LULC maps to generate the sampling data utilized in the classification process (e.g. Fonte et al. (2020)). Only polygons with matching labels in both maps were selected for constructing the training and testing datasets to increase the quality of the sampling data due to the differing image sources used for the interpretation of each year (Botón et al. 2022). In addition, we performed an inner buffer of 20 meters for all polygons to mitigate the noise linked to the extraction of labels from the borders of the vectorized maps (Maas et al. 2018). The 20 meters correspond to half of the distance of the pixel with the largest resolution, that is, the 40 meters of the coherence map raster (see 2.4 SAR Data Processing) Further,

classes with areas less than one hectare were removed from analysis to prioritize classes with greater areas. Mixed classes such as *mosaic of crops and natural species* or *secondary or transition vegetation* were also removed due to their low representation in the study area to ensure a sufficient number of sites to split them into training and testing datasets. Classes such as *peat bogs* and *floodable grasslands* hold high ecological importance due to their significant carbon storage and water filtration capabilities, so they were included in the analysis regardless of their size.

Workflow

Figure 4 shows the overall methodology workflow. First, data was downloaded from cloud platforms such as Google Earth Engine (GEE) and Alaska Satellite Facility (ASF) (section 2.4 SAR Data Processing). Secondly, we computed, extracted, and explored predictors from multitemporal dual-polarimetric backscatter intensity (MDBI) and MCM (section 2.5 Feature Computation and Extraction). Finally, we performed a pixel-based classification using four distinct models incorporating backscattering and coherence in multiple ways (see section 2.6 Classification). Thematic accuracy was assessed according to the target classes and across various CORINE land cover classification levels.

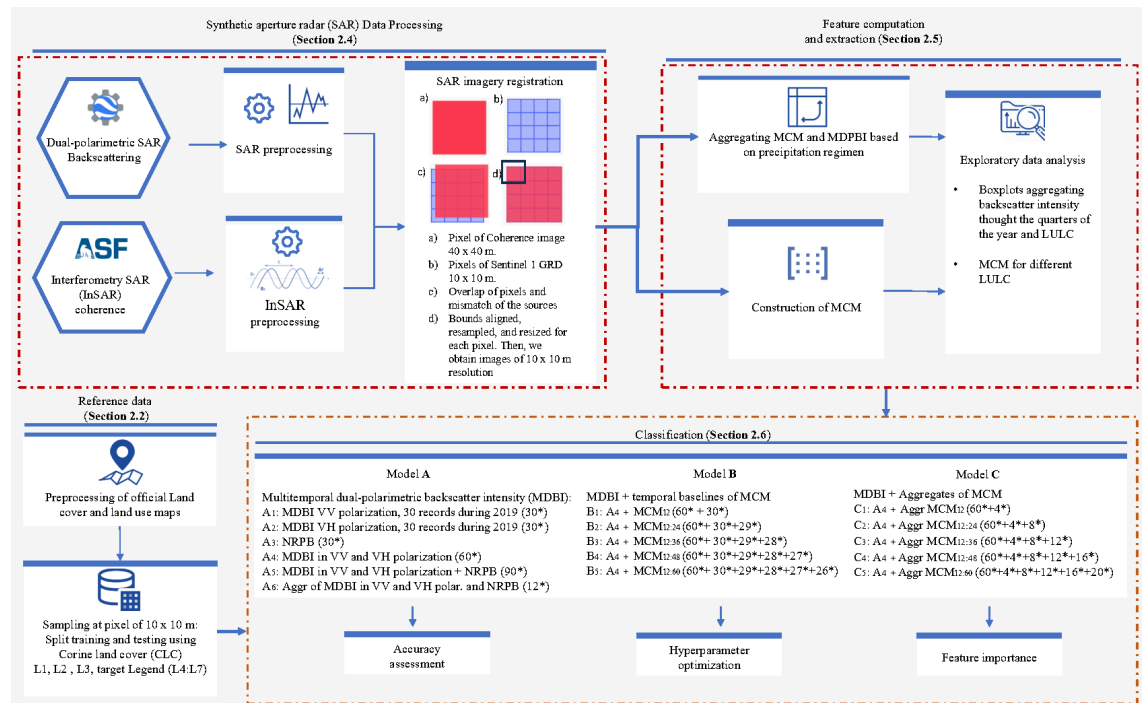


Figure 4: Workflow diagram of the data and methodology used in this study. *Number of predictors

SAR Data Processing

Sentinel-1 operates at a central frequency of 5.405 GHz (5.6 cm wavelength), flying at an altitude of 693 km (ESA 2014). Images were acquired in dual-polarimetric modes from Earth Observation cloud platforms such as GEE and ASF. GEE delivers SAR ground range detected (GRD) data (GEE 2024b), whereas the ASF specializes in providing interferometric products, specifically coherence, which is of interest in this context (see (2022)). GRD and coherence data were acquired from these platforms from January to December 2019, with baselines of 12 days. While GRD was downloaded in VV (vertical /vertical) and HH (horizontal/horizontal) polarizations at a spatial resolution of 10 meters, coherence was obtained from images in dual-band cross-polarization VV+VH at a spatial resolution of 40 m.

SAR backscattering represents the interaction between the radar microwave signal and the surface features. The intensity of the interaction is measured per unit area and is expressed in decibels (Moreira et al. 2013). SAR backscatter images of Sentinel-1 were obtained through the GEE Python API (GEE 2024a) and pre-processed using a pipeline suggested by Mullisa et al. (2021). This workflow involved border noise correction, speckle filtering, and radiometric terrain normalization. This process was repeated for the images available between January and December 2019. Besides, a normalized polarization index was calculated considering VV and VH polarizations. This procedure denoted as the NRPB (normalized ratio procedure between bands) (Filgueiras et al. 2019), was also performed to generate a higher number of predictors.

For InSAR processing, we used the hyp3 Python package, a processing pipeline from ASF that leverages GAMMA Software in the cloud (ASF 2021). Through this pipeline, we created interferograms by computing phase differences between pairs of co-registered SAR images. Additionally, we conducted phase unwrapping to obtain coherence, which quantifies the correlation between the phase's SAR signals at each pixel. Thereafter, the same process was performed with pairs every 12, 24 and 36 days, that stands for the maximum number of days, to obtain InSAR coherences along the year 2019 and finally construct the MCM by pixel. Coherence raster were produced as UTM-projected GeoTIFFs (OGP Surveying and Positioning Committee 2022) with a pixel spacing of 40 m in dual-band cross polarization VV+VH (Hogenson et al. 2023).

To integrate both sources of SAR imagery, the GRD data were reprojected to align SAR backscattering pixels with coherence pixels to integrate both sources of SAR imagery. Conversely, the coherence imagery was downsampled to match the spatial resolution of the GRD imagery of 10 m. This process was performed using the *rasterio* Python library

considering the bilinear resampling method, which computes each output pixel as a weighted average of the four nearest input pixel coherence values (Gillies 2019).

Feature Computation and Extraction

Construction of the multitemporal coherence matrix (MCM)

Considering two SAR Sentinel (S) images, their coherence is denoted by ρ and obtained mathematically as follows:

$$\rho = \frac{E\{S_1 S_2^*\}}{\sqrt{E\{|S_1|^2\} E\{|S_2|^2\}}} \quad (1)$$

Where represents the expectations operator and * indicates the complex conjugate. For practical applications, the expectations operator is substituted by a spatial average of an ensemble of pixels within a window in both SAR images (Touzi et al. 1999). In this sense the equation 1 becomes in:

$$\rho = \frac{\frac{1}{L} \sum_{l=1}^L S_1 S_2^*}{\sqrt{\frac{1}{L} (\sum_{l=1}^L S_1 S_1^*) \cdot \frac{1}{L} (\sum_{l=1}^L S_2 S_2^*)}} \quad (2)$$

The magnitude of ρ ranges from 0 to 1. Low values of ρ are detected in regions where two images, acquired at times T_0 and $T_0 + \Delta t$ are decorrelated, often due to changes in surface properties or motion. In contrast, high values of ρ indicate strong correlation between the images, suggesting minimal change in the scene between two passes, consistent with areas where the ground distances R_1 and R_2 remains stable. According to Figure 5, as the potato plants grow and the canopy becomes denser, the backscattering characteristics shift due to increased volume scattering caused by the leaves and stems. This transition introduces greater variability in the scattering mechanisms, which reduces coherence between successive observations. In contrast, regions such as *grasslands* and *espeletias* can exhibit high coherence, either due to their relatively stable physical and structural characteristics or, in waterlogged areas, through the contribution of double-bouncing mechanisms (Hong and Wdowinski 2014). The MCM is then constructed by computing the coherence values for all pairs of SAR images in the multitemporal dataset (Ni et al. 2022). Let N be the number of SAR images in the dataset, the MCM, denoted by Γ , can be obtained from (2) as follows:

$$\Gamma_{temporal} = \begin{bmatrix} 1 & \rho_{12} & \dots & \rho_{1N} \\ * \rho_{12} & 1 & \dots & \rho_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ * \rho_{1N} & * \rho_{2N} & \dots & 1 \end{bmatrix} \quad (3)$$

The MCM is symmetric so that the upper (or lower) triangular matrix provides useful coherence data to be used as input features to a classification algorithm. In this sense, we analysed the upper part of the matrix.

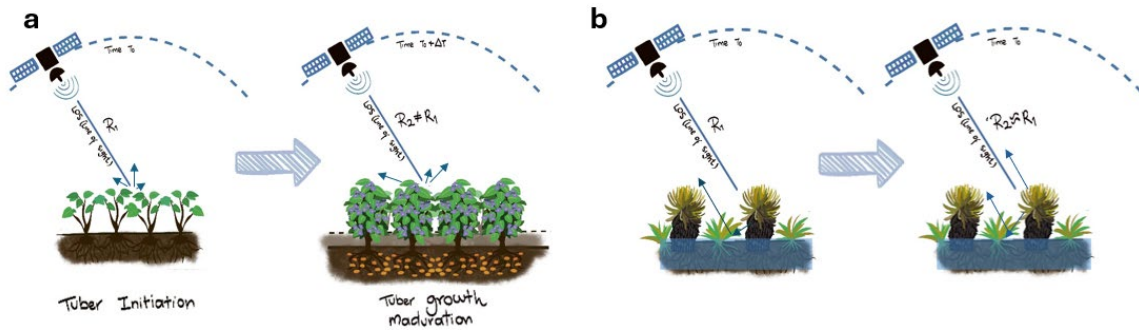


Figure 5: Two passes of an imaging SAR, conducted at times T_0 and $T_0 + \Delta t$, provide two ground distances, R_1 and R_2 , indicating ground motion. a) Decorrelation increases as the plant's canopy cover moves from the tuber initiation to the maturation stages. In contrast, b) grasslands and espeletia regions exhibit relatively greater stability in vegetation dynamics, leading to possible high coherence.

Aggregation of MCM and time series of polarimetric SAR backscattering based on precipitation regime

Inspired by Jacob et al.'s (2020) Expert Knowledge Decision Trees (EKDT) methodology, coherence was consolidated by aggregating and selecting the highest coherence value in intervals with similar precipitation conditions. By doing so, we aimed to decrease as much as possible the noise caused by severe rain conditions, potentially enhancing LULC mapping accuracy. In this sense, the highest coherence values were computed from subsets of coherence images within each temporal baseline (e.g., 12, 24, 36 days) and each season separately for both VV and VH polarizations. For example, for 12- and 24-day coherence baselines, coherence values were selected according to pre-selected periods. The pre-selected periods in this paper corresponded to the quarters of the year 2019. In this region, the precipitation occurred mainly during two periods (bimodal precipitation); the first during the months of April and June (Q2) and the second during the months of October to December (Q4). In contrast, the months from January to March (Q1) and July to September (Q3) were the months of the year with less precipitation (see Figure 6).

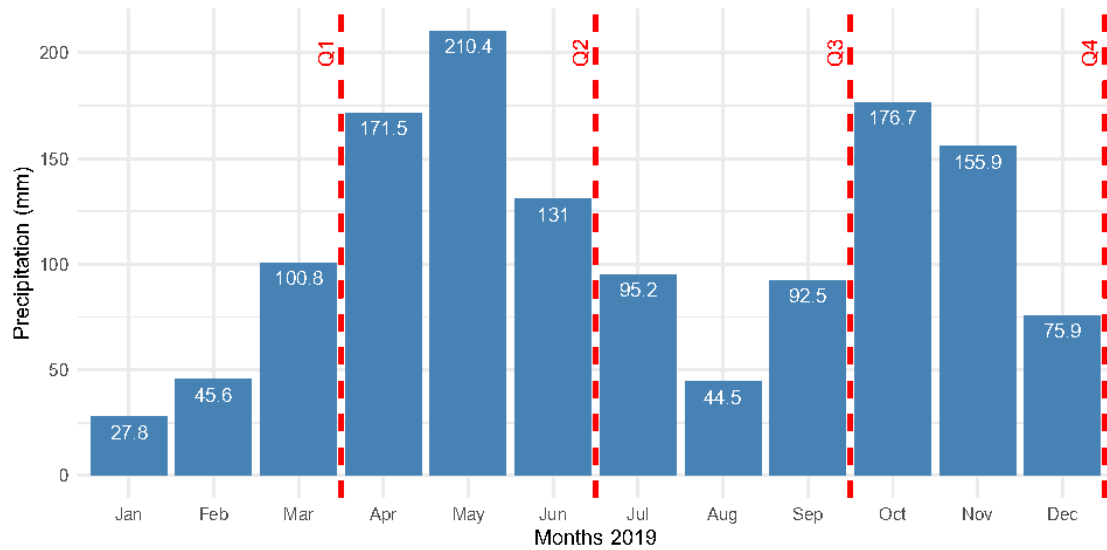


Figure 6: Monthly precipitation (mm) for 2019 in the study area. The dotted lines represent the subsets of months or annual quarters where both coherence or backscattering is calculated. Data source: WorldClim2

Multitemporal dual-polarimetric backscatter intensity was consolidated similarly. Instead of relying on 30 backscattering observations in 2019, adding up to a total of 60 observations considering both VV and VH polarization, we calculated four specific metrics to each quarter of the year. For example, the first Q1 of the year had approximately 6 observations of backscatter intensity in VV polarization. From January to March, these observations were aggregated, and the median was computed to obtain one representative value of backscatter intensity in VV polarization for this period.

Exploratory Data Analysis

For exploratory data analysis, boxplots were produced to analyse the distinct characteristics and patterns across various LULC classes and different SAR feature extraction strategies. These boxplots also served as a visual tool to understand the data distribution within each class, offering insights into the central tendency, spread, and potential outliers. The boxplots were recreated for the time series's seasonal aggregation (quarters of the year 2019). To examine significant differences in the temporal variation of backscattering intensity across these aggregations, we used a non-parametric Kruskal-Wallis test (Boschetti et al. 2006). This test assesses whether the groups have the same median without requiring the normality assumptions necessary for tests like ANOVA.

Classification

We used the random forest (RF) algorithm (Breiman 2001) in a pixel-wise and supervised classification approach for LULC mapping, utilizing the scikit-learn Python package. The RF algorithm has shown the ability to handle extensive multi-temporal and multimodal remote sensing datasets with a considerable number of input variables while simultaneously accommodating diverse types or scales of input data (Belgiu and Drăguț 2016). It also exhibits robustness against noise and overfitting. In RF classification models, two commonly optimized parameters are the number of decision trees and the number of predictors randomly sampled as candidates at each split (Breiman 2001). As the study area exhibited an unbalanced distribution of LULC classes, we adopted a stratified random approach to ensure balanced training and testing sets (Stehman and Foody 2019). The required sample size per class, denoted by n , was obtained based on the Cochran statistical method (Foody 2009):

$$n = \frac{Z_{\alpha/2}^2 P(1 - P)}{h^2} \quad (4)$$

where P is the value for the population proportion, and Z is the Z-score corresponding to the desired confidence level. We selected a margin of error (h) of 0.05 (5%) and a confidence level of 95%, resulting in a Z-score approximately equal to 1.96. The total population of samples, and thus the proportion by class, was determined by the number of pixels in the raster with the highest spatial resolution, which was 40 m for the coherence maps. Due to the limited number of samples for the target classes with a low proportion, we increased the samples per class by a factor of 10. For target classes such as *water*, *floodable grassland*, and *rocks*, the minimum number of samples was set to 50, resulting in an augmentation of counts. Table 3 shows the total number of samples per class, including the explained procedure for augmenting samples for certain classes. Concerning the split of testing and training, we opted to use 50% samples for training and 50% for testing (see Pawluszek-Filipiak and Borkowski (2020)). Each sample represented a 10 meter resolution, covering one pixel of coherence and one pixel of backscatter intensity.

To evaluate the benefits of using Sentinel-1 InSAR data for LULC mapping in *páramo* ecosystem relative to traditional SAR methods, three distinct models, along with several sub-models, were computed:

- Model group *A* focused on multitemporal and dual-polarimetric backscatter intensity. It entailed six sub-models.

- Model group *B* integrated complementary data from MDBI plus NRPB (Model A_4 with 60 predictors) and the shortest temporal baselines of MCM, that is, a series of values of coherence for intervals of 12, 24, 36, and up to 48 days, resulting in 5 sub-models.
- Model group *C* integrated complementary data from MDBI plus NRPB (Model A_4) and aggregated the shortest temporal baselines of the MCM according to the four quarters of the year (the maximum coherence value of each group is considered). This resulted in five submodels.

Accuracy assessment

To assess the model's thematic accuracy, an estimated confusion matrix in terms of the proportion of area was utilized as the basis for calculating OA. Unlike traditional confusion matrices that rely on hard class assignments, the confusion matrix proposed in Olofsson (2014), incorporates the predicted probability of occurrence of the map class *i* and reference class *j*, allowing the contributions of individual samples to be weighted according to their likelihood of belonging to each class and (e.g. Costa (2024)). This approach ensures that the analysis accounts for the inherent uncertainty in the classification process and better reflects the relative frequency distribution of the samples in the dataset. The formula used to estimate $\hat{p}_{ij}$ varies based on the sampling design. For designs with equal probability sampling, such as simple random sampling or systematic sampling, as well as for stratified random sampling where the strata align with the map classes, we have the following:

$$\hat{p}_{ij} = W_i \frac{n_{ij}}{n_i} \quad (5)$$

Where $\hat{p}_{ij}$ is the estimated proportion of area or instances that belong to the true class *i* and are mapped (or predicted) as class *j*, W_i is the weight assigned to the true class *i*, often representing the proportion of the total area (or population) covered by class *j* in the entire dataset, n_{ij} is the number of samples in the confusion matrix that are from true class *i* and are mapped (or predicted) as class *j*, and n_i is the total number of samples for true class *i* in the sample data.

Accuracy metrics calculated from a population confusion matrix with *q* classes encompass overall accuracy.

$$OA = \sum_{j=1}^q p_{jj} \quad (6)$$

, OA provided a global assessment of model performance across all classes, giving a single measure of accuracy for the entire dataset (Congalton and Green 2019). However, following the recommendation of Maxwell et al., (2018) , it is important to consider more accuracy metrics than just OA. Therefore, we also computed the F1-Score which is the harmonic mean that balances precision and recall:

$$\begin{aligned} Precision_j &= \frac{n_{jj}}{\sum_i n_{ij}} \\ Recall_j &= \frac{n_{jj}}{\sum_j n_{ij}} \end{aligned} \quad (7)$$

so that:

$$F1 - Score_j = 2 \frac{Precision_j \cdot Recall_j}{Precision_j + Recall_j} \quad (8)$$

The stratified random selection of 50% of the data for testing was performed iteratively 50 times for cross validation (see Große-Stoltenberg et al. (2016)). This approach was used to calculate the mean OA and F1-Score, and the confidence level. The goal was to better understand the significant improvements brought by incorporating MCM into the classification process.

Hyperparameter optimization

The RF classifier was trained using bootstrap aggregation. In this method, each new tree is fit using a bootstrap sample of the training data. The out-of-bag (OOB) error is calculated as the average error for each observation based on predictions from the trees that do not include that observation in their bootstrap sample. This approach allows the classifier to be simultaneously trained and validated (Hastie, Friedman, and Tibshirani 2001). The OOB error can be measured by adding each new decision tree during training (here from 10 to 500). The resulting plot allows to approximate a suitable value of the number of decision trees in the forest and three strategies for the maximum number of predictors at each split to consider at which the error stabilizes. These three strategies consist of (i) the complete feature space (i.e., the total number of predictors); (ii) the square root of the total number of predictors (for instance, if the number of predictors

for the model A_1 is 26, the algorithm constructs decision trees based on approximately 5 random features); (iii) and the $\log_2$ strategy is similar to the square root strategy, but the number of predictors for each split is calculated using the binary logarithm instead of the square root.

Feature importance

RF calculates the importance of each predictor/feature by evaluating how much each feature decreases the impurity (typically measured by Gini impurity) when making decisions across all trees in the forest. The more a feature reduces impurity when it is used to split nodes in trees, the more important that feature is considered (Breiman 2001).

Results (Section 3)

Multitemporal coherence matrices (MCMs) for the target LULC classes

Multitemporal coherence matrix (MCM) patterns based on InSAR analysis differed across the 17 target LULC classes in 2019 in the studied *páramos* ecosystem (see Figure 7). Notably, *rocks* and, to some extent, the classes of *espeletias* and *floodable grassland* showed high stability with coherence values near one. In contrast, LULC types such as *potatoes* displayed patterns characterized by brief periods of high coherence followed by longer periods of low coherence in the shortest temporal baselines (coherence values near the diagonal). This increase of coherence was depicted in the form of a triangle that showed up once or twice during the year (see red circles in Figure 7). While classes such as *dense forest*, *shrubland2*, *pine*, and *water* exhibited mainly low coherence along all temporal baselines, classes of *grasslands*, *speletias*, and *rocks* exhibited high coherence along the MCM.

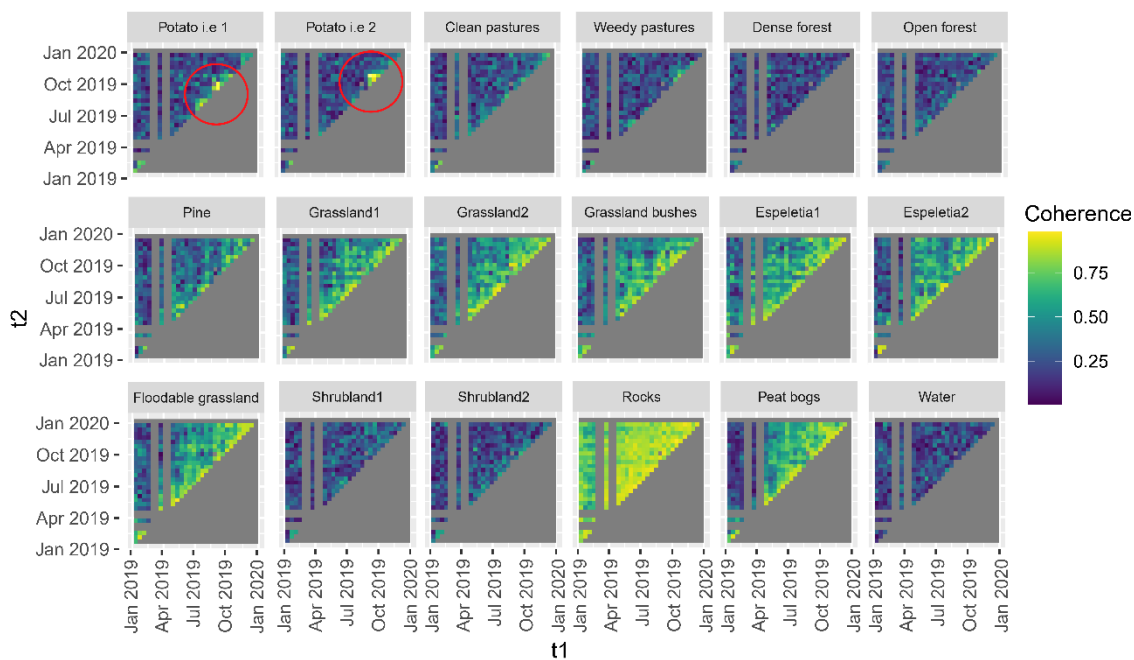


Figure 7: Multitemporal coherence matrices (MCMs) of the 17 target land use/land cover classes. Each matrix reflects the temporal coherence for all temporal combinations during 2019. High coherence values (shown in yellow) between the two images indicate the absence of coherent changes. Conversely, low coherence values (in blue) indicate changes between the two images. Red circles indicate patterns characterized by brief periods of high coherence followed by longer periods of low coherence in the shortest temporal baselines of potato (coherence values near to the diagonal). Some columns of the upper triangle of the MCM are colored grey due to data gaps on the Alaska Satellite Facility (ASF) platform.

Quarterly aggregated multitemporal backscatter intensity data for the target land use/land cover (LULC) classes

We produced boxplots (Figure 8) to examine median values and variability of backscattering intensity across aggregations of quarters of the year and different LULC classes. According to Kruskal-Wallis test, the variability of backscattering intensity between the year's quarters differed significantly for most LULC target classes. For example, classes such as *potatoes* showed seasonal patterns regarding quarterly aggregated backscatter data for VV and VH polarizations, respectively, and this variability of the backscattering intensity was significant. Low backscattering characterized this pattern values during the initial quarters of the year, followed by a substantial increase in intensity during the third quarter, and ultimately returning to low backscattering values. Despite the low variability in VH polarization for *potato*, this crop experienced pronounced dynamics backscatter observation with VH polarization compared to other classes. Besides, *rocks* and *dense forest* did not exhibit significant variations in median changes during the four quarters of the year. However, inherent differences in medians between polarization VV and VH for these *open* and *dense forest*

classes suggest potential distinctions in backscattering responses. Similarly, classes of *herbaceous* displayed inherent differences in medians of backscattering across the quarters of the year. Notably, *water* displayed temporal variability in polarization VV, yet this variability was absent in polarization VH. Furthermore, the backscatter intensity for *water* falls within the lowest range of variability across the entire graph, indicating the potential for class separation based on these patterns.

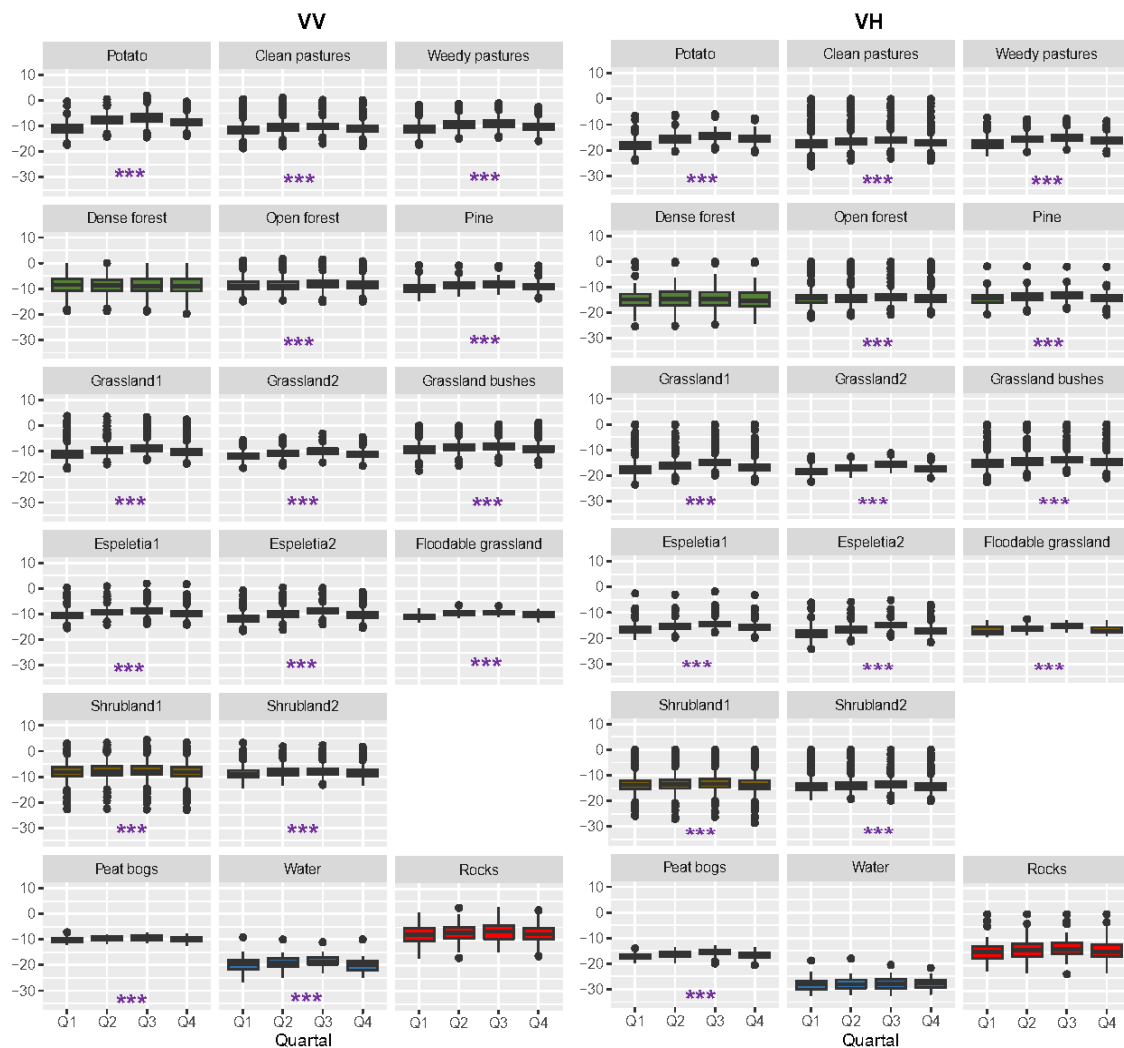


Figure 8: Quarterly aggregates of multitemporal backscattering intensity in VV and VH polarizations across the 17 target land use/land cover classes. Asterisks at the center bottom indicate significant differences of temporal variation of backscattering intensity.

Classification models

Thematic accuracy of the LULC classification for the level 1 class ranged between 0.67 and 0.74 for F1-Score and between 0.86 and 0.92 for OA. As shown in Table 2, it decreased as the level of thematic detail increased. The best model using only multitemporal dual-polarimetric backscatter intensity (MDBI) data as predictors at the

highest thematic level in terms of F1-Score (0.33) and OA (0.55) was the model A_4 . The complementary use of dual polarimetric backscattered intensity and the NRPB in the model A_5 did not improve accuracies at any level. Likewise, using aggregates of times series of backscattering intensity (Model A_6) did not outperform the use of the complete NRPB plus NDBI (Model A_5).

Concerning the use of multitemporal coherence as additional predictors in the classification model, F1-Scores increased by 7% for level 1 and approximately 9% for the target classes when comparing the models that only relied on backscatter data (see Model group B and A). OA showed larger gains when the number of classes increased across CLC levels, rising by 6% for level 1 and 11% for the target classes. Additionally, this increase depended on the number of baselines of the MCM. For example, when using up to three temporal baseline intervals of 12, 24, and 36, the F1-Score slightly increased from 0.67 to 0.74 for level 1 (Model B_3). So, choosing more intervals maintained the same F1-Score and OA, or even slightly decreased them. In contrast, the use of backscatter predictors in Model A_4 and the aggregates of MCM (Model group C) did not improve accuracy in relation to the complete series from the shortest temporal baselines of the MCM (Model group B). Subsequently, the integration of InSAR coherence (Model group B) yielded the highest accuracies of all models with low standard deviation (see green row in Table 2). In the Model group B , accuracy improvements seemed to stabilize after two or three temporal baselines (36 days).

Table 2 F1-Score and Overall Accuracy (OA) metrics for each sub-model and thematic level. Orange represents the best accuracy obtained using solely backscattering intensity features (Model group A). Green corresponds to the best accuracies obtained using complementary multitemporal dual-backscatter intensity (MDBI). Blue exhibits the integration of backscattering and aggregated data of the multitemporal coherence matrix (MCM) (Model C).

Model	Sub-Models	Layers	Polarization	Baseline	Level 1 (4)				Level 2 (7)				Level 3 (11)				Legend (17)			
					F1	sd	OA	sd	F1	sd	OA	sd	F1	sd	OA	sd	F1	sd	OA	sd
A	A ₁	INT	VH		0.66		0.85		0.46		0.74		0.35		0.63		0.30		0.52	
	A ₂	INT	VV		0.65		0.85		0.46		0.74		0.34		0.62		0.27		0.48	
	A ₃	NRPB	VH + VV		0.50		0.73		0.37		0.64		0.45		0.52		0.17		0.37	
	A ₄	MDBI	VH + VV		0.67	0.02	0.86	0.00	0.48	0.01	0.76	0.00	0.38	0.01	0.66	0.01	0.33	0.01	0.55	0.00
	A ₅	A ₅ MDBI + A ₅ NRPB	VH + VV		0.66		0.85		0.47		0.74		0.38		0.66		0.32		0.53	
	A ₆	A ₆ VHAg + A ₆ VHAg + A ₆ NRPB	VH + VV		0.62		0.77		0.45		0.69		0.36		0.59		0.27		0.41	
B	B ₁	A ₄ + MCM ₁₂	VH + VV	12	0.73		0.92		0.53		0.83		0.43		0.75		0.40		0.64	
	B ₂	A ₄ + MCM _{12:24}	VH + VV	12:24	0.73		0.92		0.52		0.83		0.43		0.76		0.41		0.66	
	B ₃	A ₄ + MCM _{12:36}	VH + VV	12:36	0.74	0.02	0.92	0.00	0.53	0.01	0.83	0.00	0.42	0.01	0.76	0.01	0.42	0.01	0.66	0.01
	B ₄	A ₄ + MCM _{12:48}	VH + VV	12:48	0.74		0.92		0.53		0.83		0.41		0.76		0.41		0.66	
	B ₅	A ₄ + MCM _{12:60}	VH + VV	12:60	0.74		0.92		0.52		0.83		0.41		0.76		0.41		0.66	
C	C ₁	A ₄ + Aggr MCM ₁₂	VH + VV	12	0.70		0.90		0.50		0.81		0.42		0.72		0.35		0.59	
	C ₂	A ₄ + Aggr MCM _{12:24}	VH + VV	12:24	0.70		0.91		0.51		0.82		0.42		0.73		0.35		0.61	
	C ₃	A ₄ + Aggr MCM _{12:36}	VH + VV	12:36	0.70		0.91		0.51		0.83		0.42		0.74		0.36		0.61	
	C ₄	A ₄ + Aggr MCM _{12:48}	VH + VV	12:48	0.71	0.01	0.91	0.00	0.51	0.01	0.82	0.01	0.42	0.06	0.74	0.00	0.35	0.00	0.62	0.00
	C ₅	A ₄ + Aggr MCM _{12:60}	VH + VV	12:60	0.70		0.90		0.50		0.82		0.41		0.73		0.34		0.61	

Figure 9 shows the median F1-Score for the 17 target classes after 50 repetitions of the RF classification for the best three sub-models (see Table 2) using only time series of backscattering intensities (Model A_4), combining backscattering intensity and the shortest temporal baselines (Model B_3) and finally integrating aggregates of MCM (Model

C). Increasing the number of decision trees in each sub-model led to the stabilization of the OOB for each prediction selection strategy, so evaluation of all models was conducted using a consistent number of decision trees (500). The number of predictors randomly sampled as candidates at each split was determined by taking the square root of the total number of predictors. The F1-Score increased for all classes when coherence was integrated, except for *pine* where the backscatter approach showed a slightly better performance. While the aggregation of MCM by quarters of the year reduced the feature space of the classification model, the accuracy was compromised, showing a slight decrease in Model C_3 . The largest impact of coherence predictors was for *rocks* and *dense forest* and *grasslands*. In general, the highest accuracies were reached for classes such as *potato*, *clean pastures*, *grassland 1 and 2* and *water* using any kind of SAR data product as predictor.

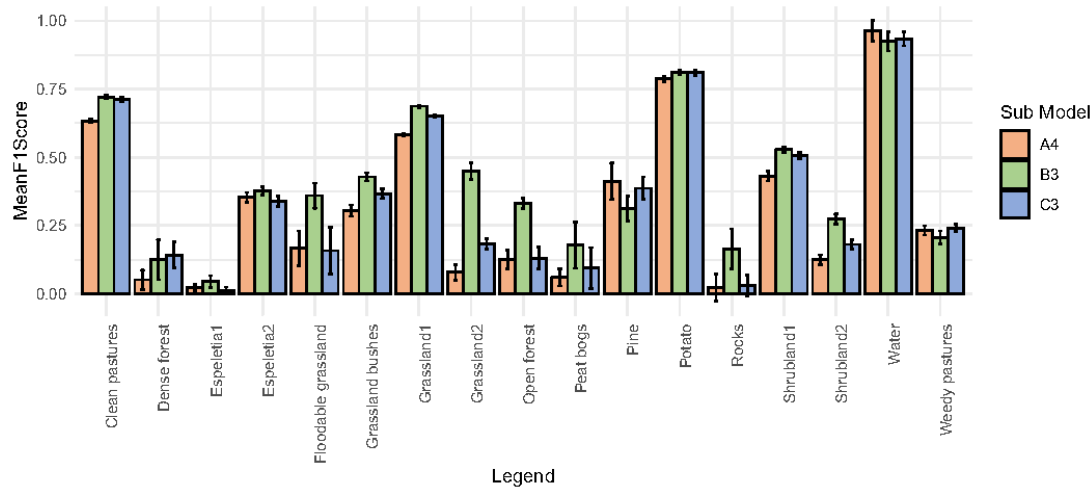


Figure 9: F1-Scores for the 17 target land use/land cover classes for three different sub-models: Model A_4 uses only multitemporal dual-backscatter intensity (orange bars), Model B_3 integrates Model A_4 and the shortest baselines of the MCM (green bar), Model C_3 integrates Model A_4 and the aggregates of MCM (blue bars).

The confusion matrix expressed in terms of the proportion of area in Figure 10 illustrates the classification accuracy and confusion for all land cover classes of the model B_3 which yielded the highest accuracies compared to all other models (Table 2). The diagonal elements indicate correctly classified proportions (multiplied by 1000), such as *Potato* (0.077), *Clean pastures* (0.138), *Weedy pastures* (0.063), and *Grassland1* (0.119), which show relatively high accuracies. However, there is significant confusion among certain similar classes, such as *Clean pastures* misclassified as *Weedy pastures* (0.032), *Grassland1* confused with *Grassland bushes* (0.031), and *Shrubland1* with *Shrubland2* (0.026). Rare classes like *Rocks* and *Peat bogs* have minimal representation, suggesting potential challenges with small sample sizes or indistinct SAR signatures. Classes like

Dense Forest Floodable grassland, and Water are rarely misclassified, indicating good separability for these categories.

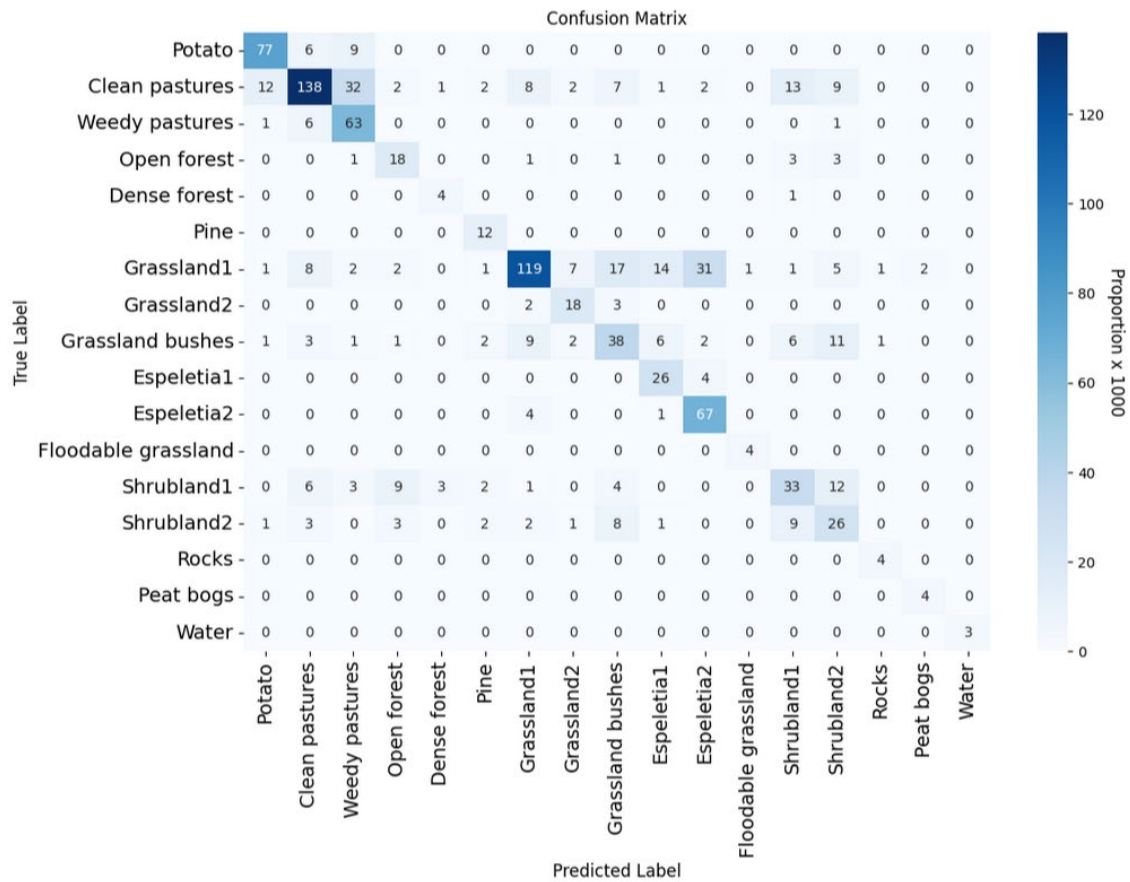


Figure 10: Figure 10 confusion matrix populated by estimated proportions of area in the case of the best Random Forest classification (sub-model B_3). The classes described correspond to the target land use/land cover classes.

Feature importance results

Figure 11 illustrates the relative importance of temporal coherence and backscatter top 25 predictors in the RF sub-model B_3 for the first three levels of the CORINE land cover system and the target classes, certain dates and predictors, are particularly influential.

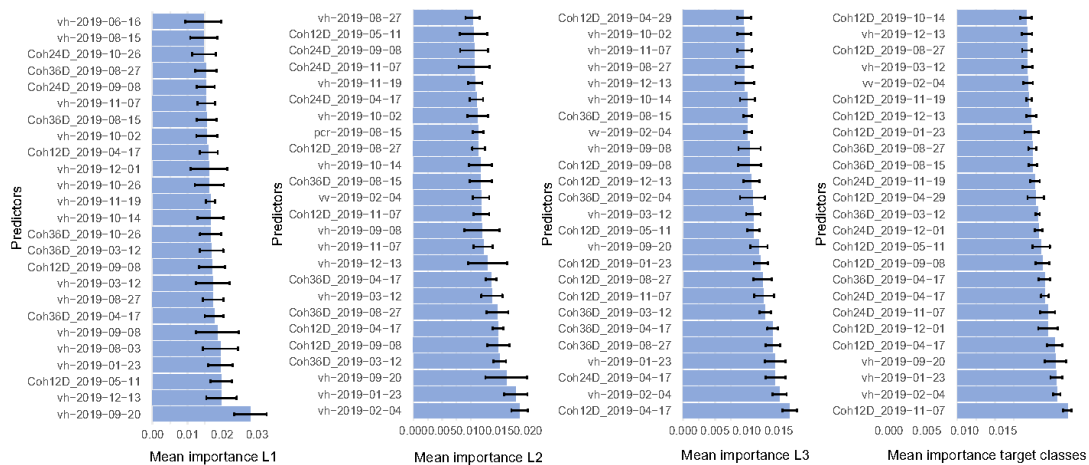


Figure 11: Feature importance of the top 25 best predictors of sub-model B_3 for the first three levels of the CORINE land cover system and the target classes based on Gini impurity.

Visual accuracy assessment

The LULC raster maps produced in this study using RF and integrated backscattering and coherence as predictors were visually not too different from the reference official LULC map in vector format obtained from visual image interpretation (see Figure 12). While the left column expresses the LULC for 2019, the various thematic levels of the CORINE land cover system in vector format, the columns in the center and right show the modeled LULC maps based only on the best model under the approach of using only backscattering (A_5) and the best model complemented with coherence (B_3), respectively. Integrating backscatter with coherence information visually improved the prediction of all classes. However, the higher the LULC thematic detail level, the stronger the salt and pepper effect, and the poorer the definition of the distribution of the classes when only predictors related to backscattering were used instead of a combination of backscatter and coherence-related predictors. The maps also depicted the overprediction of the class grassland 1 or tall *dense grassland* of land not wooded over classes initially interpreted as *espeletias* and *grassland bushes*. The map extracts in Figure 12 predominantly *clean pastures*, although there was some ambiguity with weedy pastures, which could create a salt and pepper effect across all levels of detail. Despite *peat bogs* being prominent in the vector map, they were less common. Lastly, applying the RF algorithm resulted in high accuracy for identifying agricultural activities, such as potato farming. The semi-automated mapping of these activities using this machine learning algorithm produced plausible maps comparable to manually produced reference data. This was particularly evident when both backscattering and

coherence information were used as predictors, which reduced the salt and pepper effect in this pixel-based approach.

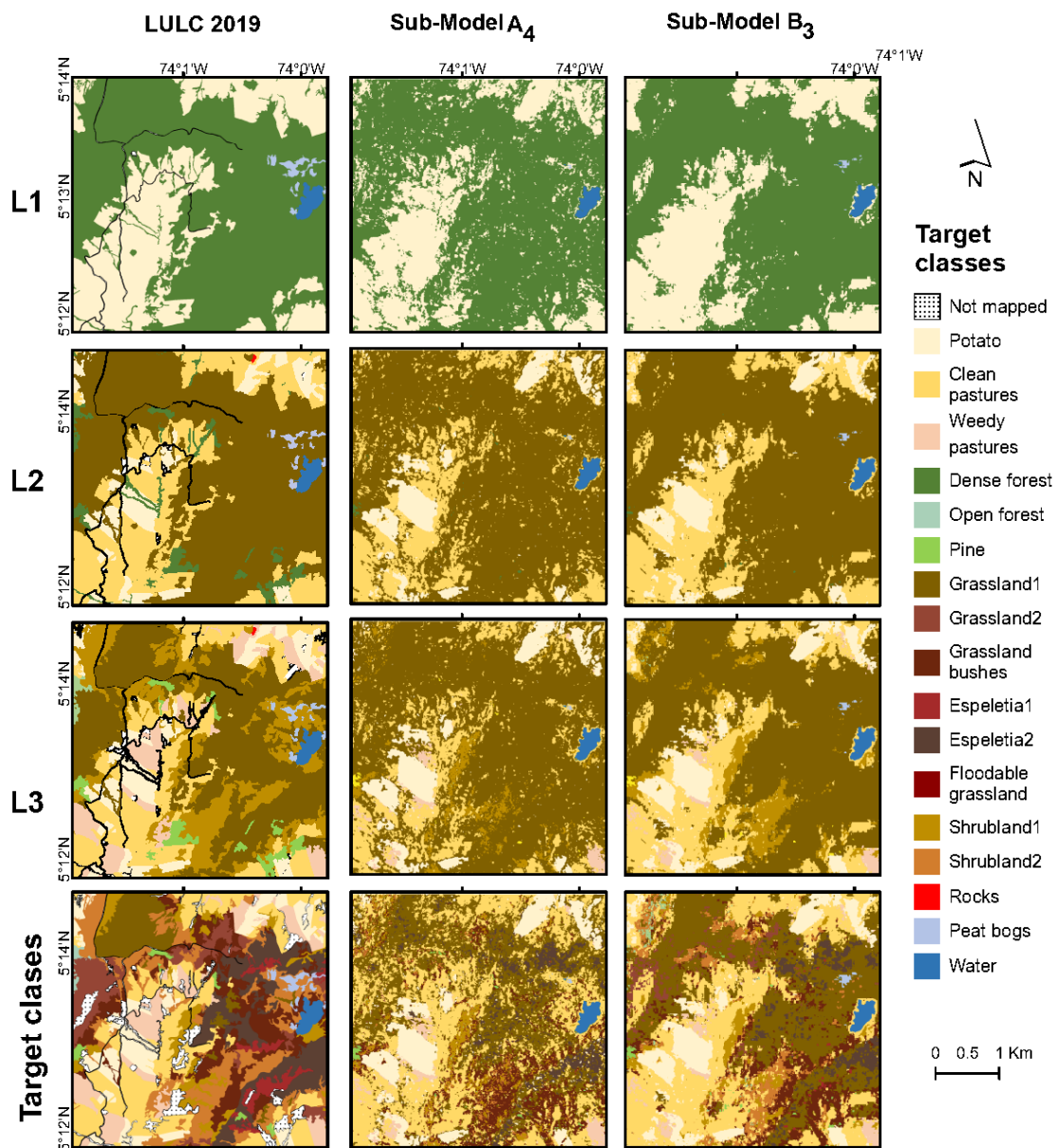


Figure 12: Reference and modeled land use/land cover maps for the first three levels of CORINE land cover system and the target classes Model A₄ is based on multitemporal dual-polarimetric backscatter intensity. Model B₃ uses the predictors from the Model A₄ and further integrates the shortest baselines of the multitemporal coherence matrix (MCM).

Discussion (Section 4)

Reliability and timeliness of LULC maps within high-mountain tropical ecosystems can be enhanced and achieved if (i) SAR data is considered a primary source for LULC mapping, specifically by integrating traditional SAR dual-polarization backscatter

intensity data with multitemporal InSAR coherence. This integration was hypothesized to improve mapping accuracy by revealing distinct temporal patterns among different land covers. Additionally, (ii) assessing the utility of readily available SAR data and preprocessing, polarimetric and interferometric workflows from Earth Observation cloud platforms can further contribute to this improvement.

The integration of InSAR coherence as an additional predictor in the classification process to generate LULC maps in *páramos* significantly improved accuracy metrics, including the F1-Score and OA across various levels of the CORINE land cover system. These findings align with previous studies integrating multitemporal coherence and backscattering intensity (Jacob et al. 2020; Pandit et al. 2022). For example, Jacob et al. (2020) report an approximate 10% increase in OA at CLC level 3, which corresponds to the increase observed after integrating backscattering and coherence in the same CLC level. The classifier effectively utilized fluctuations in coherence across various baselines to enhance accuracy across all classes. This effect became particularly pronounced as the complexity of the target classes increased, outperforming the use of backscatter alone. For instance, it successfully differentiated between human-managed *clean pastures* and natural *grasslands* reaffirming the suitability of multitemporal coherence for monitoring grasslands, as was suggested by Tamm et al. (2016), Zalite et al. (2016) and De Vroey et al. (2021).

Additionally, the method proved effective in identifying crop patterns driven by substantial changes in surface structure caused by agricultural management activities such as seed-bed preparation. In this study, potatoes served as the primary example, while Shang et al. (2020) highlighted similar applications for other land crops. Peaks of coherence, prevalent between the first and third temporal baselines (36 days), typically indicate early stages of preparation of the soil for potato plant. These stages are characterized by minimal vegetation, resulting in high coherence among observations. Conversely, decreases in coherence occur during periods of vegetation growth. While similar temporal behavior of *potato* may be observed in time series of backscattering intensity, our analysis showed that most vegetation classes exhibit temporal variations that can overlap and blur the spectral signature of this class. In contrast, the unique patterns observed in the MCM demonstrate its superior capacity to capture human-induced changes in natural ecosystems. . However, while the MCM has shown strong results for potato detection, its applicability to other crops with different phenological behaviors or farming practices may require further validation. Furthermore, although the spatial resolution of InSAR cloud data is sufficient for larger croplands in the

páramos, it may be less effective in regions with fragmented or small-scale agricultural practices, where variability in environmental conditions and farming methods could influence coherence patterns, emphasizing the need for localized calibration. The varying levels of detail in the nomenclature have allowed us to grasp the diverse ways in which coherence acts as additional input in the classification process across thematic detail. The target classes may offer an excessively detailed LULC legend, particularly when attempting to distinguish between different *herbaceous types*. So, even though we increased thematic accuracy for comprehensive target classes, opting for a less intricate legend or simpler level can even yield better results (Mancera-Flórez and Lizarazo 2020).

Integrating MDBI and MCM data presented a significant challenge due to dimensionality. In response, we explored the aggregation of time series to reduce the number of predictors. Whether through the aggregation of backscattering or coherence approaches, this method did not yield improved results in contrast to the findings of Jacob et al. (2020). This outcome could be attributed to the efficacy of the RF classifier, as noted by Fernández-Delgado et al. (2014), which is particularly adept at handling high dimensionality, a point also emphasized by Jacob et al. (2020). Further, while in our study, aggregation was solely based on one metric, precipitation, alternative methods of data grouping could be explored to determine the efficacy of aggregation. In any case, we show that while SAR data availability is increasing, enabling time series analysis, a higher amount and/or variety of predictor variables does not necessarily yield higher accuracy, and the choice of predictor variables is still specific to the case study. At the same time, we have demonstrated the overall importance of coherence predictors across different levels compared to backscatter information. While SAR backscatter predictors have been relevant in all models, the importance of coherence increased as the legend's complexity grew.

Finally, acknowledging concerns regarding the computational cost associated with both the production of SAR products and the LULC classification process to obtain thematic maps (e.g. Jacob et al. (2020)), we have developed a workflow that primarily leverages cloud-based SAR data and processing capabilities. This approach has the potential to significantly reduce the preprocessing and analysis workload on local computing systems. Earth observation cloud computing provides ample space for cost-intensive preprocessing (Amani et al. 2020; Melo et al. 2022), a characteristic well-suited for SAR data. This allows the experimental and modeling stages to be conducted with ease from low-cost computers, reducing the implementation effort (Yang et al. 2017). From an

operational perspective, this is highly beneficial, especially if the purpose is to timely produce LULC maps in high-mountain tropical ecosystems affected by cloudy conditions to identify anthropogenic activities and potential ecosystem degradation.

Conclusions (Section 5)

This study explored the potential of a novel approach for accurate and timely LULC mapping in cloud-affected, high-mountain tropical ecosystems, explicitly focusing on *páramo* landscapes. We addressed critical challenges in environmental remote sensing by integrating multitemporal dual-polarization backscatter intensity with multitemporal coherence SAR features and leveraging cloud computing platforms for Earth Observation. Our research contributes to the field in two significant ways. First, it underscores the critical importance of multitemporal SAR as a primary data source for LULC mapping in *páramos*, particularly where persistent cloud cover limits the use of optical imagery. We demonstrated that combining SAR backscatter with InSAR coherence significantly enhances classification accuracy, offering a robust solution for these challenging landscapes. Second, the study highlights the transformative role of cloud-based platforms in mitigating computational barriers, enabling efficient SAR time-series analysis that was previously resource-intensive. This work opens pathways for further exploration of SAR time-series data in LULC classification. Beyond introducing new predictors, future research could develop machine-learning and artificial intelligence workflows that incorporate temporal baselines and aggregate data, accounting for local environmental conditions and the seasonal dynamics of natural vegetation and agricultural practices. Such advancements would enable identifying distinct patterns to improve mapping accuracy in complex and cloud-affected ecosystems for mapping LULC changes.

Acknowledgement

This project is conducted as part of a Ph.D. program in geography at Universidad Nacional de Colombia. W.M was supported by the German Academic Exchange Service (DAAD) from funds of the Federal Ministry for Economic Cooperation (BMZ), SDGnexus Network (grant no. 57526248), programme ‘exceed-Hochschulexzellenz in der Entwicklungszusammenarbeit’. We also would like to thank the two anonymous reviewers for their valuable feedback and insightful comments, which greatly contributed to improving the quality of this manuscript.

Declaration of competing interest

The corresponding author considers it important to disclose that he have received financial support, in the form of scholarships, from both the German Academic Exchange Service (DAAD) and the National University of Colombia.

Data availability statement

The data supporting this study's findings are available upon request by contacting the corresponding author.

Ethical Statement

The authors declare that all ethical practices have been followed in relation to the development, writing, and publication of the article.

Declaration of generative A.I. And AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly to improve the manuscript readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Appendices

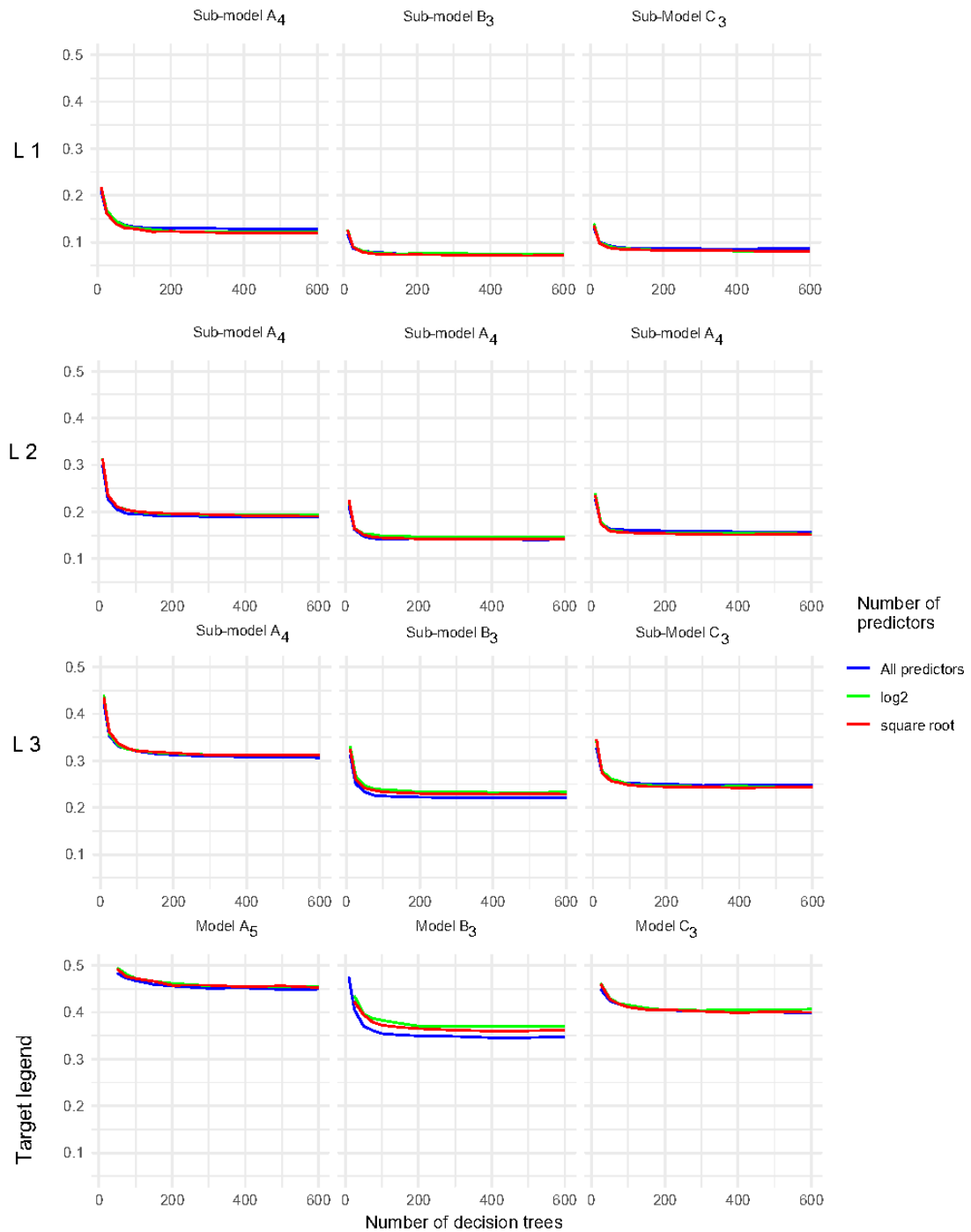


Figure 13: Out-of-bag error as a function of the number of decision trees and the number of predictors for each level of CORINE land cover system. The number of features is considered according to three strategies: All predictors, $\log_2$ of the number of all predictors

Table 3: The number of samples per target class is based on Cochran's formula. The proportion of the 40-meter resolution pixels available for each land cover type initially defines samples. This proportion is then multiplied by ten to consider a larger dataset.

Legend (L4-L7)	Area (Ha)	Number of pixels (40m)	P (%)	n	nx10	Total samples
1. <i>Potato</i>	702.5	4445	8.6	120	1200	1200
2. <i>Clean Pastures</i>	2191.2	13686	26.3	298	2980	2980
3. <i>Weedy pastures</i>	537.7	3371	6.5	93	930	930
4. <i>Dense forest</i>	39.3	250	0.5	7	70	70
5. <i>Open forest</i>	185.5	1166	2.2	34	330	330
6. <i>Pine</i>	56.6	526	1.0	15	150	150
7. <i>Grassland1</i>	1951.4	12163	23.4	276	2750	2750
8. <i>Grassland2</i>	176.0	1088	2.1	32	310	310
9. <i>Grassland bushes</i>	623.0	3897	7.5	107	1060	1060
10. <i>Espeletia1</i>	228.1	1421	2.7	41	400	400
11. <i>Espeletia2</i>	543.8	3345	6.4	93	920	920
12. <i>Floodable grassland</i>	18.5	112	0.2	3	30	30+20
13. <i>Shrubland1</i>	565.6	3532	6.8	97	970	970
14. <i>Shrubland2</i>	423.2	2653	5.1	74	740	740
15. <i>Rocks</i>	8.2	54	0.1	2	10	10+40
16. <i>Peat bogs</i>	27.8	170	0.3	5	50	50
17. <i>Water</i>	11.2	69	0.1	2	20	20+30
Total	8289.4	51948	100%			13010

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Chapter 15

Mapping terrestrial ecosystem health in drylands: comparison of field-based information with remotely sensed data at watershed level

Mojdeh Safaei^{1,}, Hossein Bashari², Till Kleinebecker,^{1,3} Sima Fakheran², Reza Jafari², André Große-Stoltenberg^{1,3}*

¹Division of Landscape Ecology and Landscape Planning, Institute of Landscape Ecology and Resource Management, IFZ Research Centre for Biosystems, Land Use and Nutrition, Justus Liebig University Giessen, Heinrich-Buff Ring 26-32, 35392 Giessen, Germany

² Department of Natural Resources, Isfahan University of Technology, Isfahan 84156-83111, Iran

³Center for International Development and Environmental Research (ZEU), 35390 Giessen, Germany

* Corresponding author

Landscape Ecology 38: 705-724 (2023), doi: 10.1007/s10980-022-01454-4

Supplementary Information: The online version contains supplementary material available at <https://doi.org/10.1007/s10980-022-01454-4>

Abstract

Context: Combining field-based assessments with remote-sensing proxies of landscape patterns provides the opportunity to monitor terrestrial ecosystem health status in support of sustainable development goals (SDG).

Objectives: Linking qualitative field data with quantitative remote-sensing imagery to map terrestrial ecosystem health (SDG15.3.1 “land degradation neutrality”).

Methods: A field-based approach using the Interpreting Indicators of Rangeland-Health (IIRH) protocol was applied to classify terrestrial ecosystem health status at the watershed level as “healthy”, “at-risk”, and “unhealthy”. Quantitative complex landscape metrics derived from Landsat spaceborne data were used to explore whether similar health statuses can be retrieved on a broader scale. The assignment of terrestrial ecosystem health classes based on field and the remotely sensed metrics were tested using multivariate and cluster analysis methods.

Results: According to the IIRH assessments, soil surface loss, plant mortality, and invasive species were identified as important indicators of health. According to the quantitative landscape metrics, “healthy” sites had lower amounts of spectral heterogeneity, edge density, and resource leakage. We found a high agreement between health clusters based on field and remote-sensing data (NMI = 0.91) when using a combined approach of DBSCAN and k-means clustering together with non-metric multi-dimensional scaling (NMDS).

Conclusions: We provide an exemplary workflow on how to combine qualitative field data and quantitative remote-sensing data to assess SDGs indicators related to terrestrial ecosystem health. As we used a standardized method for field assessments together with publicly available satellite data, there is potential to test the generalizability and context-dependency of our approach in other arid and semi-arid rangelands.

Keywords

Sustainable development goals (SDGs), Land degradation neutrality (LDN), Semi-arid ecosystems, Central Zagros Mountains Iran, Self-Organizing Map (SOM), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Procrustes analysis (PA), Moving Standard Deviation Index (MSDI), Landscape ecology and planning, Normalized mutual information (NMI)

Introduction

Arid and semi-arid ecosystems cover ~45% of the globe and provide important ecosystem services related to water supply, preserving biodiversity, flood protection, food security, and the storage and capture of carbon (UN 2019; Berdugo et al. 2020). However, the ecological functioning of these drylands is currently threatened by ecosystem degradation, unsustainable land management practices, accelerated urbanization rates, and changing demographics (IPBES 2018, 2019; Berdugo et al. 2020). These factors are recognized as the most critical drivers of the depletion of natural resources (van der Zanden et al. 2016) and terrestrial ecosystem health (Lausch et al. 2016). The ecosystem degradation in drylands is negatively affecting ecosystem functions and services and indirectly threatening the well-being of at least 3.2 billion people worldwide with costs of more than 10% of the global gross product per year (IPBES 2018; UN 2019).

Thus, understanding how arid and semi-arid ecosystems respond to ongoing environmental change is crucial in achieving sustainable development goals (SDGs) (<https://sdgs.un.org/goals>). Each SDG is assigned certain indicators that are ideally sensitive, unambiguous, quick and easy to sample, temporally consistent, and applicable to a wide range of ecosystems (Prince 2019). More specifically, fulfilling SDGs should be measurable by employing both qualitative and quantitative indicators (Hák et al. 2016). For example, SDG15 “Life on Land” addresses the urgency of stopping the degradation of natural habitats along with the integration of biodiversity and ecosystem values into development processes and local planning (UN 2019). SDG 15.3.1, in particular, addresses the need to accomplish land degradation neutrality (LDN) (Sims et al. 2021). The degree of land degradation can be quantified by sub-indicators such as (i) land cover and land cover change, (ii) land productivity, and (iii) carbon stocks above and below ground (Prince 2019; UN 2019). Therefore, spatial indicators of terrestrial ecosystem health as monitoring and decision-making tools are important for land managers to combat land degradation.

However, scaling issues can apply when translating terrestrial ecosystem information from the field level to broader levels in space and time (Wu and Hoobs 2002). Linking ecological information between finer and larger scales constitutes a fundamental challenge in landscape ecological research as well as a practical land management challenge because some ecological processes might only be noticeable at a certain level, and interactions might occur between levels. Additionally, to assess the effects of land

management, it is important to select appropriate spatial units for the studied ecological processes considering the fact that there is a spatial hierarchy of ecosystems and that there are linkages between systems, for example via sediment transport, groundwater movement, runoff, and microclimate (Bailey 1985). In a broader sense, spatially-explicit knowledge of scaling is an essential requirement to understand patterns and processes of ecosystem health status.

Terrestrial ecosystem health can be understood as the degree to which vegetation, climate, and soil integrity are capable of sustaining self-organized structures and processes (NRSC 1994). Thus, a healthy ecosystem can be regarded as resilient against disturbance (Gunderson 2000). In contrast, degradation occurs when different ecosystem states related to energy flow, nutrient cycling, and hydrological regimes are negatively affected. Particularly for semiarid lands, protecting the structure and functionality of the ecosystems and actively restoring degraded drylands are essential to ensure soil integrity, nutrient cycling, and water retention (Pyke et al. 2002; Briske et al. 2005). As a result, a wide range of terrestrial ecosystem health indicators has been developed (van der Zanden et al. 2016; Estevez et al. 2017) with the emphasis on utilizing both qualitative and quantitative indicators (Duniway et al. 2010). The Interpreting Indicators of Rangeland Health (IIRH) protocol (see Pyke et al. 2002) is regarded as an international standard to assess land health and degradation in drylands (Duniway et al. 2010; Herrick et al. 2019). IIRH is a qualitative assessment of ecological processes using 17 observable indicators and it is designed for assessing ecosystem health and functions in rangelands. However, assessing ecosystem functioning based on qualitative field data has distinct spatio-temporal limitations. These drawbacks can be investigated by properly integrating quantitative metrics from remotely sensed data (Toevs et al. 2011). A variety of remote sensing data has been used to assess and monitor ecosystem health across a range of scales (Li et al. 2014). However, remote sensing data has certain limitations in accurately assessing the state of ecosystem health (Li et al. 2014). Thus, methodological approaches combining and verifying remote sensing data with ground-based field sampling information on ecosystem health require further investigation. The question is, however, how to scale up from the qualitative field-based measures to a broader scale using quantitative remote sensing data without losing crucial functional information. An integrated approach that combines field data, experimental manipulations, GIS, remote sensing, and modeling is essential for advancing science of scale (Wu and Hobbs 2002). Integrating remote sensing with in situ data is challenging, but it has a large potential to deepen our understanding of

sustainable use of ecosystems and ecosystem resilience (Cavender-Bares et al. 2022). Common remote sensing products are land-use land cover (LULC) maps. LULC change analysis allows for mapping changes of landscape structural and functional characteristics (Matsushita et al. 2006) and supports monitoring SDG 15.3.1 (Prince 2019). LULC changes are among the main anthropogenic factors needed for health assessment in semi-arid land ecosystems (Soffianian and Madanian 2015; Baranian et al. 2017; Molaeinasab et al. 2018; Safaei et al. 2021). Beyond the commonly used Normalised Difference Vegetation Index (NDVI) (Tucker 1979), complex remote sensing-based indices that are linked to landscape functionality and degradation (Tanser and Palmer 1999; Bastin et al. 2002) as well as landscape metrics (Frank et al. 2012; Inkoom et al. 2018) have been applied to map ecosystem functioning. An example of a complex remote-sensing index is the Moving Standard Deviation Index (MSDI). It can capture the spectral diversity across images and has been applied in rangelands to map ecosystem degradation caused by overgrazing and improper management (Tanser and Palmer 1999; Jafari et al. 2008). Another example is the Leakiness Index (LI) (Bastin et al. 2002; Ludwig et al. 2007). The LI can be applied to assess sub-catchment-level resource leakage based on the hydrological regime, digital elevation models (DEM), and vegetation cover. As a result, the LI has emerged as a promising ecological index with a high potential to monitor terrestrial ecosystem health status across arid and semi-arid landscapes (Ludwig et al. 2007). To our knowledge, the LI has been underutilized in terrestrial ecosystem health assessments.

Because all remote sensing approaches present scaling issues at least to some extent (Torgerson 1958), and as data availability, transferability, and uncertainty in estimating valid health indicators remains challenging (Li et al. 2014), more research is required on using landscape metrics or complex indices for valid upscaling of field assessments based on remote sensing data to aid mapping terrestrial ecosystem health. In this study, we used multivariate methods to compare field-based, terrestrial ecosystem health indicators from the watershed scale with the landscape level by means of remote sensing. Based on a case study for central Iran, the main aim of our study is to link qualitative field data with quantitative remote sensing data to identify indicators terrestrial ecosystem health related to SDG 15.3.1 that can be monitored from space. By quantifying LULC changes over 28 years using remote sensing metrics and assigning health classes in each sub-catchment, the proportion of land degradation was estimated. We use a standardized field protocol, publicly available satellite data and mainly free and open-source software so the methodology described here can be tested

and applied in other arid and semi-arid rangelands as a decision support tool to conduct land degradation zoning and to prioritize regions for restoration efforts.

Material and methods

Study area

This study was carried out in central Iran across an area of 2238 square km located between 33°04'18" and 32°36'23" E and 49°38'40" and 50°19'25" N (Fig. 1). The region has a mean annual precipitation and temperature of 538 mm and 10.1 °C, respectively, and the climate is considered to be Mediterranean type (DeMartonne 1962).

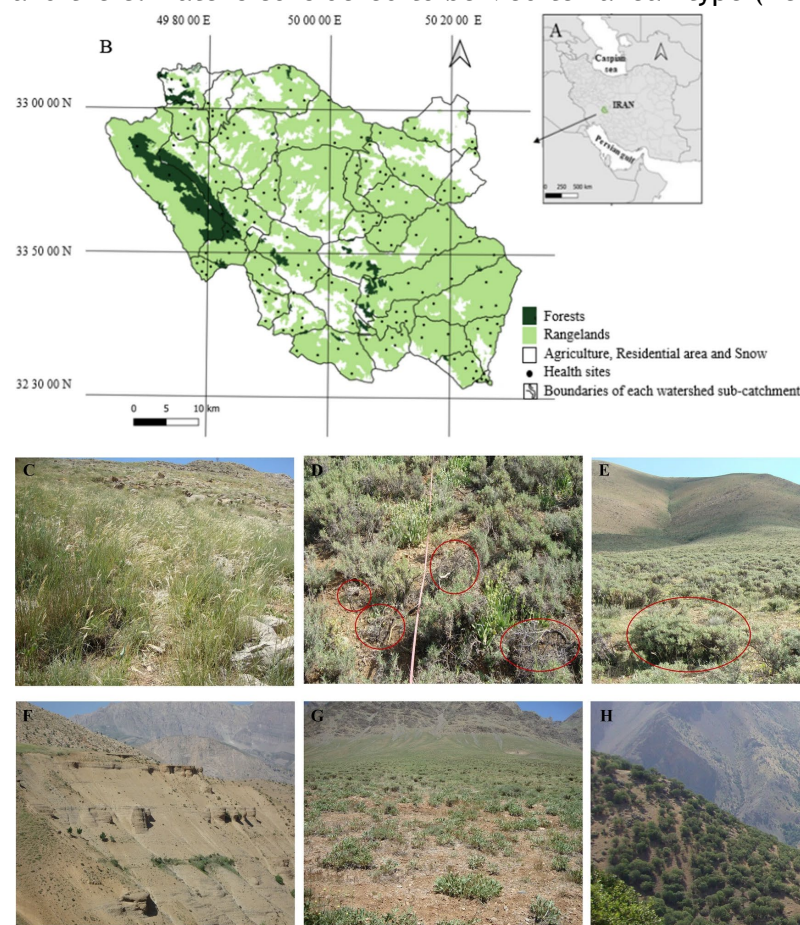


Figure 1: A Study region in western Isfahan Province, Iran. The region was divided into 40 sub-catchments. Each sub-catchment has been assigned a health class that is derived from five replications of IIRH (Interpreting Indicators of Rangeland Health) protocol assessments. B Sites of health assessment in the forest and rangelands were distributed using stratified random sampling. Photos show examples of landscape views with the recording of a few health indicators at some evaluation sites. C Rangeland in near reference state condition dominated by tall grass with shrubs, subdominant annual grasses, and rarely connected patches of bare ground. D Shrub community (*Astragalus* versus) with dead and dying branches and leaves (shown in red circles). E Native shrub with good vigor and reproductive capability (red circle). F Rills in a steep slope are the result of geologically sensitive formation. G Degraded rangeland site with large patches of bare ground. H Open forest dominated by oak trees

The natural landscape of this region, which is part of the vast central Zagros Mountains, traditionally provides forage for livestock, water, and other ecosystem services to the local people. Overgrazing and droughts with varying severities and magnitudes along with the dieback of oak tree forests (*Quercus persica* Jaub. & Spach), and other valuable rangeland species such as *Astragalus verus* (Olivier) and *Astragalus adscendens* (Boiss. & Hausskn. ex Boiss) have resulted in substantial changes in LULC (Safaei et al. 2021). Although many oak forests in Iran suffer from oak charcoal rot, which is caused by two opportunistic fungi, *Biscogniauxia mediterranea* and *Obolarina persica*, the incidence of this disease has not been reported in the study area so far (Ahmadi et al. 2020). We developed an exemplary workflow that links qualitative field data (Fig. 2, Step 1) with quantitative remote sensing data (Fig. 2, Step 2) for identifying and assessing SDG indicators related to terrestrial ecosystem health in semi-arid lands using different multivariate analyses (Fig. 2, Step 3). Finally, we tested whether this combination of analyses can be used to assess the state of terrestrial ecosystem health in the past (Fig. 2, Step 4). All steps of our workflow are illustrated in Fig. 2.

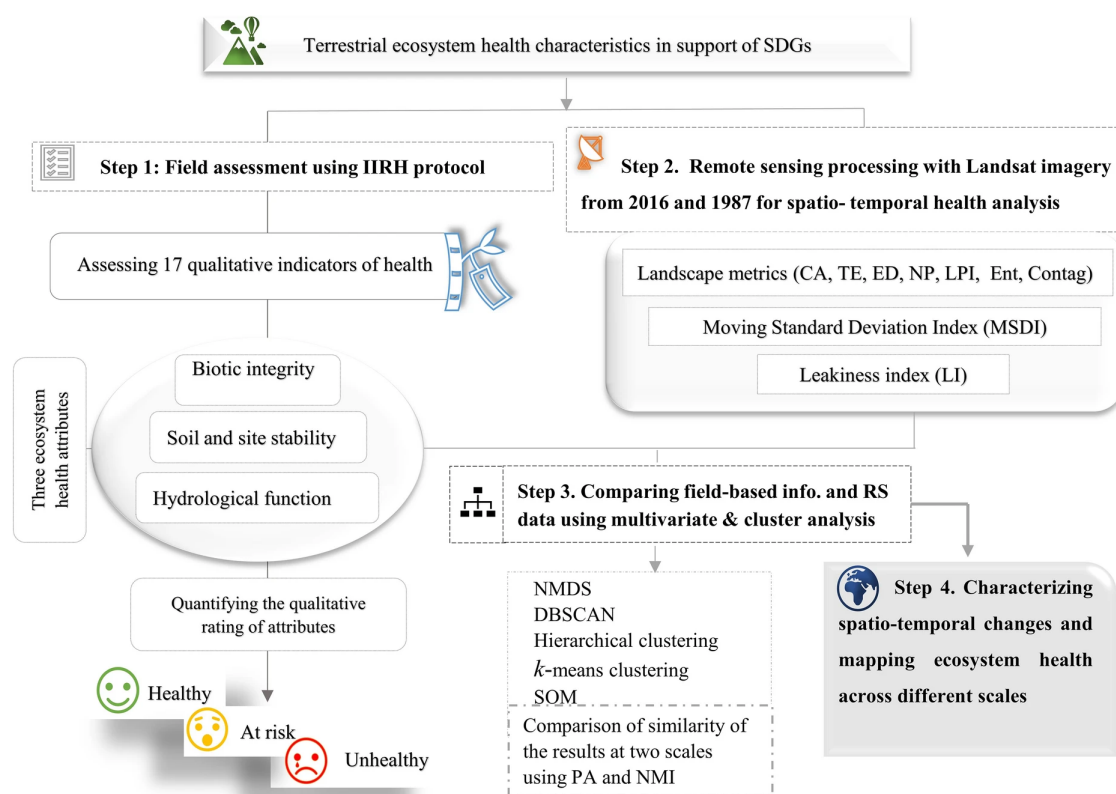


Figure 2: Graphical illustration of the workflow linking field and remote sensing data to aid our understanding of the health status of arid and semi-arid ecosystems. CA: Total (Class) Area, TE: Total Edge, ED: Edge Density, NP: Number of Patches, LPI: Largest Patch Index, Ent: Entropy, Cont: Contagion, LI: Leakiness index, MSDI: moving standard deviation index, NMDS: Non-Metric Multi-Dimensional Scaling, DBSCAN: Density-Based Spatial Clustering of Applications with Noise, SOM: Self Organizing Map, PA: Procrustes analysis, NMI: Normalized Mutual Information

Field data collection through IIRH protocol and analysis of terrestrial ecosystem health

A field survey was conducted at the sub-catchment scale to determine the most important indicators of health status according to the IIRH assessment given by Pyke et al. (2002). We considered sub-catchments as our sampling unit because their hydraulic gradient is crucial for the calculation of functionality (Ludwig et al. 2007). Of the 40 sub-catchments, rangelands were dominating in 35, and forests were dominating in 5 sub-catchments. Since the study area was large (2238 km²), careful selection of health sites at the sub-catchment scale that reflected the overall condition of each sub-catchment was important. To avoid misevaluations, the scaling of health data from sampling point to sub-catchment was done using stratified random strategy to cover the representative site conditions in each sub-catchment and the 17 Interpreting Indicators of Rangeland Health (IIRH) were assessed (Table 1). Based on the IIRH protocol (Pyke et al. 2002; Pellant et al. 2020), two sites, one rangeland, and one forest, were selected as ecological reference sites. An ecological reference site is a well-managed landscape unit in which ecological processes (i.e., energy flow, nutrient cycling, and hydrological condition) are working within the natural range of variability, and the vegetation has adequate resilience and/or resistance to typical disturbances (Pyke et al. 2002). The 17 ecological indicators were utilized to identify three ecosystem attributes that reflect ecosystem functionality including (i) soil and site stability, (ii) hydrological function, and (iii) biotic integrity (Table 1) (Pyke et al. 2002; Pellant et al. 2020). They were manually recorded on evaluation sheets in five replicates at different locations in each sub-catchment. The five replicates were representative for the degree of health in each sub-catchment. The deviation of the 17 measured indicators in each sub-catchment from the reference area conditions was rated in five quality categories (extreme to total, moderate to extreme, moderate, slight to moderate, and none to slight) (see Pellant et al. (2020) for a detailed IIRH description). As it is shown in Table 1, the deviation of nine indicators were used to rate soil and site stability, 10 indicators to rate hydrological function, and nine indicator to rate biotic integrity based on a preponderance of evidence approach using a two way table in the R package “base” (R Core Team 2021). Finally a health class including “healthy”, “at-risk” and “unhealthy” status was assigned to sub-catchment using the preponderance of evidence of three health attributes ((i) soil and site stability, (ii) hydrological function, and (iii) biotic integrity). To prevent or reduce observer bias, fieldwork was performed by two fixed observers who worked together on the same site with a sound ecological knowledge of

the study area in two months during June and July 2016. Information related to the 40 sub-catchments, as well as the assigned health status for the three ecosystem attributes, are given in the Supplementary file 1 (Table S.1).

Table 1: A brief description of the 17 Interpreting Indicators of Rangeland Health (IIRH) indicators and their relation to the three attributes of terrestrial ecosystem health. The indicators are sorted under the attributes to which they relate. Boxes that traverse multiple attributes contain indicators that relate to more than one attribute (descriptions and structure of the table were adopted from Pyke et al. 2002 and Pellant et al. 2020)

Soil and site stability	Hydrological function	Biotic integrity
1. Rills: small erosional rivulets that are generally linear		12. Functional/structural groups: a suite of species that are grouped together because of similar morphology, photosynthesis pathways, nitrogen-fixing ability, life cycle, etc
2. Water flow patterns: path that water takes as it moves across the soil surface		13. Plant mortality/decadence: the proportion of dead/decadent plants
3. Pedestals/Terrecettes: the movement of soil by wind/water		15. Annual production: total above-ground biomass as a measure of the vegetation available to harvest the sun's energy
4. Bare ground: exposed mineral or organic soil not covered by vegetation, gravel /rock, litter or biological crust		16. Invasive plants: invasive exotic and noxious weed
5. Gullies: channel that has been cut into the soil by moving water		
6. Wind-scoured, blowout, and/or depositional areas: finer soil particles have been redistributed from depositional surface that influences several ecological processes areas interspaces and deposited near an obstruction	10. Plant community composition & distribution	17. The reproductive capability of perennial plants: measure of potential of for seed or tiller production, not
7. Litter movement: relative to infiltration reflects the redistribution of litter by water contributions or wind	functional/structural groups and presence of seedlings/new clonal their associated species in plants modifying infiltration	
8. Soil surface resistance to erosion: reduced soil surface stability usually reflects lower soil biotic integrity because of organic matter and biological decomposition processes		
9. Soil surface loss or degradation: loss or degradation of soil surface (organic matter) affects site potential		
11. Compaction layer: near-surface layer of dense soil caused by repeated impact or disturbance of the soil surface		

Remotely sensed landscape metrics across terrestrial ecosystem health classes

Two LULC maps with a pixel size of 30 m including forest, rangelands in good, moderate and poor conditions, agriculture, residential area, snow and rock classes were produced based on 2016 Landsat OLI imagery with 6 bands (bands 2 to 7) with an overall accuracy of 94% (see Safaei et al. 2021) and 1987 Landsat TM imagery with 4 bands (bands 1 to 4) (Soffianian and Madanian 2015) with an overall accuracy of 84%, respectively, applying the supervised Maximum Likelihood Classification (MLC) algorithm. Both images were downloaded from the United States Geological Society (USGS) Earth Resources Observation and Science (EROS) Center ([https:// earthexplorer.usgs.gov/](https://earthexplorer.usgs.gov/)). We consider two-time steps to see whether the estimation of terrestrial ecosystem health in the past is possible. The validity of the 2016 LULC map was assessed using 401 field points assessed in 2016 (Safaei et al. 2021). The validity of the 1987 LULC map was tested using 86 reference points from aerial photographs of 1985 (National Cartographic Center; ncc.gov.ir).

Five landscape metrics including the (i) number of patches, (ii) total edge, (iii) edge density, (iv) largest patch area, and (v) total class area (see Table 2) were quantified at landscape level in each sub-catchment using Fragstats 4.2 (McGarigal et al. 2012). (vi) Entropy and (vii) contagion metrics, two indicators of fragmentation, were measured using the Guidos Toolbox 3 (Vogt and Riitters 2017). The (viii) MSDI, a proxy for landscape degradation patterns (Tanser and Palmer 1999), was computed using a 3×3 window filter moving across the Landsat OLI 2016 red band. The (ix) LI, a functionality indicator, was calculated based on a DEM with a spatial resolution of 30 m using 1:25,000 topographic maps (National Cartographic Center; ncc.gov.ir) (Safaei et al. 2021) (Table 2), and the NDVI (Tucker 1979) from Landsat OLI imagery for 2016. See Ludwig et al. (2007) for details about the LI. The reasons for choosing metrics are explained in Table 2. All metrics were calculated at landscape level in each sub-catchment.

Analysis of variance (ANOVA) followed by a post-hoc Tukey test for unequal sample sizes ($\alpha = 0.05$) was performed to assess whether landscape metrics showed significant differences among health classes. Only the landscape metric ED met the assumptions for ANOVA. For all other remotely sensed indices, a Kruskal-Wallis test followed by a Dunn's test with a bh p-value adjustment ($\alpha = 0.05$) for the multiple comparisons was applied. Autocorrelations among the remotely sensed data were checked using the R packages "tseries" (R Core Team 2021; Trapletti and Hornik 2020).

Table 2: Landscape metrics and indices used in this research (descriptions for landscape metrics)

Metrics	Equation	Description	Reason and relevance
(ED) Edge Density (Meters per Hectare)	$ED = \frac{\sum_{k=1}^m e_{ik}}{A} \times 10000$	e_{ik} = total length (m) of an edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i. A = total landscape area (m ²).	all edges in the landscape in relation to the landscape area.
(LPI) Largest Patch Index (Percent)	$LPI = \frac{\max(a_{ij}) \times 100}{A}$	a_{ij} = area (m ²) of patch ij A = total landscape area (m ²)	the percentage of the landscape covered by the largest patch in the landscape
(TE) Total Edge (Meters)	$TE = \sum_{k=1}^m e_{ik}$	Total length (m) of an edge in landscape	it measures the configuration of the landscape because a highly fragmented landscape will have many edges.
(CA) Total (Class) Area (Hectares)	$CA = \sum_{j=1}^n a_{ij} \left(\frac{1}{10000} \right)$	a_{ij} = Area (m ²) of patch ij.	the core area is the area unaffected by the edges of the patch
(NP) Number of Patches	$NP = n_i$	n_i = Number of patches in the landscape of patch type (class) i.	get the number of patches of the corresponding patch type

Metrics	Equation	Description	Reason and relevance
Contagion (Percent)	$1 + \frac{\sum_{i=1}^m \sum_{k=1}^m \left[(P_i) \left(\frac{g_{ik}}{\sum_{k=1}^m g_{ik}} \right) \times \left[\ln(P_i) \left(\frac{g_{ik}}{\sum_{k=1}^m g_{ik}} \right) \right] \right]}{2 \ln(m)}$	Pi =Proportion of the landscape occupied by patch type (class) i. g_{ik} =Number of adjacencies (joins) between pixels of patch types (classes) i and k based on the double-count method. m =Number of patch types (classes) present in the landscape, including the landscape border if present.	contagion refers to the tendency of patch types to be spatially aggregated; that is, to occur in large, aggregated or “contagious” distributions.
Entropy (Percent)	$S = \sum_i P_i \log P_i$	Pi = Disorder of pixels in a raster map	based on the Shannon’s theory (Shannon 1948) and considers disorder of pixels in a raster map.
(LI) Leakiness index (Ludwig et al., 2007)	$LI = 1 - \left[\frac{L_{max} - L_{calc}}{L_{max} - L_{min}} \right]^k$ $L_{max} = \frac{L_{calc}}{[1 - \sqrt[3]{1 - LI}]}$	Lmax = maximum leakiness, Lmin = minimum leakiness, Lcalc =progressively accumulates resources from pixel to pixel	can assess resource leakage based on the hydrologic regime, Digital Elevation Model (DEM), and vegetation cover
(MSDI) The moving standard deviation index (Tanser and Palmer 1999)			capture the spectral diversity across images and has been applied in rangelands to map ecosystem degradation caused by overgrazing and improper management

Linking field-based indicators with remote sensing metrics

To test if the sites can be grouped into the three health classes “healthy”, “at-risk” and “unhealthy” based on the NMDS, an unsupervised cluster analysis was conducted on the remotely sensed data and a supervised cluster analysis was conducted on the field data. (Tables 1 and 2). Non-Metric Multi-Dimensional Scaling (NMDS) (Kruskal 1964) with different distance measures including Euclidean, Manhattan, Mahalanobis, and Bray-Curtis were employed. The returning stress values for the different dissimilarity indices were used to identify the best dimensional ordination fit of field and remotely sensed data. Minimum stress solution was sought with Procrustean rotation (Gower 1971). The two-dimensional NMDS with 20 runs was performed in the “vegan” R package (Dixon 2003; R Core Team 2021). Terrestrial ecosystem health field indicators and remotely sensed metrics that were significantly correlated with the ordination axes were plotted in the two-dimensional ordination space.

Since it is challenging to identify the best algorithm a priori (e.g. Kozakura et al. 2017), different clustering algorithms were employed. Common types of clustering methods were tested including DBSCAN (Hahsler et al. 2019), k-means clustering (Johnson 1967), hierarchical clustering (Johnson 1967), and Self-Organizing Map (SOM) (Vialaneix et al. 2020). The clustering algorithm DBSCAN can identify clusters of any shape containing outliers and noise in the dataset. The goal of DBSCAN is to measure the number of objects close to a given point and then to identify dense regions (Ester et al. 1996). k-means clustering aims to partition “n” observations into “k” clusters based on the nearest mean (Kriegel et al. 2016), whereas hierarchical clustering is one of the most popular clustering techniques in machine learning. It places similar observations close to each other with no need to pre-specify the number of clusters as in k-means clustering (Johnson 1967). Finally, the Self Organizing Map (SOM) algorithm which is part of Artificial Neural Networks (ANNs) techniques, includes dimensionality reduction and data clustering. The SOM can be used for providing the geographic topology of the input data (Kohonen 2001; van der Zanden et al. 2016). We conducted the DBSCAN, the combination of DBSCAN + k-means clustering, hierarchical clustering, and SOM clustering analysis for both field qualitative indicators and remotely sensed quantitative metrics using the R packages “dbscan”(Hahsler et al. 2019; R Core Team 2021), “factoextra” (Kassambara and Mundt 2020; R Core Team 2021), “SOMbrero”, and “kohonen” (Kohonen 2001; R Core Team 2021; Vialaneix et al. 2020).

We compared the patterns of terrestrial ecosystem health using different multivariate and cluster analyses considering the challenges of monitoring landscapes using remote

sensing data to quantify and identify the spatio-temporal characteristics at watershed scale (Wu and Qi 2000). The combination of DBSCAN + k-means clustering was applied to check if the performance of clustering can be increased when combining methods.

Comparison of qualitative field indicators and quantitative remote sensing indices

The degree to which ecological processes and spatial patterns of both field and remote sensing level are related can be identified by testing if the assignment of terrestrial ecosystem health classes based on field indicators matched the characterization based on remotely sensed indicators. The multivariate spaces of both levels were compared using Procrustes analysis (PA) (Gower 1971). In PA, the ordination solutions are rotated to minimize the sum of squared residuals and maximize similarity (Gower 1971).

Procrustes analysis has been successfully applied to test the relation between multivariate data sets in ecology including both field and remote sensing data (Feilhauer et al. 2010; Magiera et al. 2013; Große-Stoltenberg et al. 2018). The clustering was compared using the Normalized Mutual Information measure (NMI) (Chiquet et al. 2020). The Normalized Mutual Information measure shows the consistency between two clustering results (Formula 1).

$$I(U, V) = \sum_{p=1}^P \sum_{q=1}^Q \frac{|U_p \cap V_q|}{N} \log \frac{N |U_p \cap V_q|}{|U_p| \times |V_q|}$$

where $|U_p|$ and $|V_q|$ represent the cardinality of the p-th and q-th clusters in U and V clusters on a set of data, respectively (Kozakura et al. 2017). A zero NMI value corresponds to no mutual information (e.g. no correlation between the clustering results of the field and remote sensing based NMDS ordinations), while a value of one indicates a perfect correlation.

Thus, both NMI and PA help to evaluate the similarity of datasets generated by multivariate analysis and cluster analysis, respectively (Kozakura et al. 2017). The PA was performed using the function “protest” in the R package “vegan” (Dixon 2003; R Core Team 2021) and NMI was calculated in “NMI” and “aricode” packages of R (Chiquet et al. 2020; R Core Team 2021).

Transferability of quantitative remote sensing indices to the past time

In addition, we tested whether this combination of indicators and clustering methods can be used to assess the state of terrestrial ecosystem health in the past. Therefore, after validating the remotely sensed indicators and clustering methods against field data for 2016 (see previous paragraph), metrics and clusters were computed for satellite imagery in 1987 to investigate health status in the past. The reason for choosing 1987 was because shortly thereafter extensive LULC conversions (e.g. converting rangelands to dry farmlands) caused a sharp decline in the size of rangelands and heavy grazing occurred that considerably affected the rangeland health (Baranian et al. 2017; Safaei et al. 2021), so distinct changes could be expected. While satellite data were available for 1987, there was no IIRH assessment available. Thus, after testing the validity of our approach for 2016, the RS indicators were applied to the 1987 data to derive a health status map. The plausibility of the 1987 map and the change of ecosystem health from 1987 to 2016 was assessed using published literature. Based on the available ecological report and a publication from that time (Bassiri et al. 1989; Bassiri and Iravani 2009) ecological information about the health status of the sub-catchments was obtained. The visual interpretation of the LULC map obtained from Landsat 7 in 1987 (see Supplementary file 3; Fig S.1) and 86 points derived from the aerial photographs in 1981 (National Cartographic Center; ncc.gov.ir) helped to compare good, moderate and poor rangelands as well as dense, semi-sparse and sparse forest (see Safaei et al. 2021) to health classes derived from NMDS. Expert assessments from the combination of these three data sets have been used to validate health classes in the past. Finally, to determine the efficacy of integrating field and remotely sensed data for estimating SDG 15.3.1, we quantified site-based data to assess the three health classes “healthy”, “at-risk” and “unhealthy” derived from geospatial information. The measurement unit for SDG indicator 15.3.1 is the spatial extent (km²) calculated as the proportion of land that is degraded relative to the total land area (percentage) (Table 3) (Prince 2019; UN 2019; Sims et al. 2021).

Table 3: Calculating the SDG15.3.1 by comparing the status of the three health classes "healthy", "at risk", and "unhealthy" in 1987 and 2016.

SDG15.3.1 Equation	Explanation (Sims et al. 2021)
$A \text{ (Degraded)} =$	A (Stable or unchanging): Areas of land that have persisted state since the baseline period
$A \text{ (Stable)} + A \text{ (Negative)} - A \text{ (Positive)}$	A (Negative or declining): Areas that have degraded since the baseline period
	A (Positive or improving): Areas that have improved from a degraded state to a non-degraded state since the baseline period.
$P = \frac{A \text{ (Degraded)}}{A \text{ (Total)}}$	the proportion of land that is degraded (%)

Results

Qualitative field assessment following the IIRH protocol: indicators and health class assignment

According to the IIRH protocol, nine, 11, and 20 sites were classified as “healthy”, “at-risk”, and “unhealthy” at the watershed level, respectively (Fig. 3). Among the 17 indicators, the presence of structural and functional groups, vegetation composition, productivity, and litter volume was capable of discriminating healthy sites from unhealthy ones. The most important indicators in unhealthy sites were compaction layer, plant mortality, rills and water flow pattern, invasive species, and surface soil condition. The region has no gully formation, making this factor ineffective in site discrimination and health evaluation.

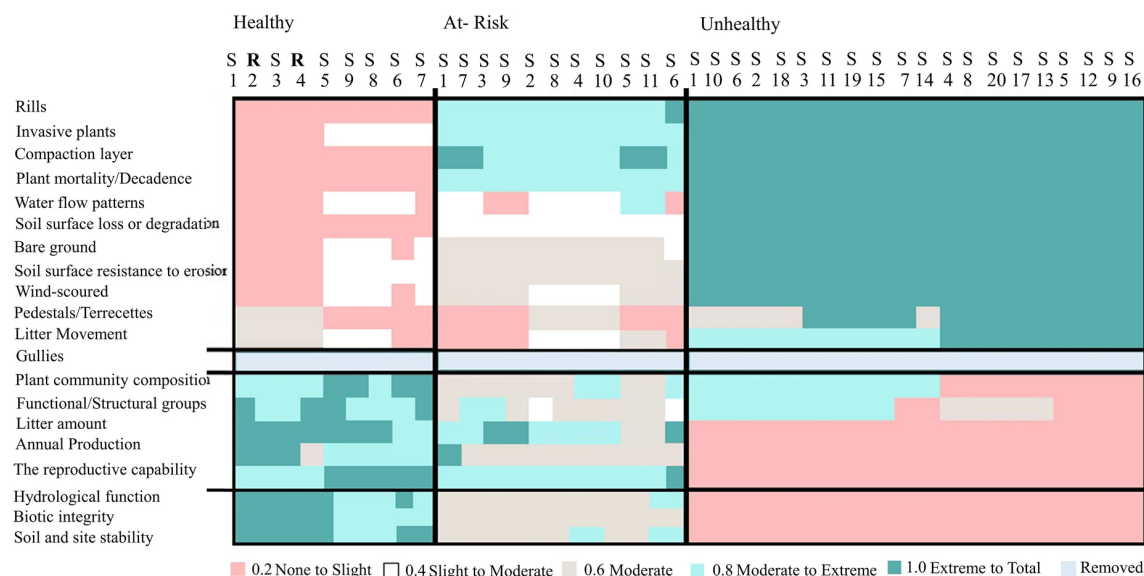


Figure 3: The two-way table provides an overlay of 17 health indicators (rows) in sites with different health status (columns) of evaluation sites (S) and reference sites (R). The color gradient from pink (0) to green (1) indicates the increasing importance of the index in each site. The horizontal black lines differentiate the three functional attributes from the 17 indicators. Due to the lack of gullies in the study area, no scores were included (grey colored line in the middle of the figure). The vertical black lines separate the three health classes.

Remotely sensed landscape metrics across terrestrial ecosystem health classes

Healthy sites had the largest patch sizes (LPI) (Fig. 4A) as well as the lowest edge length (Fig. 4C, and G) and lowest number of patches (NP) (Fig. 4B) compared to at-risk and unhealthy sites ($p < 0.05$), while the total class area (CA), (Fig. 4D) was similar across health classes. The entropy metric showed that the degree of disorder in each site was

low in healthy and high in at risk and unhealthy sites (Fig. 4E), indicating that these were more fragmented than healthy ones. Accordingly, contagion showed an opposite trend relative to entropy, highlighting that regions with a low spatial contagion, i.e. unhealthy sites, were severely fragmented (Fig. 4F).

Both the MSDI index and the LI were significantly lower for healthy sites than for unhealthy ones (Fig. 4H, I) indicating lower degradation with lower water and soil resource loss at healthy sites.

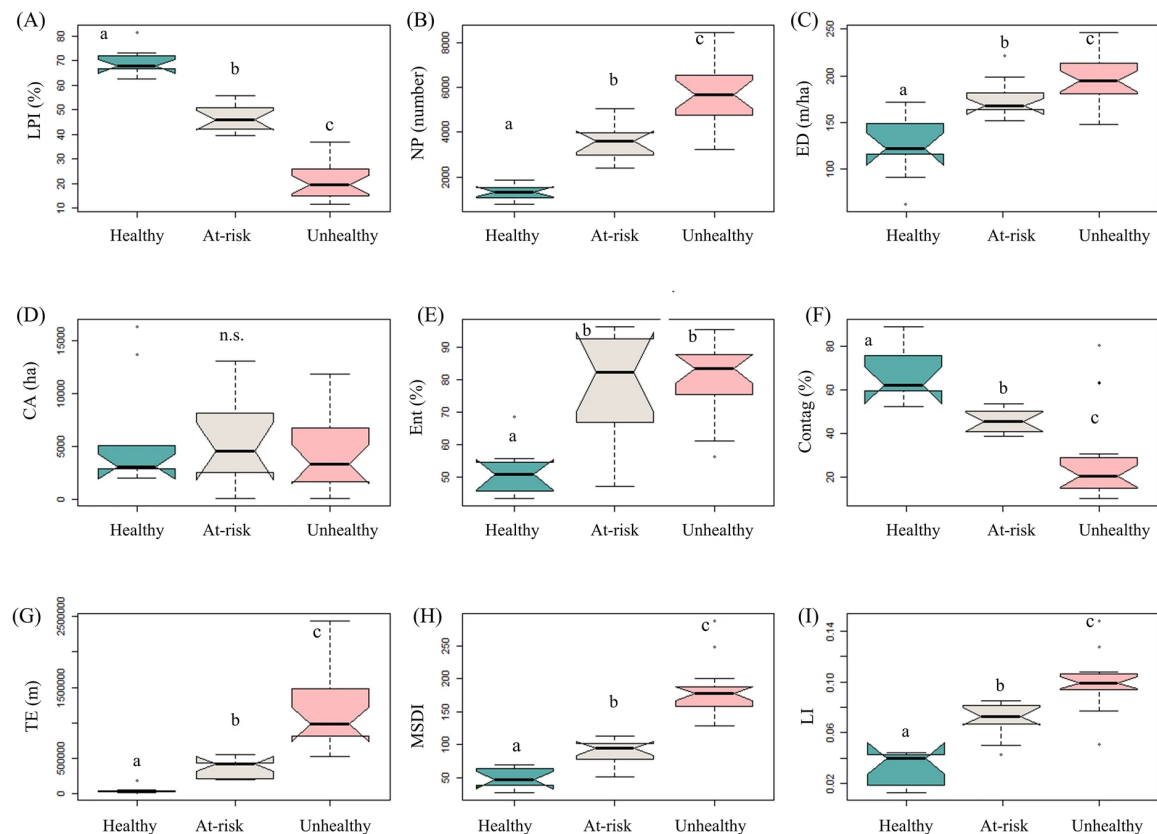


Figure 4: Boxplots of landscape metrics across different health classes. A: LPI (largest patch index); B: NP (number of patches); C: ED (edge density); D: CA (total class area); E: Ent (Entropy); F: Contag (Contagion); G: TE (Total edge); H: MSDI (moving standard deviation index); I: LI (leakiness index). Lowercase letters indicate significant differences across health classes after Tukey test ($P < 0.05$). n.s. in Fig. 4D indicates no significant differences across classes

Comparison of qualitative field indicators and quantitative remote sensing indices

The multivariate analysis (NMDS) coupled with clustering (DBSCAN, k-means clustering, hierarchical clustering, and SOM) performed well (Table 4) to categorize both field qualitative and remotely sensed quantitative data (Fig. 5). Among the different distance measures (Euclidean, Manhattan, Mahalanobis, and Bray-Curtis), Manhattan performed

best with the lowest stress value (0.022) for the qualitative field data, while Euclidean performed best with the lowest stress value (0.067) for remotely sensed data (Supplementary file 5; Fig S.3 and S.4).

*Table 4: Normalized mutual information value for each clustering method. A zero NMI value corresponds to no mutual information, whereas one indicates a perfect correlation. Each NMI value is calculated based on the correlation of clusters between remotely sensed quantitative data and field qualitative assessment data. *Graphical results of different methods are shown in Supplementary file 5; Fig. S3. Hierarchical clustering is presented by heatmaps based on ward linkage and Manhattan distance. Since DBSCAN + k-means clustering and SOM performed best, they were used to produce health status maps for 2016 (Fig. 6A, B, C, Table 3)*

Method*	Types of data	NMI
DBSCAN	Raw data	0.57
	Ordination score	0.57
DBSCAN + k-means clustering	Raw data	0.54
	Ordination score	0.91
SOMbrero	Raw data	0.75
	Ordination score	0.84
Hierarchical clustering*	Raw data	0.67
	Ordination score	0.64

Based on the NMDS for field health indicators (Fig. 5A), higher values for soil surface loss and degradation, plant mortality and decadence, compaction layer, soil surface resistance to erosion, rills, and water flow patterns were related to unhealthy sites. In contrast, higher values for structural and functional groups, annual production, the reproductive capability of perennial plants, and plant community composition were related with healthy sites. The NMDS revealed that larger patch values were associated with healthy sites (Fig. 5B). High edge density, number of patches, entropy, MSDI, and leakiness values were related to unhealthy sites. These data confirmed the results obtained from the univariate analyses of single measures (Fig. 4).

We used PA to determine if similar NMDS relationships of health indicator data and sites can be retrieved from both field-based indicators and remotely sensed metrics to validate the metrics derived from remote sensing analyses. There was a high Procrustes correlation derived from the symmetric Procrustes residual (0.88) between terrestrial ecosystem health groups based on field indicators (Fig. 5A) and derived from remotely sensed metrics (Fig. 5B) (Supplementary file 4; Fig. S.2).

The NMI differed between clustering approaches. The minimum was 0.54 (DBSCAN and k-means clustering, raw data) while the combination of DBSCAN and k-means clustering on two-dimensional NMDS data performed best (NMI = 0.91). The NMI value for the SOM on NMDS data showed the second-best performance (NMI = 0.84) (see Table 4, Supplementary file 5 and 6; Fig. S3, and S4). Collectively, NMI differed between methods and data types, although using a combination of clustering methods based on ordinated data performed best.

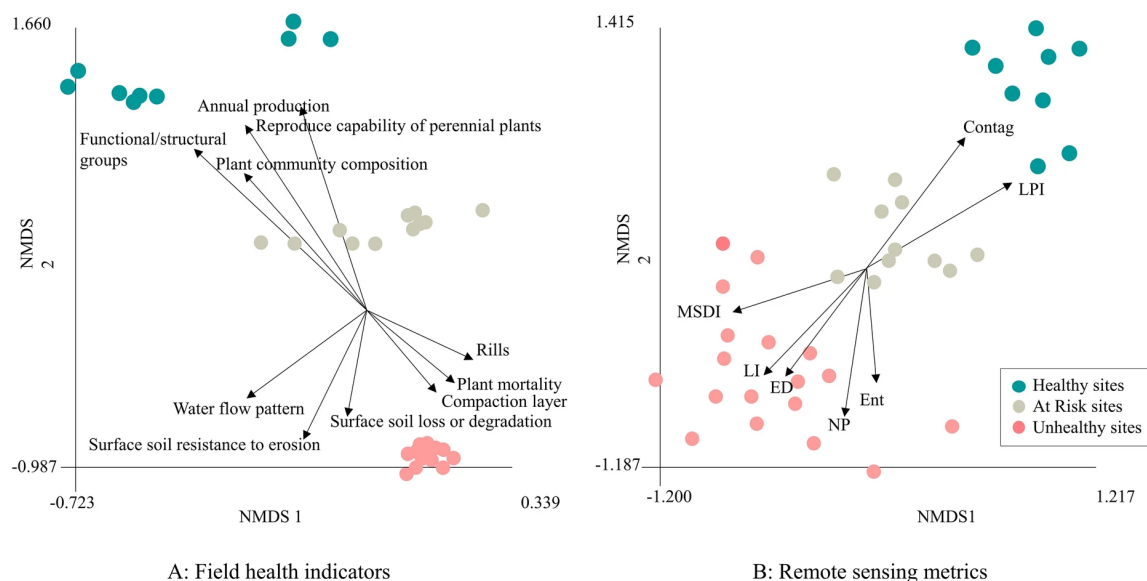


Figure 5: Two-dimensional ordination NMDS of 40 sample sites. **A** 10 vectors of health indicators significantly correlated ($p = 0.001$, $\alpha = 0.05$) with the 2-D ordination axes (stress 0.14 Manhattan Metric); **B** Seven vectors of remotely sensed metrics significantly correlated ($p = 0.001$, $\alpha = 0.05$) with the 2-D ordination axes, (stress: 0.07 Bray-Curtis Metric). Each color includes groups of sites assigned to the three health classes. MSDI moving standard deviation index, LI leakiness index, Ent entropy, Contag contagion, LPI largest patch index, NP number of patches, ED edge density

Compared to the field-based map, both DBSCAN + k-means clustering and SOM overestimated the health status for one site (“At-risk” instead of “Unhealthy”, site 16), SOM additionally underestimated the status for a further site (“Unhealthy” instead of “At-risk”, site 21). Generally, both field and remote-based maps of terrestrial ecosystem health were consistent (Fig. 6A, B, C; Table 3), and inconsistencies of the RS-based maps accounted for 2.5% (DBScan and k-means clustering) and 5% (SOM), respectively. Finally, a LULC map with an overall accuracy of 84% (See Supplementary file 3; Fig. S1) was created for 1987, and a terrestrial ecosystem health status map for 1987 was produced following the classification approach for 2016 (Fig. 6D and see Supplementary file 5 and 6; Fig. S3, 4). Compared to 2016, there were 23 “healthy” sites, 11 “unhealthy” sites, and six “at-risk”. There was a clear degradation of ecosystem health status in the Western part of the study area (Fig. 6D). The interpretation of the aerial images and the LULC maps (Supplementary file 3; Fig. S1),

indicated that degradation occurred due to the conversion of forest in 1987 to poor and moderate rangelands in 2016 (Supplementary file 3; Fig. S1A, C, D). The increasing number of patches and total edge, as well as the decreasing largest patch index, has resulted in a higher level of fragmentation.

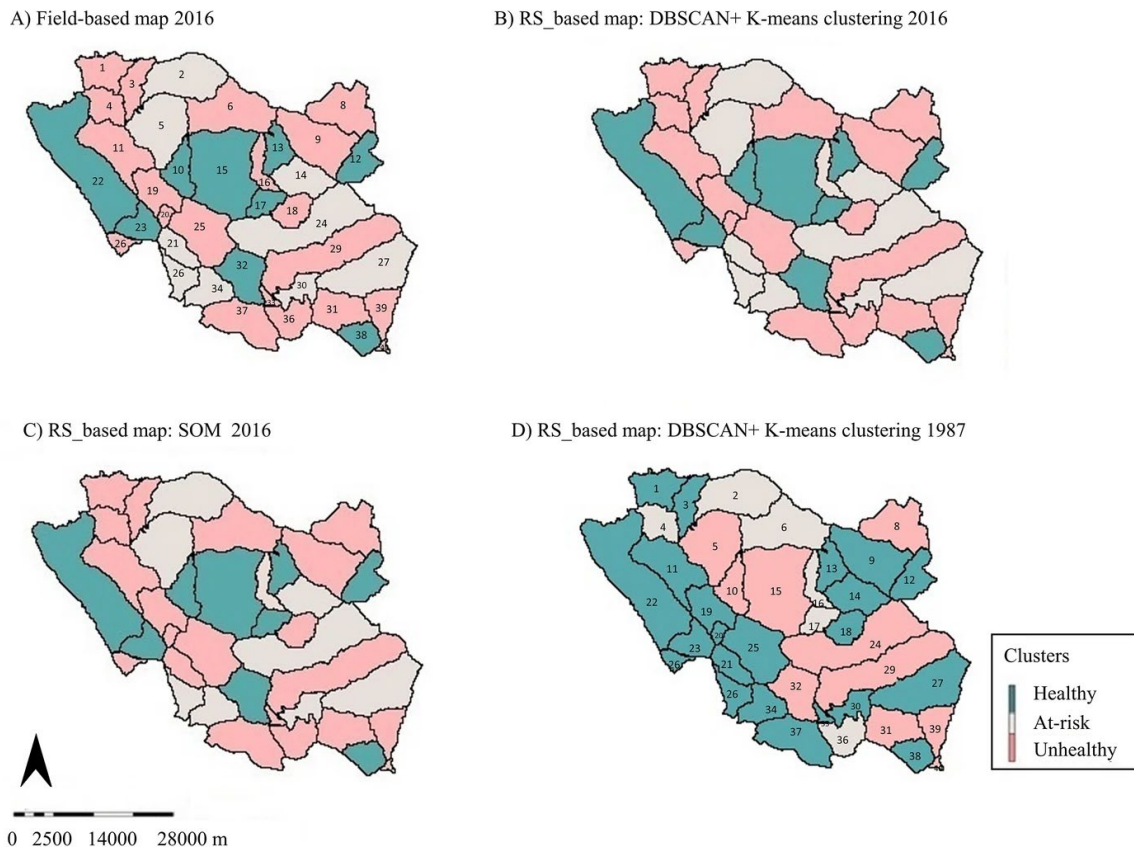


Figure 6: Terrestrial ecosystem health status maps across space and time and comparing methods. **A** Field assessment in 2016, **B** DBSCAN + k-means clustering on NMDS scores of remote sensing (RS) data in 2016, **C** Self-organizing map on NMDS scores of RS data in 2016, and **D** DBSCAN + k-means clustering on NMDS scores of RS data in 1987

Discussion

The overall results of this study illustrate that standardized field assessments of terrestrial ecosystem health in drylands following the established IIRH protocol can be accurately reproduced with satellite data by combining multivariate methods together with unsupervised cluster analysis in this region. So we present an exemplary workflow on how to integrate a standardized in situ data set with publicly available satellite imagery to monitor land degradation (SDG indicator 15.3.1). The best approach, DBSCAN + k-means clustering, reached a very high correlation (PA = 0.88 and NMI = 0.91) between field and spaceborne data. Only the status of one out of 40 sites, which

accounted for 0.93% of the total area, was misclassified by one health class (“at-risk” instead of “unhealthy”). Therefore, if field indicators of ecosystem health are linked with the appropriate RS metrics, there is potential for combining the data at different scales and extents, which could be tested in further studies in other rangelands to explore the transferability of our approach. Indeed, integrating in situ ecological data with remote sensing is both promising and challenging (Cavender-Bares et al. 2022). There is an urgent need for identifying indicators that anticipate change in terrestrial ecosystem health caused by human impacts to allow for timely management at the landscape scale (Briske et al. 2005; Estevez et al. 2017), because human, social and economic development relies on the health of natural habitats (UN 2019). Due to the complexity and the variety of available indicators, assessing terrestrial ecosystem health status across field and RS scale is a challenging task, but integrating expert knowledge and ecological data with remote sensing data has a large potential (Herrick et al. 2019), and in this study we present an exemplary methodological approach on how to deal with this challenge. In the following discussion, we describe the efficacy of combining field-based and remote sensing methods in determining health indices regarding structural and functional changes across health status.

Field assessment and IIRH protocol: health classes and indicators influencing terrestrial ecosystem health

Even though the IIRH protocol is a well-established method, adequate information of the studied ecological units is essential to interpret its indicators (Pyke et al. 2002). The classification of our study sites into three groups (“healthy”, “at-risk”, and “unhealthy”) based on the indicators defined in the IIRH protocol directly provides useful information for land managers and decision-makers. Here, both the unhealthy and the at-risk sites were characterized by a clear deviation of indicators from the optimal state for all three attributes (soil and site stability, hydrological function, and biotic integrity). On the other hand, the healthy sites were characterized by good status of indicators related mainly to biotic integrity. The differences in the ratings of IIRH attributes were likely due to a combination of disturbances associated with the proximity to nomadic and rural areas, land-use/ cover conversion to abandoned rainfed lands, and decreasing coverage of under-canopy perennial plants (Duniway et al. 2010; Molaeinasab et al. 2018). Such disturbances lead to soil degradation and erosion, decreasing the frequency of productive, perennial, and palatable grass species like *Bromus tomentellus* and *Agropyron tricophorum*, and increasing the frequency of

annual, toxic, and invasive plants in the study area (Safaei et al. 2021). This combination of disturbances affects various ecosystem functions and explains the combination of indicators in all three attributes, which are relevant for the unhealthy ecosystem status. Thus, integrating “moment-in-time assessments” such as the IIRH (Pyke et al. 2002) with scientific knowledge of ecosystem processes of a region can help to stimulate the understanding of terrestrial ecosystem health status. Since healthy ecosystems significantly reduce the destructive impact of human and natural disasters in arid and semi-arid ecosystems (Li et al. 2014; Lausch et al. 2016; Estevez et al. 2017; Molaeinasb et al. 2018), this understanding could help to develop expert knowledge-based benchmarks (Herrick et al. 2019) to support UN sustainable development indicators (Hák et al. 2016) in terms of land degradation neutrality (LDN, SDG.15.3.1).

Assessment of terrestrial ecosystem health using remotely sensed metrics

In the studied area, remote sensing methods have been successfully applied to assess terrestrial ecosystem health status and to investigate impacts on ecosystem functioning and services. There has been a lot of discussion about how to relate landscape metrics to ecological processes (Bastin et al. 2002; Lausch et al. 2016; Robinson and Weckworth 2016; Wu and Hobbs 2002). However, scale issues and data availability as well as uncertainty in estimating health indicators from remote sensing can limit the applicability and accuracy (Li et al. 2014). For example, the diagnostic value of vegetation indices such as the NDVI to assess ecosystem degradation can be increased when changes in the spectral reflectance are linked to the underlying ecosystem processes using scientific knowledge (Herrick et al. 2019). In semi-arid lands, there are various methods to determine terrestrial ecosystem health using structural and functional indicators (Estevez et al. 2017; Berdugo et al. 2020). Here, we examined changes in landscape metrics related to landscape function (LI) and landscape degradation (MSDI) in rangeland and forest ecosystems. The LI can be used to assess and monitor changes in the leakiness status of various landscapes and at different scales. Combining coarse or fine-scale satellite imagery with low or high-resolution DEM allows for LI to be derived at different spatial scales (Ludwig et al. 2007). Most landscape indices such as the LI and MSDI differed significantly between health classes and showed the same trend as, for example, the number of patches and the largest patch area. Indeed, decreasing terrestrial ecosystem health in this region can lead to an increase in the number of fragmented patches and leakage of resources, showing less integrated

ecosystems with a higher degree of fragmentation (Safaei et al. 2021). The spectral heterogeneity was relatively high in degraded and unhealthy sites. Results from this and other studies all found that the MSDI serves as an appropriate complementary or alternative method to expensive field investigation for measuring landscape status and land degradation in arid and semi-arid regions (Tanser and Palmer 1999; Jafari et al. 2008). On the basis of these findings, the current structural condition of these ecosystems, which stems from past changes and conversions, is an indication of increasing land degradation. Given that one significant consequence of landscape degradation and conversion is health reduction, numerous ecological consequences are expected to rise (Tanser and Palmer 1999). Due to the importance of landscape structure and functionality for land management, it would be beneficial to consider RS based landscape metrics such as LI and MSDI in future research to outline management practices and to identify appropriate management strategies.

Integration of field-based indicators with remote sensing metrics to map and assess terrestrial ecosystem health status across spatio-temporal scales

The validation of remotely sensed information on terrestrial ecosystem health with expert field assessments can contribute to a science-based and data-driven assessment of rangeland health (Herrick et al. 2006, 2019). In this study, comparing field data with remote sensing metrics using multivariate statistical methods turned out to be a promising approach for clustering terrestrial ecosystem health classes at the landscape scale in the studied area. We compared eight clustering methods to identify the appropriate clustering approaches on both field-based and remote sensing metrics, as the performance of different classification algorithms might vary clearly for a chosen dataset (Abbas 2008; Wiwie et al. 2015). The accuracy between maps using field and remote sensing data differed between best-performing clustering methods and pre-processing procedures. Here, DBSCAN combined with k-means clustering using NMDS ordination data showed the best performance in terms of concordance between field and remote sensing assessments of terrestrial ecosystem health gradients. Our results outline the potential of NMDS to deal with mixed data types (McCune and Grace 2002), the utility of Procrustes rotation of ordination data coupled with cluster analysis to assess survey data at larger spatial scales (Gonzalez-Mejia et al. 2018), and of combining distance and density-based clustering algorithms (Dash et al. 2001). Our results particularly highlight the recent popularity of DBSCAN (Ester 1996; Saha 2021). It has

the typical characteristic to group data points with many nearby neighbors and to accurately identify clusters containing outliers and noise in the dataset (Ester et al. 1996). The results of this and other studies (Kozakura et al. 2017) demonstrated that combining clustering algorithms is a promising avenue to approximate clusters and to find the optimal clustering method suited to different types of ecological data. This approach enabled us to identify appropriate RS indicators of land degradation such as complex vegetation indices that cannot be calculated from field data alone (Toevs et al. 2011). The linkage between field and remotely sensed indices helped to better interpret the numerical appearance of metrics and the respective ecological patterns and processes. With the assignment of health status clusters to the landscape indices using a combination of multivariate analysis and cluster analysis, we go beyond the patch-based metrics (Wu and Hobbs 2002) and illustrate how landscape metrics can be applied to assess ecological processes at the watershed level, which highlights the potential to monitor land degradation from space. Further studies to test the transferability of our approach to other rangelands or across spatial scales are possible as we used a standardized field protocol, mainly free and open-source software as well as publicly available satellite data. Future directions could include identifying ecological thresholds (Andersen et al. 2009) or spatial early warning signals of ecosystem transitions to alternative stable states (Kéfi et al. 2014) based on complex remote-sensing indices and the IIRH protocol to test the integrity of land degradation monitoring in rangelands in the field, from space and based on ecological conceptual frameworks and theory.

The primary challenge in defining the benchmark of land degradation is the lack of historical data (Herrick et al. 2019). However, from a remote sensing perspective, the use of archive data from long-lasting satellite programs such as Landsat (Wulder et al. 2016) can partly fill such data gaps. Here, the remote sensing-based model for the assessment of terrestrial ecosystem health in 2016 was validated by field surveys and projected to Landsat data from 1987 (Fig. 6). From 1987 to 2016, decreasing areas of forest and dense rangeland together with increasing fragmentation exert negative trends on the ecosystem health status (Supplementary file 3; Fig. S1). Briefly, terrestrial ecosystem health maps derived from field information and remotely sensed indicators were consistent. This allowed for a transfer of the methods to historical satellite data, which produced plausible results. Providing an overview of the current and past state of ecosystem conditions is important because it affects the delivery of services and, therefore, human well-being (Rendon et al. 2019). Decreasing soil quality (Molaeinasab

et al. 2018), increasing soil erosion, dust problems, and tree mortality in unhealthy sites have been attributed to the long history of over-grazing with domestic livestock like sheep and goats, and the conversion of forests and rangelands to arable lands (Baranian et al. 2017). When transferring our remote sensing approach to assess terrestrial ecosystem health from 2016 to satellite data from 1987, we found 32% of degradation and, therefore, a deviation from SDG 15.3.1 and its main aim to achieve land degradation neutrality (Prince 2019; UN 2019). In fact, it has been estimated that the actual number of livestock in some parts of the western rangelands of Iran including the study area exceeds considerably the grazing capacity (Farahpour 2002). It is partly because herders rely more on other feed sources for their livestock such as hay from farming lands (Abolhassani 2011). It is worth mentioning that rangeland management in the study area changed considerably following the Nationalization of Rangelands and Forests Act (Ghorbani et al. 2013). Before the land reform, rangelands were managed by nomads in common, public rangelands, while private rangelands were controlled by landlords. As a result, the rangelands were in better condition due to appropriate management, specifically due to the lower number of livestock and herders compared to the present time. Based on the land reform law, all rangelands were allocated to the government, resulting in “tragedy of the commons” dilemma (Baland and Platteau 1994). Another cause of rangeland health decline is extensive land conversion to farms by local farmers and villagers whose primary intention is to claim ownership of land rather than agricultural goods. These farmers are well aware that rainfed agriculture in degraded rangeland is not profitable but would help them acquire more land by taking advantage of an inefficient long-lasting land management system in the region (Baranian et al. 2017). The current approach holds bright prospects for outlining policies that contribute to the range and forestry development efforts, integrated management of resource exploitation, and reducing resource degradation (Matsushita et al., 2006; Miller 2008).

In summary, the presented workflow on how to combine ecological information from the field with ecological information from space to map ecosystem health in space and time is in line with Wu and Hobbs (2002), who introduced an integrated approach that combines field data, experimental manipulations, GIS, remote sensing, and modeling for developing a science of scale. Using a combination of multivariate and cluster analysis to compare field and remotely sensed data turned out to be suitable to map ecosystem degradation. As the quality and availability of data over large areas and extended time periods are critical for modeling (Wu and Hobbs 2002), and continuously

gathering field data over large areas has limitations, complex remotely sensed indices that are verified against field data provide one of the best opportunities to overcome these challenges. Future research could investigate the combined use of different sensors and platforms including the analysis of time-series data, and the transfer to different sites and ecosystems.

Conclusion

In this paper, we showed that assessing rangeland health based on satellite data can coincide accurately with an assessment based on common field approaches (IIRH protocol). Thus, there is potential for the integration of standardized in situ data with remote sensing imagery to enable continuous monitoring of land degradation (SDG 15.3.1). We presented a methodological approach on how this information on ecosystem health can be linked using multivariate statistics, cluster analysis, and complex remote sensing metrics based on publicly available satellite data. As spatial data-driven monitoring approaches are essential to achieve SDGs, this approach could contribute to the development of benchmarks for land health and monitoring of indicators for land degradation neutrality based on remote sensing. Identification of spatial indicators of degradation could also help to establish links to conceptual frameworks such as ecological regime shifts with the objective to determine spatial early warning signals of shifts to alternative stable states. In the next step, our approach could be tested at the national or even continental scale in arid and semi-arid regions or could be transferred to other study areas and ecosystems to support monitoring land degradation neutrality from space.

Acknowledgements

We thank the anonymous reviewer whose comments and friendly suggestions helped improve and clarify this manuscript.

Author contributions

All authors contributed to the study conception and design. Material preparation and data collection were performed by MS, with significant guidance from AGS and HB. Analyses were performed by MS. The first draft of the manuscript was written by MS

and commented by AGS, HB, TK, and SF to prepare the final manuscript. All authors approved the final manuscript.

Funding

Open Access funding enabled and organized by Projekt DEAL. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability

The datasets generated during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Chapter 16

16 Concluding summary

This habilitation thesis sought to give an overview of the many facets of remote sensing and geospatial modelling to map ecosystem conditions focusing on three main drivers of ecosystem degradation, namely LULC change, climate change and biological invasions, for different ecosystems. A common theme of all studies was to highlight the potential of the complementary use of different kinds of remote sensing and auxiliary geospatial data in this context. In the following, the main findings of the studies are summarised based on the aforementioned objectives including outlooks for future research directions and finalized by concluding remarks.

16.1 Remote sensing of invasive alien species

In Chapters 4-7, we summarized the general state-of-the-art of ecological applications of remote sensing to study plant invasions across scales (Chapter 4), we gave a detail overview of ecological applications of remote sensing to examine the invasion of Australian wattles at global level (Chapter 5), we developed a sensor-based framework to investigate spatio-temporal impacts of invasive plant species (Chapter 6), and we present a proof-of-concept on how to map impacts on ecosystem functioning after plant invasion using airborne hyperspectral and LiDAR data (Chapter 7). In Chapter 4 we demonstrated that although the interest in using remote sensing to study plant invasions in terms of published literature is increasing, most studies focus on mapping invasive species, but examples of transfer to practice are rarely found. Most workflows likely lack the potential of transferability to other contexts, and methodological approaches regarding processing and analysis lack standardization. Further, as remote sensing products differ from field-based assessments, e.g. regarding thematic detail and

accuracy, more communication between ecologists and practitioners is required to better explain the limitations and benefits of remotely sensed information. Future directions include leveraging the potential of novel algorithms and drone technology, integrating citizen science data, and using cloud-based solution for data processing and analysis. An underexplored research topic is, e.g., the assessment of impacts using remote sensing. In Chapter 5, we showed that while Australian *Acacia* spp. are invasive around the globe, research regarding remote sensing approaches mostly focusses on a few species and, likewise, few countries. The potential to conduct comparative studies remains unexplored. Further, most studies follow the general trend and focus on mapping the invaders, while other topics related to impact assessment, monitoring control and restoration measures as well as invasion dynamics receive less attention. Comparative studies based on multiscale and multitemporal remote sensing data analysed using novel algorithms are suggested. In Chapter 6, we addressed the research gap of mapping impacts of ecosystem functioning after plant invasion by developing a conceptual framework. We argue that while a large of body of knowledge on invasion ecology exists, and while there is recent progress in sensor technology and modelling approaches, there is also a lack of integration of knowledge, models and tools. Impact of invasive plants on ecosystem functioning is context-dependent, and it is confined by a certain spatial-temporal dimension. Once the impact including its magnitude and its spatio-temporal characteristics are understood using field-based methods, high resolution remote sensing data provide the means to map structure and functioning of the invaded system, and modelling approaches such as mixed models can account for heterogeneous conditions between sites. Therefore, we envision advancements in mapping plant invasion impact in time and space if the expertise of different discipline from invasion biology and ecosystem research to remote sensing and spatial modelling are combined and integrated. In Chapter 7, we applied the concept as developed in Chapter 6. We showed that the impact of an invasive tree species on ecosystem functioning can be mapped by integrating airborne LiDAR with hyperspectral data. Proxies of ecosystem functioning were derived from hyperspectral vegetation indices. The invader altered ecosystem functioning beyond its canopy, and the total impact was underestimated when the spatial dimension was ignored, and high impacts were noticeable at low invader cover. Ecosystem structure of the heterogeneous dune ecosystem was derived from airborne LiDAR data, and the total impact was overestimated when the structure of the invaded ecosystem was excluded. Combining the hyperspectral vegetation in one functional diversity metric showed that the invader

caused a decrease in functional diversity, and thus initiated a functional homogenization of the ecosystem. Transferability between the studied sites was ensured using a mixed modelling approach. Therefore we presented a showcase of how 2D and 3D remote sensing data can be integrated to map impacts after invasion, and futures studies testing the potential to upscale this approach to satellite level could be a promising future direction of research.

16.2 Urban tree health

In Chapters 8 and 9, we evaluated the potential of publically available optical satellite data to map the health of urban trees, and we aimed to identify stress factors that could negatively affect urban tree health. In Chapter 5, we show that even though urban tree condition can be mapped using vegetation indices related to plant health and derived from satellite data in combinations with field assessments, and even though stress factors can identified from using freely available geospatial data sets, urban ecosystems such as parks are complex and characterized by a high heterogeneity. Therefore, the use of mixed model approaches is encouraged to account for this heterogeneity. Further, it could be tested if mapping urban tree health could be improved if the spatial and/or temporal resolution using either commercial or public satellite data was increased. In addition, there are new satellite missions that gather data related to evaporative stress and photosynthetic activity, which could be beneficial for urban studies. Finally, studies along urban-rural gradients are encouraged to examine the effects of urbanization on urban tree health using remote sensing, which we subsequently explored in Chapter 6. In this study, we found that urban tree health is negatively affected by high traffic, by high temperatures and by surface imperviousness. However, the patterns differ between the two studied cities, Bucharest and Leipzig, and they differ along urban-rural gradients. This highlights again the context-dependency of urban tree health, and the need to use ancillary geospatial data in addition to remote sensing imagery for urban tree health assessments.

16.3 Effect of the severe drought of 2018 across LULC types with focus on coniferous forests in a Central European Landscape

In Chapters 10 and 11, we evaluated the effects of the severe drought of 2018 across LULC types (Chapter 10) Hesse with focus on coniferous forests (Chapter 11) using the Dynamic Habitat Index (DHI) based on times series of the MODIS NDVI vegetation index

product between 2017-2020. More specifically, we test how the components of the DHI related to seasonality, annual productivity minimum vegetation cover changed before and after the drought. In Chapter 10, we show that all LULC had plausible DHI profiles, and that the DHI responded to drought events such as in 2018. However, the response depended on soil properties and drought conditions, and these conditions varied throughout the study area, which underlined the benefits of using additional geospatial datasets to interpret remote sensing imagery. Future studies could explore the use of optical remote sensing data with higher spatial resolution, the use of other vegetation indices, the benefits of advanced land surface phenological metrics, or the complementary use of other types of data such as thermal or radar data. In Chapter 11, we investigated specifically the DHI profiles of coniferous forests in Hesse that died off or remained after the 2018 drought. We found that even before the drought of 2018 and, thus, before die-off these two classes differed regarding their DHI metrics, and that the DHI profiles did not return to their pre-2018 state. More specifically, coniferous forest that died off after the severe drought showed lower productivity, lower minimum cover and higher seasonality even before 2018. Furthermore, the DHI were among the most important predictors to discriminate between the two coniferous forest classes in addition to predictors related to temperature, precipitation and elevation. Therefore, composite vegetation indices such as the DHI and its single components provide insights into forest health affect by disturbances caused by drought when combined with further environmental geospatial data. Future directions included the use of data derived from active satellite remote sensing systems such as LiDAR or multitemporal radar that inform on vegetation structure or, in the case of SAR, on soil moisture, or multitemporal thermal data to map vegetation stress.

16.4 Dynamics of traditional agroforestry systems and the potential of small woods features for carbon sequestration in agricultural landscapes

In Chapters 12 and 13 we quantified the dynamics of traditional agroforestry systems in Hesse between 1952-1967 and 2010 (Chapter 12), and we modelled the contribution of small woody landscape features and agroforestry systems to carbon sequestration in agricultural landscapes in Germany (Chapter 13). In Chapter 12, we used an existing geospatial data on the occurrence of traditional orchards, or “Streuoobstwiesen” in German, in 2010 in Hesse, and compared it to their occurrence in 1952-1967, which we derived from manual interpretation of historical aerial imagery. We found that overall

the number of orchards declined to ca. 30% from about 66 000 historically to about 21 500 in recent times, while the area of orchards declined to ca. 20% from 504 km² to 117 km². Orchard densities that are regarded as high these days were once common throughout Hesse. This decline varied across regions and districts. Orchard hotspots in North and South Hesse were most affected. South Hesse was the region with both the largest and the lowest loss rates, and also inhabited the highest density of orchards that existed since 1952-1967. Regarding their characteristics, historical orchards generally had larger areas, a higher shape complexity, and were located closer to settlements, while orchards established after 1952-1967 were located at steeper slopes and at higher elevations. Main drivers of orchard loss were the increase of urban areas including artificial surfaces and residential buildings as well as the conversion into agricultural land. Locally, traditional orchards were also converted to forest, or developed into woody landscape features, but to a lesser degree compared to the main drivers of orchard loss. This study highlighted that georeferenced historical aerial images are an important data source to assess LULC changes especially for comparably small, but ecologically important landscape features such as traditional orchards. This type of information is required for a continuous monitoring of traditional orchards, but it is also unavailable at broad spatial extents. Future studies could explore the potential of novel methods based on artificial intelligence to fill this gap. In Chapter 13, we quantified the carbon sequestration of small woody landscape features in agricultural landscapes in Germany, and we modelled the carbon sequestration potential following an increase of these landscape features as well as agroforestry system using LULC change scenarios. To do so, we used publicly available geospatial data sets, which are available at national and pan-European level. We show that small woody features cover up to 4.6% of agricultural land in Germany with cropland having the lowest small woody feature density. According to our calculations, they contribute up to 111 ± 52 SD terragrams of carbon to the national carbon budget on agricultural land, and an increase of their density could result in a surplus of carbon sequestration between 0.2 and 2 Tg of carbon per year. As we used existing geospatial data sets related to LULC and occurrence of small woody features to model carbon stocks, our approach is transferable and updatable. Our estimation can thus be refined once improved coefficients of carbon sequestration potential for the respective landscape features and LULC are available, or when base data regarding LULC and distribution of small woody features becomes available with higher spatial resolution, higher accuracy or enhanced thematic detail.

16.5 Land Use/Land Cover change in a Colombian *páramos* ecosystem

In Chapter 14, we investigated the potential of multitemporal SAR data to map LULC in biodiverse, tropical, high-altitude grasslands, also known as *páramos*, in Colombia. We used multitemporal SAR data to map these changes as the use of optical remote sensing data is hindered in this region due to dense cloud cover. Using coherence metrics in addition to traditional backscatter parameters, the accuracy of the resulting maps increases between 8% and 10%. Regarding indicators of land use intensification in terms of agriculture, the class “potato” reached accuracies over 0.75, and became second just behind the class “water”. All in all, 15 out of 17 classes reached higher accuracies when coherence metrics were used in the random forest-based classification models, underlining the importance of using multitemporal SAR data and respective metrics to map LULC in regions where optical remote sensing reaches its limits, and the use of active remote sensing is required for land monitoring. The use of such time series data inevitable leads to data volumes, which were processed in a cloud-based approach. Thus, the study also highlights the importance of cloud-based solutions to leverage the full potential of SAR time-series data, i.e. to produce LULC maps with high thematic detail and high accuracies regarding specific target classes at broad spatial extents in biodiversity hotspots that provide a wide range of ecosystem services and where cloud cover impedes the use of passive sensors. As we used freely available data, our approach is transferable to other regions and ecosystems where the use of multitemporal SAR data could be beneficial or is required.

16.6 Rangeland health

In Chapter 15, we developed a workflow on linking field-based data of rangeland health at watershed following the standardized “Interpreting Indicators of Rangeland Health” field protocol to remotely sensed data including LULC as well as complex indices related to landscape degradation in drylands. By combining multivariate statistics with cluster analysis and statistical shape analysis, we show that assessments of rangeland health based on field data aligns well and with accuracy to assessments based on optical satellite data. This means that there is potential to map rangeland health at broad spatial extents from space. In the bigger picture, we present an example of how satellite remote sensing can contribute to monitoring degradation in drylands, and, thus, contribute to a spaceborne monitoring of Sustainable Development Goals such as

SDG15.3.1, which is related to terrestrial ecosystem health and land degradation neutrality. As our approach is based on standardized, internationally recognized field methods and freely available Landsat satellite data, transferability in time and space can be tested. Future studies in other arid or semi-arid rangelands or using other satellite data with higher spatial or temporal resolution as well as archived data are encouraged to test, refine and develop further our workflow linking data across with high relevance for land management.

16.7 Concluding remarks

In the presented research papers of his habilitation thesis, data from both active and passive remote sensing instruments acquired by aircraft and satellite platforms at single dates or in multitemporal mode were used to map ecosystem condition and degradation. Beyond technical remote sensing aspects, the studies give insights on the importance of spatial modeling approaches in ecological applications, e.g. to account for the spatial heterogeneity of ecosystem properties. However, the increasing availability of remote sensing data poses both new opportunities and challenges in ecological or ecosystem studies, which are addressed in the conceptual and review paper of this thesis, e.g., dealing with large data volumes during processing and analysis. Future progress can be expected in fast evolving fields such as the use of drones, sensor-networks and crowd-sourced data together with interpretable artificial intelligence to study ecosystems. Such data could support the analysis of airborne and satellite data in terms of validation and upscaling, or could be applied to produce super resolution data. Further, very high resolution multispectral, thermal and radar satellite data is becoming more and more available, adding to the already filled toolbox from a data point of view. Nevertheless, a profound understanding of the ecological processes or mechanisms to be studied remains a fundamental requirement, as technological progress does not per se imply progress in using sensor-based approaches to study ecological phenomena. The increasing amount of studies and initiatives joining knowledge from different disciplines demonstrate that if we succeed in integrating expertise from different backgrounds, then we can create an innovative atmosphere that can lead to progress in using novel technologies to tackle urgent challenges regarding the degradation of our ecosystems.

Chapter 17

Acknowledgements

First, I would like to express my deepest gratitude to my advisor, Prof. Dr. Till Kleinebecker, for his invaluable support and encouragement throughout the course of my research and the writing of this thesis. I deeply appreciate the freedom and opportunities you gave me to pursue my own line of research.

I would like to thank the members of the Work Group Landscape Ecology and Landscape Planning for their professional support and collaboration throughout this work. Their contributions, including technical assistance, and productive discussions, have been instrumental in advancing the research presented in this habilitation thesis. I would like to extend my special thanks to the student helpers as well as the graduating students who contributed their time and effort to various aspects of this work. I would also like to extend special thanks to my PhD students for their dedication, hard work, and willingness to embrace new challenges.

I would like to express my sincere appreciation to my co-authors, whose partnership was integral to the research underlying this habilitation thesis. Their domain expertise, constructive feedback, and willingness to engage in critical discussions were invaluable throughout our collaborative journey. Our shared efforts—ranging from refining experimental designs and reviewing the relevant literature to analysing data and shaping the final manuscripts—greatly strengthened the rigor and impact of the work presented here.

I owe a special debt of gratitude to the mentors and educators who have shaped my academic journey over the years. Their wisdom, belief in my potential and early encouragement instilled in me a passion for discovery that ultimately led me here. Thanks for sending me care packages with nice coffee, for engaging in deep discussions over good meals, and for making urgent video calls when needed.

Finally, none of this would have been possible without the steadfast love and understanding of my family and friends. Their emotional support, patient listening, and gentle reminders to maintain balance in life have carried me through both the challenges and triumphs of this endeavour.

I dedicate this thesis to my parents.

Eigenständigkeitserklärung

Ich erkläre: Ich habe die Habilitationsschrift selbständig und nur mit den Hilfen angefertigt, die ich in der Arbeit angegeben habe.

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