Received: 20 December 2022 | Revised: 24 May 2023 | Accepted: 24 May 2023
DOI: 10.1111/jac.12656

DROUGHT STRESS

Journal of Agronomy and Crop Science WILEY

Cover crop water consumption: Analysing performance of the agrometeorological model for the calculation of actual evapotranspiration (AMBAV) in a container experiment

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Abstract

Due to anthropogenic climate change, cover crop water consumption in winter could potentially increase drought stress for a succeeding crop. Simulation of cover crop evapotranspiration (ET) losses could be a tool for farmers to make smart management decisions. In Germany, the model AMBAV is used by the German Meteorological Service (DWD) to advise farmers in irrigation management. We compared measured ET of phacelia (*Phacelia tanacetifolia*), oilseed radish (*Raphanus sativus* var. *oleiformis*) and white mustard (*Sinapis alba*) cultivated in a container experiment with simulated data and conducted a sensitivity analysis to identify the meteorological and crop-specific parameters, which had the strongest effect on simulated ET. In general, measured ET exceeded simulated ET. Different statistical criteria showed that AMBAV performed best for the simulation of evaporation from a bare soil surface. Model performance was also strongly influenced by the irrigation regime in the container experiment. However, the sensitivity analysis showed that changes in irrigation hardly influenced simulated ET. We recommend optimization of the model for irrigated agriculture. Furthermore, we identified temperature and humidity as the most important meteorological and leaf area index as the most important crop-specific parameter for ET simulations with AMBAV. Since farmers' management decisions depend on the accuracy of ET simulations, they should be aware that even small regional deviations of meteorological conditions and soil cover can significantly affect model predictions.

KEYWORDS
catch crop, irrigation, sensitivity analysis, water dynamics

Key points

- Comparison of measured and simulated evapotranspiration (ET) of cover crops.
- Measured ET exceeded simulated ET.
- AMBAV model is highly sensitive to changes in temperature, humidity and LAI.
- Sensitivity analysis showed that data accuracy is essential for reliable ET simulation.

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1 | INTRODUCTION

Anthropogenic climate change has increased the occurrence of weather extremes such as drought or heavy precipitation events on a global scale. In central Europe and the Mediterranean, an increase of agricultural and ecological drought has been observed since the 1950s (IPCC, 2021). Evapotranspiration (ET) losses—the sum of evaporation (E) and crop transpiration (T)—are projected to increase with rising temperatures due to an increasing atmospheric water demand. This increase in ET will potentially lead to a decrease in soil moisture (Arias et al., 2021). In consequence, the growth-limiting factor water could become even more scarce during the vegetation period of grain and other cash crops. Zhu et al. (2021) found that between 1980 and 2018, water limitation accounted for 32% of all wheat yield decreases. In their study, high ET corresponded to high yield shock probability across various regions in Europe (Zhu et al., 2021).

The increasingly common practice of cover cropping—the cultivation of crops in otherwise fallow periods to reduce nutrient losses—might intensify the drought stress for a succeeding cash crop as cover crops consume up to 270 mm water during their vegetation period (Selzer & Schubert, 2023). This is a major concern for farmers who have to choose between the benefits of cover cropping and cash crop yields (Mase et al., 2017; Woods et al., 2017; Zinngrebe et al., 2017). As a decision-making tool, farmers oftentimes rely on computer models to predict the evapotranspirative water demand of different cash and cover crops in relation to the changing climatic conditions since the direct measurement of actual ET in the field is highly complex. Many of the models used today are based on the Penman–Monteith equation (Monteith, 1965; Penman, 1948). They include meteorological data and crop and soil-specific characteristics and are regularly validated in field experiments. On the basis of model simulations, farmers can be supported in different decision-making processes: Which cash and cover crops are most suitable for cultivation under the given climatic conditions? Does the water supply support these crops? Is additional irrigation necessary? Do the benefits of cover cropping outweigh the additional water losses linked to with their growth?

One of those models is AMBAV (Agrarmeteorologisches Modell zur Berechnung der aktuellen Verdunstung). It is an SVAT (soil–vegetation–atmosphere–transfer) model developed by the German Meteorological Service (DWD). The model was updated and adapted several times since its first introduction in 1983 (Löpmeier, 1983) to precisely calculate historic ET and predict ET under various climate scenarios (Braden, 2013). While the focus of these calculations lay on cash crops in the past, the DWD incorporated three of the most important cover crops in Germany—white mustard, oilseed radish and phacelia—through parametrization in lysimeter experiments in recent years. Based on ET simulations with AMBAV, the DWD advises farmers and uses the model for irrigation necessity prognoses (Friesland & Löpmeier, 2007). Model evaluations have shown that ET simulations with AMBAV show 'reasonably good accordance' with measured ET of different cash crops under varying climatic and environmental conditions (Friesland & Löpmeier, 2007). However, to our knowledge except for two validation trials (Helle, 2021; Kollhorst, 2019), model performance of AMBAV for cover crops has not yet been investigated intensively.

Cover crop trials are performed under varying conditions ranging from field experiments to container, minirhizotron and pot experiments. The controllability of water inputs increases with decreasing scale while the value for farmers increases with increasing scale. Selzer and Schubert (2021) have shown that the container technology established in the Institute of Plant Nutrition of the Justus Liebig University in Giessen can be used to investigate the nutrient use efficiency of various cover crops. The container technology provides a sufficient soil volume for natural root development; crops can be sown at field densities, and the containers can be subjected to natural meteorological conditions while closely monitoring water fluxes such as ET (Hohmann et al., 2016; Hütsch & Schubert, 2021; Selzer & Schubert, 2021). However, since cover crop parametrization for AMBAV took place in lysimeters in field experiments of limited regional variation, it has not been investigated yet whether the simulation of water fluxes with AMBAV can be applied to different cover crops grown under various climatic and soil conditions.

The objective of this study was to investigate whether AMBAV is suitable to accurately simulate cover crop water losses in the form of ET. Simulated ET (ET_{AMBAV}) was compared with measured ET (ET_m) from a cover crop experiment conducted under semi-controlled conditions in container technology in 2020 and 2021 (Selzer & Schubert, 2023). We hypothesized that there were no significant differences between ET_m and ET_{AMBAV}.

Simulations are always dependent on the accuracy of data input. If used for irrigation scheduling, ET_{AMBAV} estimates should be reliable. It has been shown, however, that seemingly small errors of ET estimates can amount to substantial amounts of water (Allen et al., 2011b). Moreover, Kroes et al. (2006) have highlighted that AMBAV is strongly influenced not only by meteorological input data but also by crop and soil characteristics. For simulation purposes, the DWD often uses generalized default data since crop-specific measurements of leaf area index (LAI) or crop height rarely exist for individual farms. Our aim was to identify the parameters with the highest impact on ET_{AMBAV}. Since variations in water supply (precipitation and irrigation) were responsible for up to 65% of cover crop ET_m in the container experiment in 2020 (own data), we hypothesized that ET_{AMBAV} is most sensitive to this meteorological parameter. A high LAI is positively correlated with high transpiration losses and negatively correlated with soil evaporation (Allen et al., 1998). Therefore, we hypothesized that ET_{AMBAV} is more sensitive to changes in the crop-specific parameter LAI than to changes in crop height.

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2 | MATERIALS AND METHODS

2.1 | Cover crop cultivation

Cover crops were cultivated in container technology under semi-controlled conditions at the experimental station of the Institute of Plant Nutrition (PN), Justus Liebig University from 24 August to 6 November 2020 (50.5981° N, 8.6671° E). The three cover crops relevant for this study are white mustard (*Sinapis alba* L. cv. Gisilba), oilseed radish (*Raphanus sativus* L. var. *oleiformis* Pers. cv. Bento) and phacelia (*Phacelia tanacetifolia* Benth. cv. Amerigo) sown at plant densities of 270, 252 and 525 plants m^{-2}, respectively. Prior to sowing, soil moisture was adjusted to 50% of its maximum water-holding capacity (WHC). A detailed description of cultivation and nutrient supply to the cover crops can be derived from Selzer and Schubert (2021). Soil characteristics are shown in Table 1. A bare fallow was included as a control treatment to monitor evaporation from a bare soil surface. Each treatment had seven replicates, three of which were used for intermediate harvests (2020: 23, 38 and 66 days after sowing (DAS); 2021: 23, 41 and 63 DAS) to monitor biomass production for precise ET measurements. The four remaining replicates were harvested after the first frost event 74 and 63 DAS in 2020 and 2021, respectively.

2.1.1 | Crop development

During the vegetation period, the phenological growth stages of the three cover crops were closely monitored. Plant height and LAI (ACCUPAR LP-80 PAR/LAI Ceptometer; METER Group) were measured weekly. Since the length of the LAI sensor exceeded the width of the containers, LAI had to be corrected with a transformation factor of 2.14 (Selzer & Schubert, 2023).

At the final harvest, shoot fresh and dry (105°C) weights were determined for each container (0.16 m^2). Results were extrapolated to 1 m^2. In 2020, maximum rooting depth was determined by placing an auger (Ø 7.6 cm) between the rows of cover crops to sample core soils in 6-cm increments. The depth of the last soil sample that included roots was recorded as the maximum rooting depth. Maximum rooting depth was not measured separately in 2021, since roots of all three cover crops equaled depth of the container in 2020.

TABLE 1 Soil characteristics for cover crop cultivation in 2020 and 2021.

	2020	2021
Sand (%)	44.3	52.9
Silt (%)	34.6	28.2
Clay (%)	21.2	18.9
Organic matter (%)	≤2	≤2
pH_{CaCl_2}	7.5	7.4
N_{min} (mg kg^{-1})	14.5	2.1
CAL-P (mg kg^{-1})	8.3	10.3
CAL-K (mg kg^{-1})	43.5	66.5

2.1.2 | Meteorological conditions

Meteorological conditions were monitored throughout the vegetation period. Wind speed was measured using the WSW G0010 wind sensor (F&C GmbH) at 2.67 m height in combination with a data logger (DK312 MultiLog rugged Plus; Driesen+Kern GmbH) at 60 s intervals. The same frequency was used to record temperature and relative humidity (DK320 HumiLog Plus; Driesen+Kern GmbH). Hourly rainfall data were derived from a tipping bucket at the nearby experimental station 'Weilburger Grenze' (WG) (50.6017° N, 8.6536° E). Data on relative short wave and long wave radiation as well as sunshine duration were provided by the meteorological station 'Giessen-Wettenberg' (GW) (50.6° N, 8.65° E) run by the DWD.

In 2020, with a total of 88 mm, precipitation during the 74-day cultivation period was lower than during the same period in the previous 10 years in Giessen (2010–2019: 114 ± 12 mm) (Figure 1a). With 13.3°C the average temperature was close to the mean for this period between 2010 and 2019 (12.3 ± 0.3°C). In 2021, precipitation in the 63-day cultivation period only amounted to 35 mm and the average temperature was similar to 2020 (13.1°C) (Figure 1b).

2.1.3 | Measured evapotranspiration (ET_m)

Measured evapotranspiration (ET_m) of cover crops in the container experiment was quantified gravimetrically by weighting the containers twice a week as described by Selzer and Schubert (2021). A drainage layer at the bottom of each container allowed for the collection and quantification of leachate. ET_m was determined using Equation (1) (Selzer & Schubert, 2023).

$$ET_{m(ij)} = \left(C_i - L_{hi} + P_{ij} + I_{ij} - FW_{CC} - C_j\right) \cdot 6.25, \quad (1)$$

with $ET_{m(ij)}$ = measured evapotranspiration between time i and time j in L m^{-2}, C_i = weight of container at time i in kg, L_{hi} = leachate accumulation between time h and time i, P = precipitation between time i and time j in L $container^{-1}$, I = irrigation between time i and time j in L $container^{-1}$, FW_{CC} = cover crop shoot fresh weight in kg, C_j = weight of container at time j in kg and 6.25 = conversion factor from an individual container (surface area = 0.16 m^2) to 1 m^2.

2.2 | Simulated evapotranspiration (ET_{AMBAV})

2.2.1 | Data requirement for AMBAV

Evapotranspiration for the vegetation period was simulated using the graphical user interface AMBAV Global GUI (V0.9509). Data requirements and data availability for the simulation of potential

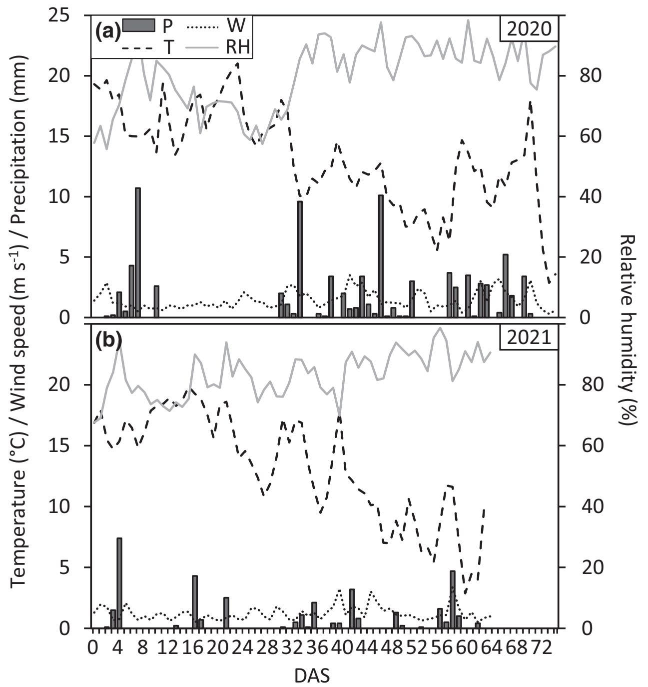

FIGURE 1 Meteorological conditions during the vegetation periods (a) 2020 (until 74 DAS) and (b) 2021 (until 63 DAS). *P*, daily precipitation sum; RH, daily mean relative humidity; *T*, daily mean temperature; *W*, daily mean wind speed.

ET with AMBAV can be derived from Table 2. The required measurement frequency for meteorological data is $1\,h^{-1}$. Due to technical difficulties with the above-mentioned wind sensor, wind speed data from WG were used for the simulations (measuring height = 10 m).

In 2020, the maximum leaf area index (LAI_{max}) was 4.33, 5.79 and $5.7\,m^2\,m^{-2}$ for white mustard, oilseed radish and phacelia, respectively. Maximum crop height (h_{max}) in that year was 1.24, 0.69 and 0.64 m for white mustard, oilseed radish and phacelia, respectively. With LAI_{max} of 3.81, 5.56 and $4.71\,m^2\,m^{-2}$ and h_{max} of 1.23, 0.45 and 0.52 m white mustard, oilseed radish and phacelia were a bit shorter and had slightly lower LAI_{max} in 2021 than in 2020. Since root depth was only measured after the termination of the growth period, data for the parameter 'days until maximum root depth reached' were not available (Table 2). The default value in AMBAV assumes maximum rooting depth to be reached at crop maturity (DWD, 2021). For 2021, maximum root depth was not measured separately since roots reached the bottom of the containers in all treatments in 2020. Therefore, maximum root depth was set at 0.7 m, which is equivalent to the soil depth in the containers.

Irrigation was simulated using the 'drip irrigation' option in AMBAV, which is defined as the addition of water 'which only wets the soil' (DWD, 2021). Time of irrigation was set to 8:00–9:00 AM which resembles the timespan of irrigation in the experiment.

TABLE 2 AMBAV input data (DWD, 2020). Availability of data is indicated: '×' = data available; '–' = data not available. Location of meteorological data measuring point indicated in brackets: PN, plant nutrition (50.5981° N, 8.6671° E); WG, Weilburger Grenze (50.6017° N, 8.6536° E); GW, Giessen-Wettenberg (50.6° N, 8.65° E).

	Availability of data
Meteorological data	
Air temperature 2 m above the ground surface (°C)	× (PN)
Precipitation 2 m above the ground surface (mm)	× (WG)
Relative humidity 2 m above the ground surface (%)	× (PN)
Wind speed in 10 m measuring height ($m\,s^{-1}$)	× (WG)
Downward short-wave radiation ($W\,m^{-2}$)	× (GW)
Downward long-wave radiation ($W\,m^{-2}$)	× (GW)
Crop-specific data	
Shoot	
Maximum LAI ($m^2\,m^{-2}$)	×
Maximum crop height (m)	×
Roots	
Maximum root depth (m)	×
Root expansion shape factor	×
Days until maximum root depth was reached	–
Phenology	
Crop-specific growth stages	×
Daily irrigation ($L\,m^{-2}$)	×
Soil data	
Clay (%)	×
Silt (%)	×
Bulk density ($g\,cm^{-3}$)	×
Water potential at wilting point ($m^3\,m^{-3}$)	×

Abbreviation: LAI, leaf area index.

2.2.2 | Comparison of measured and simulated evapotranspiration

The performance of simulated evapotranspiration (ET_{AMBAV}) in comparison with the measured data was evaluated using the statistical criteria (a) coefficient of determination (R^2, Equation 2), (b) Nash-Sutcliffe efficiency (NSE, Equation 3), (c) root mean square error (RMSE, Equation 4) and (d) mean absolute error (MAE, Equation 5).

$$R^2 = \left[\frac{\sum_{t=1}^{T} \left(ET_m^t - \overline{ET_m}\right)\left(ET_{AMBAV}^t - \overline{ET_{AMBAV}}\right)}{\sqrt{\sum_{t=1}^{T} \left(ET_m^t - \overline{ET_m}\right)^2}\sqrt{\sum_{t=1}^{T} \left(ET_{AMBAV}^t - \overline{ET_{AMBAV}}\right)^2}} \right]^2, \quad (2)$$

$$NSE = 1 - \frac{\sum_{t=1}^{T} \left(ET_m^t - ET_{AMBAV}^t\right)^2}{\sum_{t=1}^{T} \left(ET_m^t - \overline{ET_m}\right)^2}, \quad (3)$$

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$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{T} \left(\mathrm{ET}_{\mathrm{AMBAV}} - \mathrm{ET}_{\mathrm{m}}\right)^2}{N}}, \tag{4}$$

$$\mathrm{MAE} = N^{-1} \sum_{t=1}^{N} \left| \mathrm{ET}_{\mathrm{m}}^{t} - \mathrm{ET}_{\mathrm{AMBAV}}^{t} \right|. \tag{5}$$

with ET_{m} = measured evapotranspiration at time t in mm, $\overline{\mathrm{ET}_{\mathrm{m}}}$ = average measured evapotranspiration in mm, $\mathrm{ET}_{\mathrm{AMBAV}}$ = simulated evapotranspiration at time t in mm, $\overline{\mathrm{ET}_{\mathrm{AMBAV}}}$ = average simulated evapotranspiration in mm, t = timesteps between ET measurements and N = number of observations.

The coefficient of determination (R^2, $0 \leq R^2 \leq 1$) shows which proportion of ET_{m} can be described by $\mathrm{ET}_{\mathrm{AMBAV}}$. NSE was described by Nash and Sutcliffe (1970) and is also known as the coefficient of efficiency. Values can range from $-\infty < \mathrm{NSE} \leq 1$ and is an indicator of how well a model can predict peaks. Negative values of NSE indicate that $\overline{\mathrm{ET}_{\mathrm{m}}}$ is a better predictor than the model (Legates & McCabe, 1999). Since both R^2 and NSE are dimensionless and sensitive to outliers, calculations of RMSE and MAE were included, which estimate the difference of the simulated and the measured values in their respective units. RMSE ($0 \leq \mathrm{RMSE} < \infty$) and MAE ($0 \leq \mathrm{MAE} < \infty$) differ in how they weigh errors: Errors with larger absolute values are given more weight than errors with small absolute values by RMSE while the MAE does not make that distinction. All errors are treated as equal by MAE (Chai & Draxler, 2014).

2.2.3 | Sensitivity analysis

Sensitivity analysis of AMBAV was performed similarly to Bormann et al. (2007) by calculating relative changes of simulated evapotranspiration ($\mathrm{ET}_{\mathrm{AMBAV}}$) where one meteorological parameter was changed in the range of $i = -50\%$ to $i = +50\%$ of its original value ($\mathrm{ET}_{\mathrm{AMBAV}\ 0 \pm i}$) in 10% increments relative to simulated ET using the original, hourly measured meteorological data from 2020 and 2021, respectively. The analysis was performed for the parameters (1) temperature (max. = 40°C (Helle, 2021)), (2) wind speed, (3) precipitation, (4) irrigation and (5) relative humidity (min. = 20%, max. = 100%). The same analysis was performed for the crop-specific parameters such as maximum LAI and maximum crop height.

2.3 | Statistical analysis

Simulated and measured ET were compared using a Student's t-test for each measuring date. Irrigation was compared with a one-way ANOVA followed by a post-hoc FDR-test. Heteroscedastic data was compared using the White-adjusted one-way ANOVA and which was also followed by a post-hoc FDR-test. All statistical analyses were performed in RStudio (R version 4.1.0). The significance level for the tests was chosen at $p < .05$. Mean values ($n = 4$) and the standard error (SE) were calculated with Microsoft Office Excel (2019). In the context of this study, ET is defined as a water loss and therefore depicted with negative values.

3 | RESULTS

3.1 | Comparison of measured and simulated evapotranspiration

3.1.1 | Vegetation period 2020

In general, simulated evapotranspiration losses ($\mathrm{ET}_{\mathrm{AMBAV}}$) were lower than measured evapotranspiration losses (ET_{m}) in 2020. From 16 DAS onwards, this difference was significant for phacelia and white mustard (Figure 2). Differences between $\mathrm{ET}_{\mathrm{AMBAV}}$ and ET_{m} were especially pronounced between 21 and 38 DAS for the three cover crop treatments (Figure 2b–d) and from 59 DAS onwards for white mustard and phacelia (Figure 2b,d). While the period from 21 to 38 DAS was characterized by low precipitation ($\sum P = 2$ mm), high temperatures, relatively high maximum wind speeds and low relative humidity (Figure 1a), which led to the high measured ET losses in all treatments, the period from 59 DAS onwards was characterized by a mixture of low ($T_{\mathrm{min}} = -2.6$°C, 73 DAS) and high ($T_{\mathrm{max}} = 23.2$°C, 70 DAS) temperatures, high wind speeds and high relative humidity (Figure 1b).

Since water supply was adjusted according to the water demand of the cover crops, high ET_{m} coincided with high water supply in the form of irrigation (Figure 3). $\mathrm{ET}_{\mathrm{AMBAV}}$ most accurately resembled ET_{m} of all treatments in times of low ET_{m} (Figure 2) and consequently low to none irrigation necessity (Figure 3).

In 2020, AMBAV performed best in the simulation of evaporation from a bare soil surface as indicated in Figure 2a and Table 3. Total $\mathrm{ET}_{\mathrm{AMBAV}}$ was only 25 mm lower than ET_{m} while ET_{m} and $\mathrm{ET}_{\mathrm{AMBAV}}$ in the cover crop treatments differed by 123 (oilseed radish) to 228 mm (white mustard). Out of the three cover crops, model performance of AMBAV was poorest for white mustard and phacelia, indicated by low R^2 and NSE, high RMSE and MAE and a high discrepancy between $\sum \mathrm{ET}_{\mathrm{m}}$ and $\sum \mathrm{ET}_{\mathrm{AMBAV}}$ (white mustard: 228; phacelia: 202.3 mm) (Table 3). The model performed better for oilseed radish (higher NSE, lower RMSE and MAE, and less discrepancy was observed between $\sum \mathrm{ET}_{\mathrm{m}}$ and $\sum \mathrm{ET}_{\mathrm{AMBAV}}$). The bare fallow was the only treatment with RMSE < MAE. Based on the statistical criteria in Table 3, performance of AMBAV in 2020 followed the order: Bare fallow > oilseed radish > phacelia > white mustard.

3.1.2 | Vegetation period 2021

Water supply to the cover crops was reduced to keep soil moisture at 45% of its water-holding capacity in 2021. Consequently, total ET in 2021 was lower than in 2020. Furthermore, the reduction of soil moisture improved the performance of AMBAV in comparison with the previous vegetation period. $\mathrm{ET}_{\mathrm{AMBAV}}$ of the bare

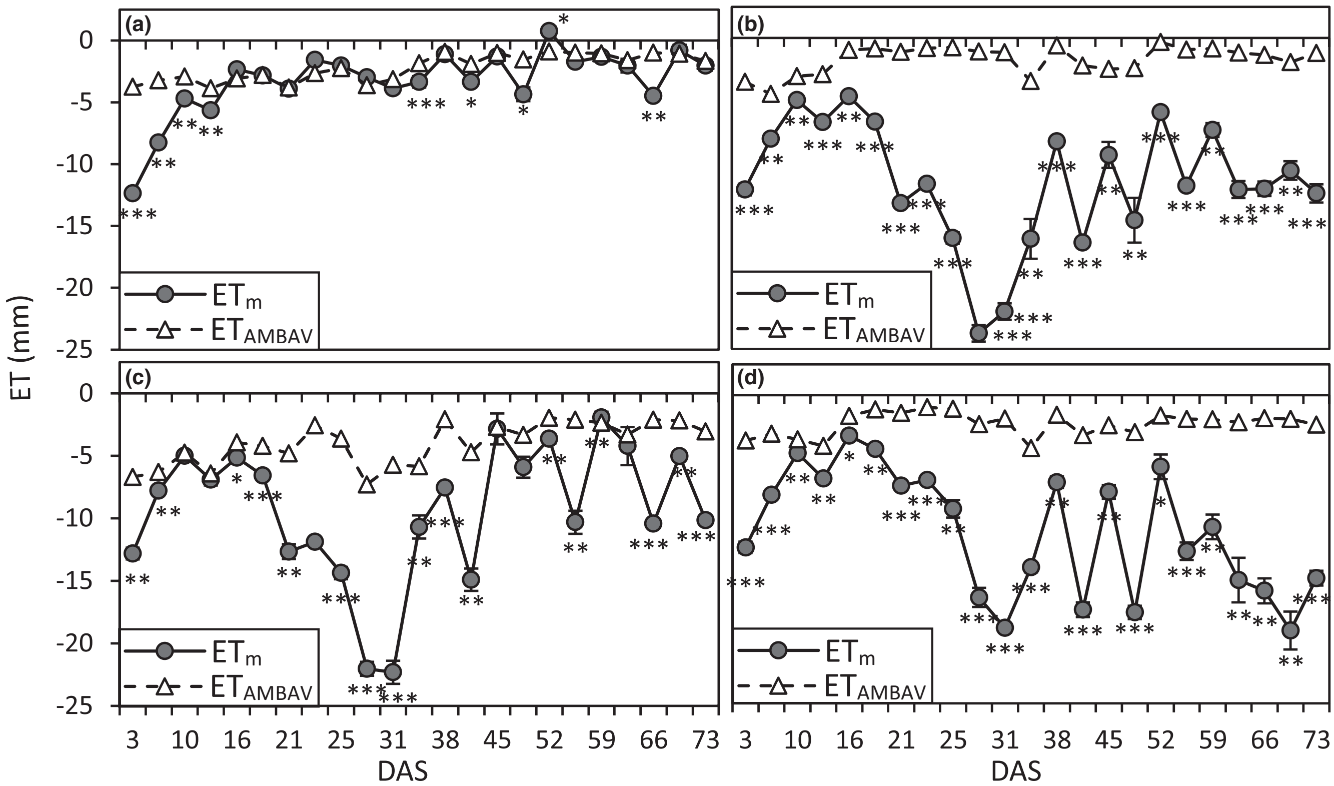

FIGURE 2 Comparison of simulated (ET_{AMBAV}, Δ) and measured (ET_m, ●) evapotranspiration of (a) a bare fallow, (b) white mustard, (c) oilseed radish and (d) phacelia throughout the vegetation period from August 24, 2020, until harvest at 74 DAS. Comparison of ET_m and ET_{AMBAV} with a two-sided Student's *t*-test (**p* < .05; ***p* < .01; ****p* < .001). Mean values (*n* = 4) ± SE.

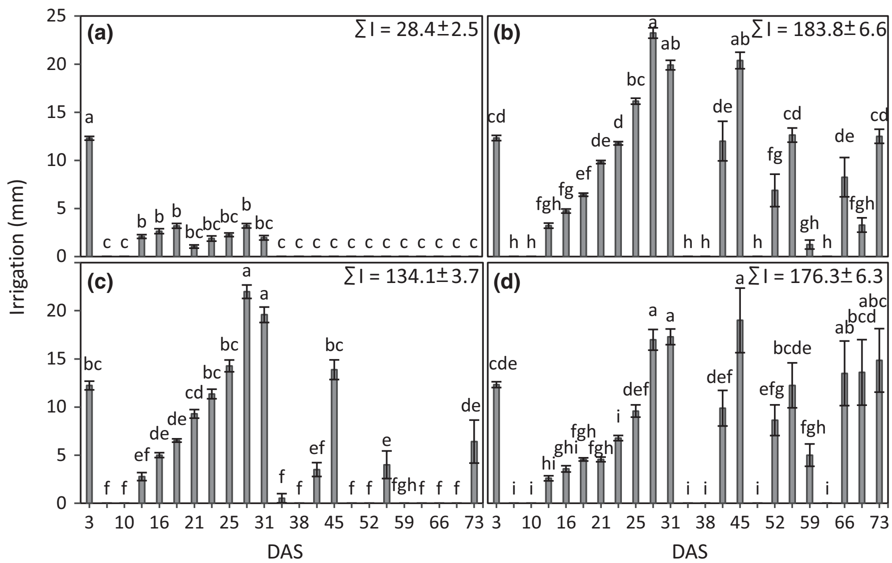

FIGURE 3 Irrigation to (a) a bare fallow, (b) white mustard, (c) oilseed radish and (d) phacelia during the vegetation period 2020 until harvest at 74 DAS. One-way ANOVA and comparison of means adjusted according to FDR for irrigation. Different letters indicate significant differences (*p* < .05). Mean values (*n* = 4) ± SE.

fallow showed a close resemblance of ET_m (Figure 4a). Overall, discrepancies between ET_{AMBAV} and ET_m of the cover crops were not as severe as in 2020. Similar to 2020, discrepancies became more pronounced 20–23 DAS (Figure 4b–d). The maximum difference between ET_{AMBAV} and ET_m amounted to 18.8, 10.6 and 9.3 mm for white mustard, phacelia and oilseed radish 34 DAS, respectively.

With 35.2 mm total precipitation during the vegetation period was 60% less in 2021 than in 2020 (Figure 1). However, the amount of irrigation water needed was <80% of irrigation in 2020 (Figures 3 and 5) due to the reduction of soil moisture.

The better performance of AMBAV with data from 2021 was also reflected in the statistical indicators, which describe model performance (Table 3). With a difference of just 4 mm, model

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TABLE 3 Comparison of simulated (ET_{AMBAV}) and measured (ET_m) evapotranspiration of three cover crops and a bare fallow based on different statistical criteria.

	Bare fallow	White mustard	Oilseed radish	Phacelia
2020				
$\sum ET_m$ (mm)	−75.5	−268.0	−215.0	−256.1
$\sum ET_{AMBAV}$ (mm)	−50.5	−40.0	−92.0	−53.8
R^2	0.39	0.00	0.28	0.04
NSE	0.2	−4.2	−0.8	−3.1
RMSE (mm)	1.3	11.0	6.5	9.8
MAE (mm)	1.5	9.9	5.4	8.8
2021				
$\sum ET_m$ (mm)	−40.5	−197.5	−148.3	−150.5
$\sum ET_{AMBAV}$ (mm)	−36.5	−32.7	−82.3	−45.3
R^2	0.59	0.11	0.44	0.02
NSE	0.6	−3.3	−0.4	−3.9
RMSE (mm)	0.7	10.6	4.8	6.4
MAE (mm)	1.2	9.2	4.4	6.0

Abbreviations: ∑ET, cumulative evapotranspiration; MAE, mean absolute error; NSE, Nash–Sutcliffe efficiency; R^2, coefficient of determination; RMSE, root mean square error.

performance for the bare fallow was very good. This impression was confirmed by the high R^2, high NSE and low RMSE and MAE (Table 3). For the cover crop treatments, performance of AMBAV was best for oilseed radish ($R^2=0.44$). For white mustard, AMBAV model performance was better in 2021 than in 2020. The most pronounced improvement was the 11% increase of R^2 which was coupled with slight improvements of the other statistical criteria (Table 3). There was also a slight improvement in the accuracy for phacelia: In 2020, $\sum ET_{AMBAV}$ was 79% lower than $\sum ET_m$. In 2021, $\sum ET_{AMBAV}$ was 70% of $\sum ET_m$. The errors decreased from RMSE = 9.8 and MAE = 8.8 in 2020 to RMSE = 6.4 and MAE = 6.0 in 2021. However, R^2 and NSE for phacelia decreased, which indicates that almost no variability of ET_m was detected by ET_{AMBAV}, and it failed to precisely predict peaks of ET_m.

Based on RMSE and MAE, the performance of AMBAV in 2021 followed the same order as in 2020. However, based on R^2 and NSE, the performance of AMBAV in 2021 followed the order: Bare fallow > oilseed radish > white mustard > phacelia.

3.2 | Sensitivity analysis

The sensitivity analysis (Figure 6) showed for all treatments that changes in temperature and relative humidity had the greatest influence on $\sum ET_{AMBAV}$. For the meteorological data from 2020 (Figure 1a), a 50% reduction of mean daily temperature led to an increase of $\sum ET_{AMBAV}$ by 61% and 27% for phacelia and oilseed radish, respectively, while $\sum ET_{AMBAV}$ of white mustard was unaffected by a temperature decrease and simulated evaporation of the bare fallow even decreased by 13% (Figure 6a). With increasing temperature $\sum ET_{AMBAV}$ decreased in all treatments by up to 52% (oilseed radish) (Figure 6a). Similar results were found for the vegetation period 2021 for oilseed radish (Figure 6b). However, $\sum ET_{AMBAV}$ of phacelia was less sensitive to changes in temperature in 2021 compared with 2020.

The influence of relative humidity on $\sum ET_{AMBAV}$ was even more pronounced than that of changes in temperature (Figure 6c,d). In 2020, a change of relative humidity by −50% and +50% resulted in a change of $\sum ET_{AMBAV}$ by +76% (oilseed radish) to +119% (bare fallow) and −44% (oilseed radish) −68% (bare fallow), respectively (Figure 6c). The analysis for the vegetation period 2021 supported this highly sensitive reaction of $\sum ET_{AMBAV}$ to changes in relative humidity (Figure 6d).

The model was less sensitive to changes in wind speed (Figure 6e,f) and precipitation (Figure 6g,h), although a close correlation between water supply and ET_m was shown (Figures 2 and 3). Due to higher total water availability in 2020, when soil moisture was kept at 50% WHC, increasing precipitation resulted in a <5% increase of $\sum ET_{AMBAV}$ (Figure 6g). In comparison, changes in precipitation had a more pronounced effect on $\sum ET_{AMBAV}$ in 2021 when soil moisture and total precipitation were lower (Figure 6h). The effect of decreasing precipitation was most significant for white mustard in that year while $\sum ET_{AMBAV}$ of oilseed radish was hardly affected by these changes at all.

Out of all the parameters tested, the model was least sensitive to changes in irrigation: An increase in irrigation of up to 50% only resulted in a <1% increase of $\sum ET_{AMBAV}$ in both years (Figure 7).

Out of the two plant-specific parameters tested in this study, changes in maximum leaf area index (LAI_{max}) had the highest influence on $\sum ET_{AMBAV}$ for phacelia and oilseed radish while $\sum ET_{AMBAV}$ response of white mustard was somewhat inconsistent with changes in LAI_{max} (Figure 8). $\sum ET_{AMBAV}$ of oilseed radish decreased by 12% with a 50% reduction of LAI_{max} and increased by 2% with a 50% increase in LAI in 2020 (Figure 8a). $\sum ET_{AMBAV}$ of phacelia responded similarly to changes in LAI_{max} in 2020 (Figure 8a) while the changes were less pronounced in 2021 (Figure 8c). Changes in maximum plant height (h_{max}) resulted in changes of $\sum ET_{AMBAV} < \pm 5\%$ for all three crops in 2020 (Figure 8b) and 2021 (Figure 8d). Consistent with results for changes of LAI_{max}, $\sum ET_{AMBAV}$ of oilseed radish and phacelia was more sensitive to changes of h_{max} than $\sum ET_{AMBAV}$ of white mustard.

4 | DISCUSSION

4.1 | Methodology as the main source for discrepancies between ET_m and ET_{AMBAV}?

The results presented above clearly show that ET_m exceeded ET_{AMBAV} for all three cover crops (Figures 2 and 4), indicating that AMBAV is not suitable to simulate ET of cover crops grown in container technology. The magnitude of the discrepancy is surprisingly

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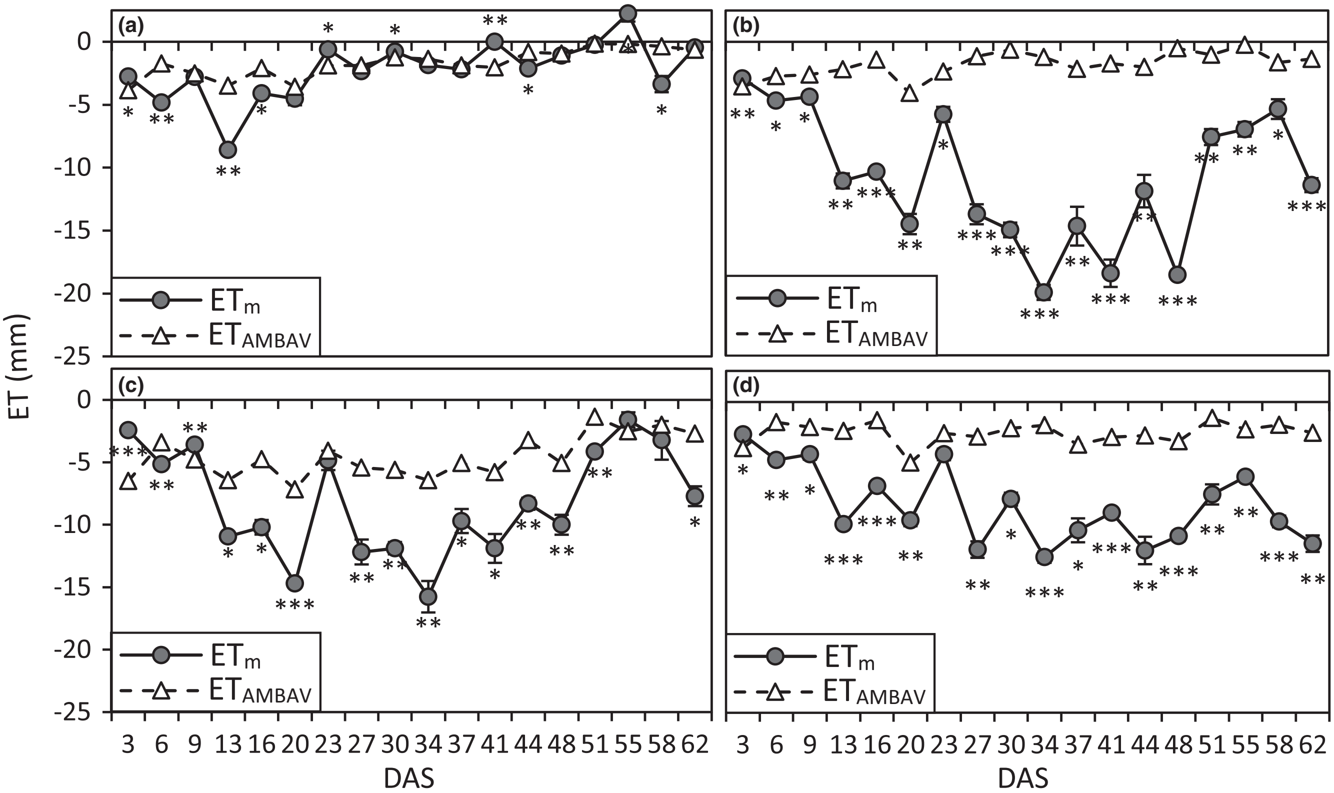

FIGURE 4 Comparison of simulated (ET_{AMBAV}, Δ) and measured (ET_m, ●) of (a) a bare fallow, (b) white mustard, (c) oilseed radish and (d) phacelia throughout the vegetation period from August 25, 2021, until harvest at 63 DAS. Comparison of ET_m and ET_{AMBAV} with a two-sided Student's *t*-test (*$p<.05$; **$p<.01$; ***$p<.001$). Mean values ($n=4$) ± SE.

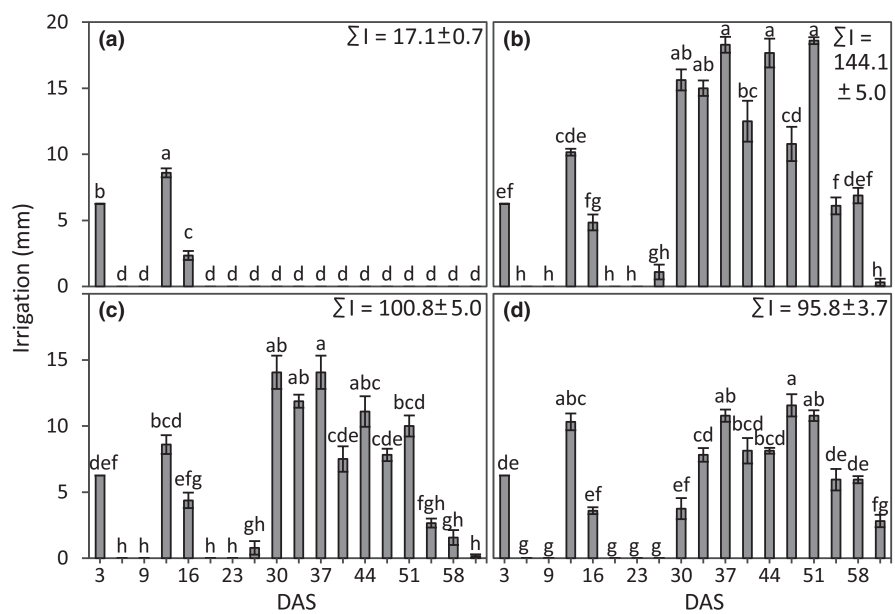

FIGURE 5 Irrigation to (a) a bare fallow, (b) white mustard, (c) oilseed radish and (d) phacelia during the vegetation period 2021 until harvest at 63 DAS. One-way ANOVA and comparison of means adjusted according to FDR for irrigation. Different letters indicate significant differences ($p<.05$). Mean values ($n=4$) ± SE.

high considering that the model was parametrized especially for these crops. Hence, we must assume that the discrepancy is likely to be a result of differences between the experimental setup of the container trial and the field lysimeter experiment which the DWD used for the parametrization of AMBAV. We chose to conduct our experiments in containers instead of a field trial to avoid

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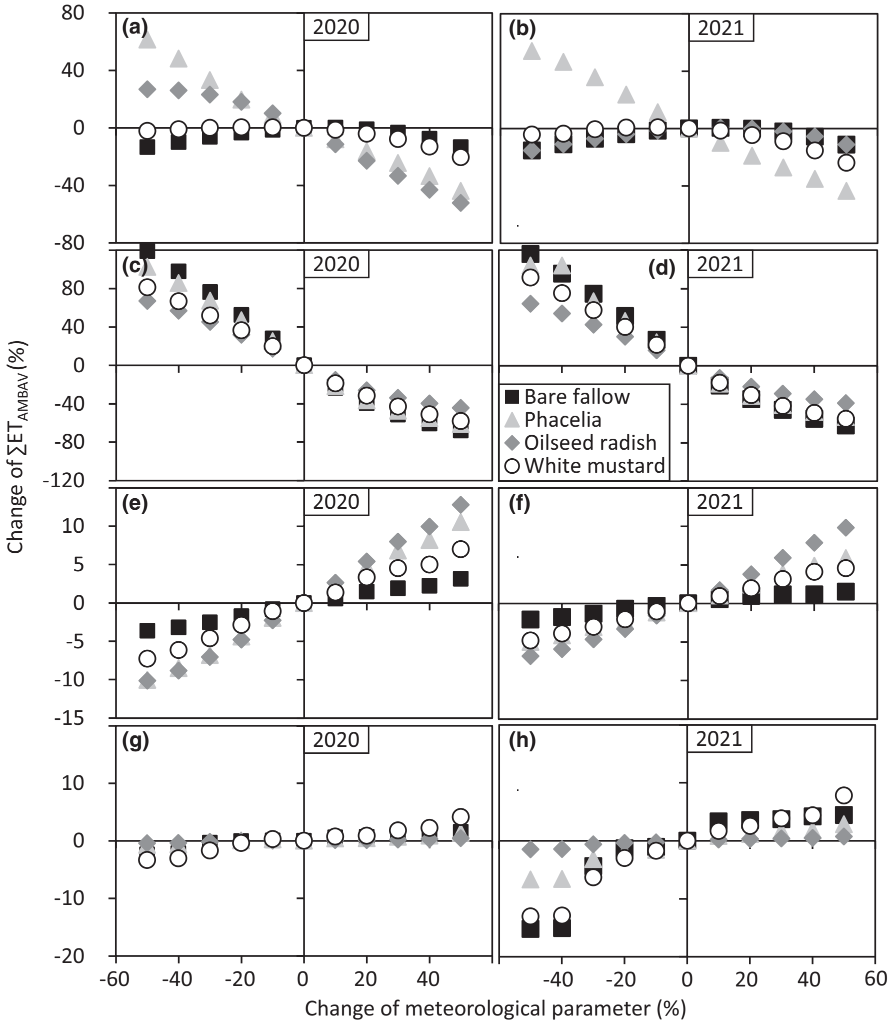

FIGURE 6 Sensitivity analysis for AMBAV simulation of cumulative evapotranspiration ($\sum ET_{AMBAV}$) based on meteorological data (Figure 5) at the experimental station of the Institute of Plant Nutrition in Giessen (50°35′53.30″N, 8°40′1.56″E) for the vegetation periods 2020 and 2021. Influence of percentage change (±50%) of measured temperature (a, b), wind speed (c, d), relative humidity (e, f) and precipitation (g, h) on $\sum ET_{AMBAV}$ of a bare fallow (■), phacelia (▲), oilseed radish (♦) and white mustard (○).

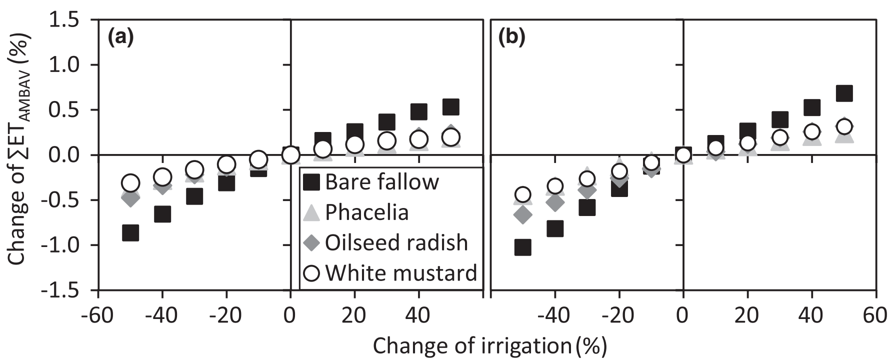

FIGURE 7 Sensitivity analysis for AMBAV simulation of cumulative evapotranspiration ($\sum ET_{AMBAV}$) based on irrigation during the vegetation periods 2020 and 2021. Influence of ±50% change of irrigation (min. = 0 mm) of a bare fallow (■), phacelia (▲), oilseed radish (♦) and white mustard (○) on $\sum ET_{AMBAV}$ of the same treatments in (a) 2020 and (b) 2021.

typical problems associated with other forms of ET measurements, e.g., spatial and vertical variability of soil properties, unquantifiable deep percolation losses and other factors affecting the accuracy of ET measurements, which are explained extensively by Allen et al. (2011a).

Here, we want to illustrate a few of the methodological differences that are likely to have impacted ET_m and ET_{AMBAV}:

1. The cover crops were manually irrigated with a watering can twice a week to keep soil moisture at 50% WHC in 2020 and 45% WHC in 2021. The option 'irrigation' in AMBAV only provides the choice between 'drip' or 'sprinkler' irrigation. By choosing 'drip' irrigation the model calculated ET_{AMBAV} under the assumption that the irrigation water was supplied evenly over the specified time range and not instantaneous, as was the case in the container experiment. Thus, the actual water content of the topsoil might have differed from the simulated water content. This would also explain why, except phacelia, model performance was generally better in 2021 (Table 3) when the amount of irrigation was reduced to keep soil moisture at 45% WHC.

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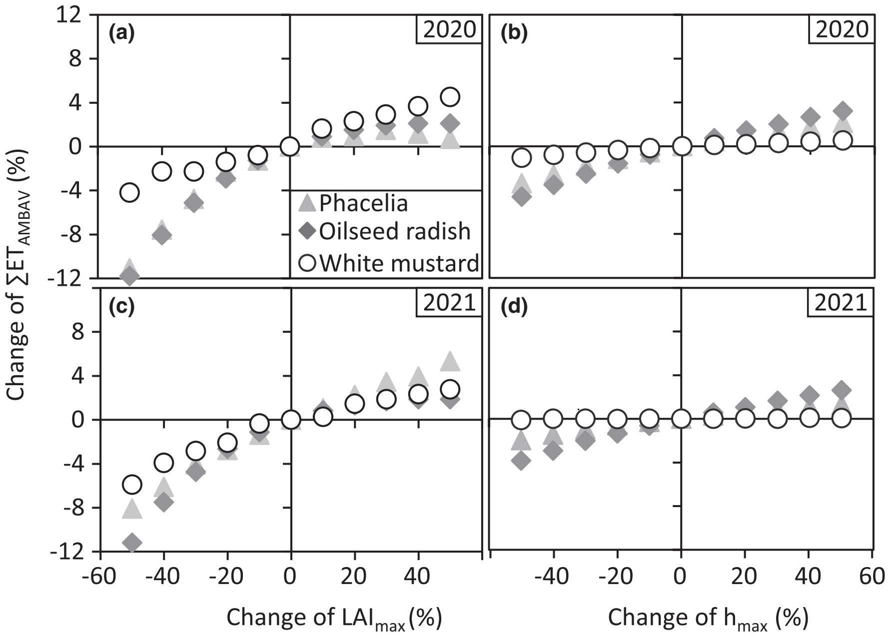

FIGURE 8 Sensitivity analysis for AMBAV simulation of cumulative evapotranspiration ($\sum ET_{AMBAV}$) based on plant-specific parameters from the vegetation periods 2020 and 2021. Change of $\sum ET_{AMBAV}$ in response to $\pm$50% change of maximum leaf area index (LAI_{max}) (a, c) and maximum crop height (h_{max}) (b, d) of phacelia (▲), oilseed radish (♦) and white mustard (○).

2. The model simulates soil water content (SWC) at a given soil bulk density and soil type (Table 1) and uses these data to calculate ET. However, the confinement of the soil in the containers might have inhibited the natural flow of water in the soil leading to a higher SWC than under field conditions, where water can 'escape' not only vertically but also horizontally. In the container experiment, high SWC in the topsoil could have resulted in increased ET_m while the model calculated ET_{AMBAV} for field conditions.
3. The containers were set up closely together to minimize wind exposure. However, since containers were moved regularly and the bare fallow containers were mixed with the containers for cover crop cultivation, a closed soil cover with minimum wind exposure similar to field conditions could not be achieved. It is likely that wind had a stronger influence on ET_m in the container experiment than shown in Figure 6e,f for ET_{AMBAV}. The influence of wind on ET is more pronounced under dry air conditions than under humid conditions (Allen et al., 1998) which relates well to the high ET_m losses during the first 38 DAS in 2020 (Figure 3) when humidity was low and temperature was relatively high, as well as to lower ET_m losses from 52 DAS onwards when humidity was higher (Figure 1).
4. Another aspect that needs to be considered is differences in soil temperature. Daily soil temperature fluctuations are more pronounced when using the container technology than under field conditions (Figure S1). Deviating from field conditions, the soil in the containers is subjected to atmospheric temperature and solar radiation. In the field, the surrounding soil acts as a buffer that regulates soil temperature. Since this buffer is missing in container experiments, the soil is heating and cooling more quickly than under field conditions. In addition, the dark green colour of the containers can cause an increased absorption of solar radiation thereby increasing the already existing temperature differences. Soil temperature is an important factor for evaporation. Quick heating of the soil promotes soil evaporation (Allen et al., 1998) and could have contributed to higher ET_m losses that were not recognized by the model.

For the identification of how significant the methodological error was, the best-performing treatment needs to be considered. Based on the statistical criteria, AMBAV performed best in the simulation of evaporation from a bare soil surface (Table 3), which means that only a discrepancy of 25 mm and 4.0 mm can be explained by the above-mentioned methodological differences (1) to (4) in 2020 and 2021, respectively (Table 3). The vast majority of the error, however, was caused by crop-specific parameters which determine transpiration losses. These parameters (LAI, height, rooting depth) were closely monitored.

The experimental setup only allowed a maximum rooting depth of approximately 70 cm. This does not represent all field conditions where oilseed radish has been shown to reach rooting depths of >2 m (Thorup-Kristensen, 2006). However, the sensitivity analysis showed that changes of rooting depth did not have a significant influence on ET_{AMBAV} (max. $\pm$0.01% change of ET_{AMBAV} with $\pm$50% change of rooting depth), which indicates that rooting depth is negligible for ET simulations with AMBAV (data not shown).

Since LAI is the main variable in computer models for the calculation of photosynthetic activity and ET (Weiss et al., 2004), we might assume that LAI measurements in this study conducted with the ACCUPAR LP-80 PAR/LAI Ceptometer, henceforth abbreviated 'LP 80', were not accurate enough for the model. Adeboye et al. (2019) have shown that LAI measurements with the LP 80 overestimate LAI in the initial growth phase of soybeans and once LAI reaches $\geq$1.11 $m^2 m^{-2}$, the ceptometer underestimates LAI. Although a very good correlation ($R^2 \geq 0.85$) was found between LAI measured with the LP 80 and measurements with the central leaflet width method, the underestimation in the mid-season amounted to a difference of

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up to approximately 2 $m^2 m^{-2}$ (Adeboye et al., 2019). Additionally, Pokovai and Fodor (2019) have shown that the accuracy of LAI measurements with LP 80 is highly sensitive to light conditions. They conclude that inadequate light conditions of plant-available radiation (PAR) <1700 $\mu mol\, m^{-2} s^{-1}$, which are common during the winter cover crop growing season in Germany, lead to an underestimation of LAI. Especially towards the end of the vegetation period of the container experiment PAR even fell below 600 $\mu mol\, m^{-2} s^{-1}$ during the measurements, which were taken at the same time of day on a weekly basis. It is likely, therefore, that LAI_{max}, which was used for calculation of ET_{AMBAV}, was underestimated and caused $ET_{AMBAV} < ET_m$ in this study. Correction of LAI measurements on overshadowed days should be considered in future experiments.

Moreover, the methodological error could be minimized by using lysimeters, which are inserted into the ground to quantify ET losses instead of using large containers in an above-ground setting. In lysimeter experiments, the factors wind exposure and soil temperature should be similar to the surrounding field conditions allowing for precise ET determination (Rafi et al., 2019).

4.2 | Arguments against methodology as the sole reason for discrepancies between ET_m and ET_{AMBAV}

Although significant differences between the container technology and field experiments are apparent, based on the results presented above we cannot assume that these were the sole reasons for the strong discrepancies between ET_m and ET_{AMBAV}. The following arguments suggest that the model itself needs further optimization for a reliable application for ET simulation of cover crops:

1. It seems that the water input through irrigation is not recognized by the model. Although significant amounts of water were added to the soil in times of high evaporative and transpirative water losses, ET_{AMBAV} did not peak after this additional water input. Changes in the amount of irrigation rarely had an effect on ET_{AMBAV} (Figure 7). This insensitivity cannot be a simple result of differences in soil moisture after irrigation between field conditions and the container technology, as suggested above. According to the technical documentation of the model, total precipitation (P_t) is defined as the sum of natural rainfall (P) and irrigation (I) (DWD, 2021), suggesting that both parameters should have the same weight for the calculation of ET_{AMBAV}. However, the sensitivity analysis showed that the model was less sensitive to changes in irrigation (Figure 7) than to changes in precipitation (Figure 6g,h). This assumption is supported by the close relationship between ΔET ($\Delta ET = \sum ET_m - \sum ET_{AMBAV}$) and $\sum I$ (Figure S2). The higher sensitivity of ET_{AMBAV} to natural rainfall can be partly explained by the fact that while irrigation water was applied directly to the soil, natural rainfall can be intercepted by leaves, thus increasing direct evaporation of water from the leaf surface resulting in higher $\sum ET_{AMBAV}$. If this were to be the main reason for the differences in sensitivity, we would expect the crop with the highest soil coverage (LAI_{max}), that is, the highest rain storage capacity (s_{max}), to have the highest $\sum ET_{AMBAV}$ under high-precipitation conditions. According to Figure 6g,h this was clearly not the case. In fact, oilseed radish had the highest LAI_{max} in both years but was least sensitive to changes in precipitation. This is likely due to the restriction of soil evaporation under a closed biomass cover (Allen et al., 1998). Furthermore, it must be noted that (1) evaporation of intercepted water can only occur after leaves are wetted by natural rainfall and that (2) the transpiration rate from wet leaves is lower than that of dry leaves (Klaassen et al., 1998). Consequently, the effects of higher evaporation and lower transpiration after natural rainfall may override each other. We therefore come to the conclusion that in times of high irrigation, the model is not able to reliably predict ET.
2. Simulated evaporation from a bare soil surface hardly differed from ET_{AMBAV} of the three cover crops during both vegetation periods (Figures 4 and 6), indicating that the model underestimates transpiration losses. For instance, bare soil evaporation was higher than ET_{AMBAV} of white mustard and phacelia several times in 2020 and 2021 although these crops had already produced a significant amount of biomass and soil coverage (Figure S3). Factors that are included in the calculation of transpiration losses in AMBAV are the aerodynamic resistance (r_a) and the canopy resistance (r_c). While r_a affects the water-vapour transfer between the crop and the atmosphere that surrounds the crop, r_c is a term that describes the water transfer within the crop as well as the water transfer within the soil. Therefore, calculation of r_c requires knowledge of vegetation resistance (r_v) and soil resistance (r_s) (DWD, 2021). Vegetation resistance (r_v) depends on leaf stomatal resistance which is highly influenced by meteorological conditions such as light intensity, humidity and vapour pressure deficit (VPD) (Damour et al., 2010). However, the AMBAV GUI V0.9509 uses 'fixed daytime and nighttime leaf stomatal resistances' for white mustard and phacelia (DWD, 2021). Thus, crop-specific variations of r_s during the course of the day cannot be reflected by ET_{AMBAV} and might explain the under-estimation of transpiration losses which resulted in poor model performance for these crops (Table 3). For oilseed radish, which had an overall better model performance (Table 3), a parametrization was already prepared for AMBAV (DWD, 2021) following the Jarvis model (Jarvis, 1976). Parametrization of phacelia and white mustard for AMBAV could improve estimation of transpiration and thereby improve the accuracy of the simulation output. Helle (2021) has performed measurements of stomatal conductance on all three cover crops for implementation in AMBAV. It will have to be tested whether this leads to an improvement in model performance once the adjusted model is available.
3. The driving force for ET is solar radiation which not only provides the energy for water vaporization but also heats the atmosphere, thereby increasing air temperature and VPD (Allen et al., 1998). VPD is furthermore influenced by humidity: The higher the relative humidity, the lower the evapotranspirative demand of the

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atmosphere (Allen et al., 1998). Thus, high ET losses generally occur on clear (high radiation), warm (high temperature) and dry (low humidity) days. It is peculiar, therefore, that the sensitivity analysis showed a general decrease of ET_{AMBAV} with increasing temperature for phacelia (2020) and oilseed radish (2020, 2021) (Figure 6a,b). Considering the quick development of the cover crops (Figure S3), we can assume that ET was governed by transpiration during most of the vegetation period. As mentioned above, transpiration is determined by a combination of meteorological conditions and crop-specific factors such as stomatal conductance. Based on the multiplicative relationship between different environmental drivers which affect stomatal conductance (g_{st}) proposed by Jarvis (1976), AMBAV calculates g_{st} as follows (Equation 6):

$$g_{st} = g_{st,max} \prod_{i=1}^{n} F_{v,i}. \tag{6}$$

with $g_{st,max}$ = crop-specific maximum leaf stomatal conductance in m s^{-1}, n = number of drivers considered for the calculation of g_{st}, and $F_{v,i} = F_v(\mathrm{VPD}) \cdot F_v(T_a) \cdot F_v(S_\downarrow) \cdot F_v(\theta)$ with VPD = vapour pressure deficit in kPa, T_a = air temperature in °C, $S_\downarrow$ = shortwave radiation in W m^{-2} and θ = volumetric SWC in m^3 m^{-3}. It is widely accepted that in addition to these drivers, stomatal conductance is affected by ambient CO_2 concentration (Jarvis, 1976; Kirschbaum & McMillan, 2018). For simplification of the modelling process and due to the short-term nature of crop cultivation, atmospheric CO_2 concentrations are considered to be constant at 400 ppm in the simulation. Equations for the calculation of the single drivers can be derived from DWD (2021). The dependence of g_{st} on temperature is given by $F_v(T_a)$ which is defined as (Equation 7):

$$F_v(T_a) = \left[\frac{(T_a - T_{min})(T_{max} - T_a)}{(T_{opt} - T_{min})(T_{max} - T_{opt})} \right]^c \quad (0 \le F_v(T_a) \le 1). \tag{7}$$

with T_{min} = crop-specific minimum temperature in °C (T_{min} = 0°C (Helle, 2021)), T_{max} = crop-specific maximum temperature in °C (T_{max} = 40°C (Helle, 2021)), T_{opt} = crop-specific constant and $c = (T_{max} - T_{opt})/(T_{opt} - T_{min})$ (DWD, 2021). T_{opt} values for the three cover crops proposed by Helle (2021) are 15°C, 24°C and 16°C for white mustard, oilseed radish and phacelia, respectively. Thus, we would expect maximum stomatal conductance ($F_v(T_a) = 1$) and maximum transpiration to be reached at these temperatures if all other drivers are neglected. Due to the comparatively high T_{opt} of oilseed radish, we would also expect this cover crop to have higher transpiration losses when temperature increases than white mustard and phacelia which have approximately the same T_{opt}. Calculating the temperature dependent term $F_v(T_a)$ for the meteorological data on which we based our sensitivity analysis confirms these assumptions (Figure S4a,b). However, this increase in stomatal conductance with increasing temperature is not reflected in Figure 6a,b, eliminating this explanation.

Another possible explanation for decreasing ∑ET with increasing temperature is stomatal closure to prevent water losses at high atmospheric temperatures (Damour et al., 2010). When ambient air temperature significantly surpasses T_{opt}, stomata close, that is, $F_v(T_a) \approx 0$. Consequently, g_{st} decreases to values close to zero. We tested this by calculating $F_v(T_a)$ for each measuring point. The number of values where $F_v(T_a) < 0.1$ (near stomatal closure) was higher for white mustard and phacelia than for oilseed radish in both years (Figure S4c,d) so that stomatal closure at high/low temperatures cannot explain the unexpected relationship between changes in temperature and ∑ET for oilseed radish.

The sensitivity analysis shown in Figure 6 was performed several times with the same results and the technical documentation for AMBAV does not provide a satisfying explanation as to why a temperature increase might cause a decline of ET_{AMBAV} apart from the two possibilities discussed above. Further insight into the programming script behind the calculations would be necessary to identify the cause for this finding.

4.3 | Sensitive parameters for simulation of ET_{AMBAV}

The sensitivity analysis showed that, differently than hypothesized, ET_{AMBAV} is most sensitive to changes in temperature and humidity and not to changes in water supply (Figure 6). Changes in irrigation and precipitation did not affect ET_{AMBAV} although we found a highly significant relationship between water supply and ET_m ($p < .001$). As previously discussed, this could be due to methodological differences and internal model configurations.

As for the crop-specific parameters, the sensitivity analysis confirmed our hypothesis that ET_{AMBAV} is most sensitive to changes in LAI_{max}. The general increase of ET_{AMBAV} with increasing LAI_{max} for all three cover crops (Figure 8) clearly shows that the increased water loss through transpiration outweighs the reduction of evaporation losses with increasingly closed soil cover (Allen et al., 1998). Due to the comparably high sensitivity to this parameter, the analysis furthermore shows that when using AMBAV for irrigation scheduling or other applications, using the default LAI_{max} provided by model can result in a severe under- or overestimation of actual ET. This is in agreement with Kroes et al. (2006) who recommend farmers to provide their own crop and soil-specific data to reduce the uncertainty of the model. Since manual measurements are time-consuming, digital imaging could be a solution for farmers. Different web-based and mobile applications have been developed in recent years to estimate soil cover based on digital images taken approximately 1 m above the ground (Riegler-Nurscher et al., 2018) or—depending on field size—on drone or satellite imaging (Kavoosi et al., 2020). These applications allow for a precise pixel-wise classification to distinguish between soil, stones, living and dead plant material (Riegler-Nurscher et al., 2018). The suitability of this soil cover data for estimation of LAI_{max} and its use for simulation of ET_{AMBAV} should be investigated further to provide farmers with an appropriate method to quickly determine LAI non-destructively for precise ET prognoses.

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In the same way as LAI, using meteorological data (temperature and humidity) from a nearby meteorological station cannot guarantee reliable simulation of cover crop ET since regional deviations of relative humidity and temperature have been shown to have a significant influence on ET_{AMBAV} (Figure 6). It is not realistic, however, that farmers monitor meteorological conditions for each of their fields to obtain more reliable ET prognoses.

5 | CONCLUSIONS

The study has shown that measured evapotranspiration (ET_m) losses in a container experiment with three different cover crops were underestimated by the simulation with AMBAV. Sensitivity analysis showed that ET_{AMBAV} is most sensitive to changes in temperature, humidity and LAI_{max} while changes in wind speed, water supply and crop height only had minor effects on ET_{AMBAV}. The poor performance of AMBAV in the given study is partly due to the experimental setup which strongly differed from the conditions under which the initial parametrization of the cover crops for AMBAV took place. In addition, the model parametrization for the cover crops needs further optimization through validation trials under various climatic conditions. Especially (a) the influence of irrigation on total ET losses and (b) cover crop transpiration should be investigated in more detail to allow for reliable simulations. Furthermore, we found that ET_{AMBAV} is highly dependent on the accuracy of the input data. Using the default data of the model can lead to a severe deviation of ET_{AMBAV} from actual ET which farmers should bear in mind when using simulated data for irrigation scheduling or other applications.

AUTHOR CONTRIBUTIONS

Tabea Selzer: Conceptualization; investigation; writing – original draft; writing – review and editing. **Sven Schubert:** Conceptualization; writing – review and editing; supervision.

ACKNOWLEDGEMENTS

We thank the German Meteorological Service (DWD) for the provision of the AMBAV Global graphical user interface (GUI). We are especially grateful for the assistance and advice by Dr. Torben Meinert and Dr. Eva Falge. Open Access funding enabled and organized by Projekt DEAL.

FUNDING INFORMATION

This research did not receive any specific grant from funding agencies in the public, commercial or not-for-profit sector.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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How to cite this article: Selzer, T., & Schubert, S. (2023). Cover crop water consumption: Analysing performance of the agrometeorological model for the calculation of actual evapotranspiration (AMBAV) in a container experiment. *Journal of Agronomy and Crop Science*, *209*, 747–760. https://doi.org/10.1111/jac.12656

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