C-Factor Mapping Using Remote Sensing and GIS

A Case Study of Lom Sak / Lom Kao, Thailand

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1. Introduction

1.1. Background

Vegetation cover acts as a kind of buffer layer between the atmosphere and the soil. Leaves and stems as above-ground components of plants absorb some of the energy of raindrops and surface water. Below-ground components as the root system contribute to the mechanical strength of soil. Interception decreases the volume of rain reaching the soil surface. The effectiveness of the plant cover in reducing the raindrop impact depends on the height and the continuity of the canopy and the density of the ground cover. The height is important because water drops falling from trees can attain high percentages of their prior velocity. In addition large drops may form on leaves which are more erosive than the original raindrops. Stemflow can also concentrate rainfall at the ground surface. A further effect of vegetation and litter is the reduction of overland flow. Plants reduce the runoff velocity and protect surface pores, sustaining infiltration. The level of runoff reduction depends upon morphology and the density of plants, as well as their height in relation to the depth of flow. Greatest reductions in velocity occur with dense, spatially uniform, vegetation covers.

The cover management factor is one of the most important parameters of the Universal Soil Loss Equation (USLE) since it measures the combined effect of all interrelated cover and management variables and it is the factor which is most easily changed by men (FOLLY et al. 1996). It is defined as the ratio of soil loss under a given crop to that from bare soil. Generally the C-factor will range between 1 and almost 0. Hereby C=1 means no cover effect and a soil loss comparable to that from a tilled bare fallow. C=0 means a very strong cover effect resulting in no erosion.

For land cover types like forest, range lands and undisturbed areas a subfactor method was developed to compute separately the effects of canopy cover, ground cover, root density etc. (KOOIMAN, 1984). This method gives a numerical value to each subfactor, which are later used to compute an overall C-factor for this particular cover type. Since the soil loss varies with the morphology and density of the plant cover it becomes necessary to take in account the changes of vegetation cover within a year and thus arriving at an annual value. Therefore the year is divided into different stages of crop growth. Using large number of erosion studies in the United States ratio values for different crops in different growing periods were obtained. Taking in account the correspondence of the annual status of plant cover (this counts mainly for crops) with periods of highly erosive rain the C-Factor of the same crop will vary in different geographical locations. Consequently the C-factor is calculated as the sum of the soil loss ratios and EI (total storm energy (E) times the maximum 30-min intensity (I_{30})) values and therefore depends on the crop development and the rainfall distribution over the year (WISCMEIER and SMITH 1978). However, in many countries detailed information for computing the C-factor in this way does not exist (MORGAN 1996).

1.2. Research Objectives

Attempts to study land degradation processes and the necessity of degradation prediction have resulted in the creation of erosion models. One of the major problems with modelling is how to obtain the necessary information. Data requirements are large and include information on vegetation cover and soil properties, which can only be measured directly in the field or can be derived from other kinds of data such as supplied by remote sensing. However, field surveys are labour intensive and expensive and yield normally only information of one geographical location. For many applications these expenses are not feasible and remote sensing techniques may prove as a useful alternative. However, it has to be understood that remote sensing does not measure attributes as land cover directly. Remote sensing provides row data from which the needed information has to be derived. This always requires ground truth data, which makes some field survey necessary.

The aim of this study is to investigate the use of remote sensing in order to obtain information on land cover, which can be transformed into the USLE C-factor. The following two main research objectives were formulated:

- Application of different techniques in order to obtain C-factor values of for the different land cover types in the study area of Lom Sak / Thailand

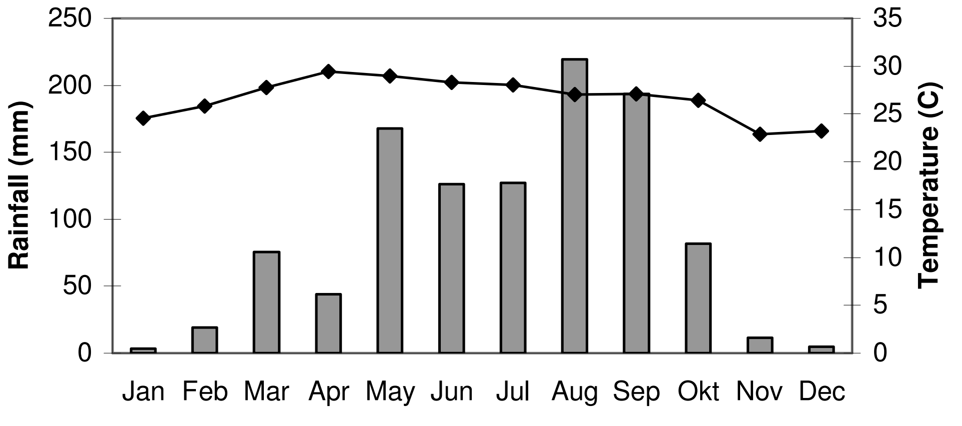
- Comparison and valuation of these techniques, especially with respect to field data requirements.

2. Description of the Area

The study area is located in the Lom Sak and Lom Kao districts, in the province of Petchabun, in the north of Thailand. It covers an area of approximately 240 km^2 between the latitudes 16°47' and 17°52' N and the longitudes 101°09' and 101°14' E. Elevation varies from 114 m to 1023 m above sea level. The present geomorphic configuration of the Pasak river area is the result of tectonical, denudational and sedimentation processes. Mountains, hillands, piedmont and the Pasak river valley build the major landscape units of the study area. Soils vary according to these different geomorphological units. Most common soils are Inceptisols in the valley, Alfisols and Ultisols in the Piedmont areas. Mollisols occur in mountains, hillands and piedmont landscapes under natural vegetation and Entisols are found on steep and very steep slopes of the mountains and hillands.

The climate is humid tropical, influenced by north-eastern and south-western monsoons. It is characterized by high humidity, moderate to high temperature and a distinct climatic variation between dry and wet season. The mean monthly temperatures and mean monthly rainfall of the time period between 1987-1996 are shown in Figure 1.

Figure 1: Climatic data diagram of the study area (1987-1996)



Extracted from HASANKADI (1998:27)

The cropping period is between April/May and October, which can be considered as the rainy season. The main food crop in the area is rice. It is grown during the rainy season in the valley and on low glacis terraces and followed by second crops such as tobacco, mungbean, chilli and other vegetables. In the valley coconut palm, mango and other fruit trees are grown on levees, which are mainly occupied by settlements. The lower undulating and rolling areas of the high glacies, hillands and low mountains are used for the cultivation of corn, bean and peanuts. In addition sweet tamarind plantations are increasingly covering hilland and the lower mountain areas, as tamarind became the most important cash crop of the district. The natural vegetation of the hilly and mountainous areas has been strongly disturbed by human encroachment in order to obtain new agricultural land. The remaining forest is classified as deciduous forest with medium and small trees including *Bombax, Dalbergia, Pterocarpus*, Bamboo and *Shorea* (HANSAKDI 1998).

3. Methodology

3.1. C-Factor Mapping by Land Cover Mapping

One approach to determine the C-factor from satellite images is by land cover classification (FOLLY et al. 1996, JUERGENS and FAHNDER 1993). The use of satellite images in preparation of land cover maps has been widely applied in natural resource survey. Satellite image data provide up to date information on land cover and land use in digital format, which are major advantages in comparison with aerial photographs. Land cover mapping can be improved by using a combination of techniques (FOLLY et al. 1996). In the case of Lom Sak a visual interpretation of a mono-temporal Landsat TM image was used to improve a multispectral classification of the same data.

3.1.1. Visual Interpretation

A preliminary land cover map was obtained by visual interpretation. Using TM bands 4, 5 and 3 and TM bands 4, 3, and 2 two false colour composites of the December image were created. Using own field data and the land use map produced by the ITC in 1994 the following main land cover classes were distinguished.

- Forest
- Open forest
- Shrubs and bush vegetation
- Low cover vegetation (maize fallow)
- Bare soil (annual field cropping with rice)
- Bare soil (rice cultivation + secondary crops)
- Bare soil (maize cultivation)
- Residential areas with home gardens
- Water body

Available field data was displayed on the screen and used as guideline for the identification of boundaries between major units. The interpretation process was directed by information obtained from topographic maps, land use maps, aerial photographs, crop calendars and other information collected during the fieldwork. Using image characteristics as pattern, texture and colours and tones on the image, polygons were drawn around features by screen-digitising.

3.1.2. Digital Classification

Multi-spectral image classification is used to extract thematic information, as information on land cover, from satellite images in a semi-automatic way. A large number of image classification methods exist, which can be generally distinguished into unsupervised and supervised classification types. The supervised approach, which was used in this project, requires a good knowledge of the working area. The user has to know how many land cover types exist in the study area. For the digital classification of the Lom Sak image the above mentioned 9 cover classes were used.

Using the GPS positions taken in the field, sampling areas for each cover type were found. Since these samples are used from the system to classify all the pixels into the various cover types they were selected from homogeneous areas. For further processing in ILWIS a sample set had to be created in which the relevant data regarding the input bands were stored (TM Bands: 1, 2, 3, 4, 5 and 7). During the sampling process different feature spaces were plotted in order to check whether the classes could be spectrally distinguished from each other and to judge whether each sample was representative for its own class. If a sample was spectrally too different from its own class or if the single pixel values of a sample were too heterogeneous and scattered in the feature space this sample was deleted. However, it was not possible to avoid all spectral overlapping between the different classes. If the overlapping was significant they were merged into a single class.

After the sampling was finalised and corrected the classification of the image was carried out. Classification algorithms are used in order to separate the feature space according to the selected training samples. Several classification algorithms exist from which the box classifier, the minimum distance-to mean classifier and the maximum likelihood classifier were tested for the classification of the Lom Sak image. The results of the different algorithms were evaluated by checking the correct classification of field observations, which were not used as sample areas. Furthermore visual comparison of the classification results with colour composites was done. Best results were obtained by using the maximum likelihood classifier, which considers especially the variability of training samples. The result of the box classifier was unsatisfactory. Possible reasons for this are the partial overlapping between different classes and the variability of training samples. After it was decided to use the maximum likelihood classifier for further processing the classification process was repeated. By checking wrong classified areas of the prior classifications training samples were stepwise improved.

In order to achieve a homogeneous appearance of the classification the majority filter was applied several times. The majority filter selects the predominant value of a pixel and its 8 neighbours. Especially isolated pixels within a cluster of pixels belonging to another class can be easily eliminated in this way. On the other hand filtering results in a generalisation of the image and it should be used with care, especially if small areas are of high relevance for the application.

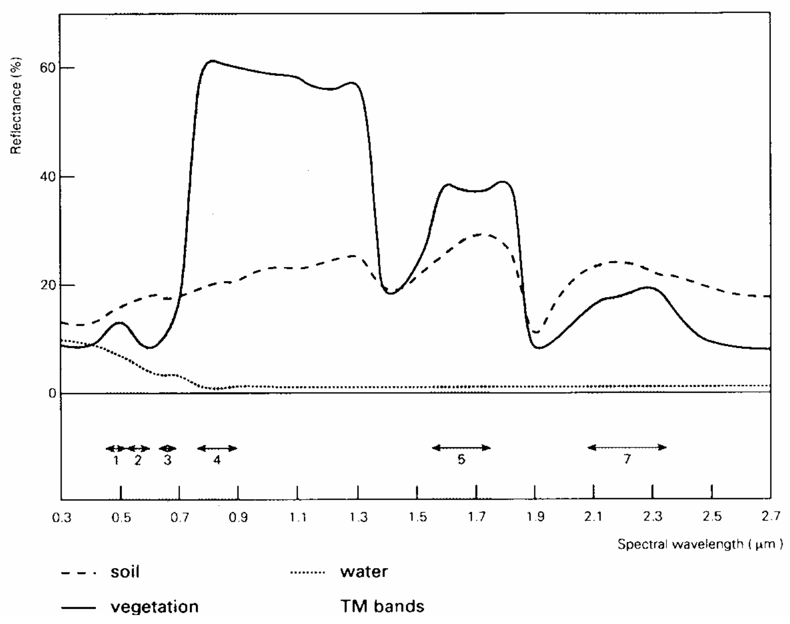
3.1.3. Production of a C-factor map

The results of the visual interpretation and digital classification were combined by overlay operations. Thus, different land cover types with the same reflectance as forest areas and home gardens, which were incorrectly classified using the maximum likelihood classifier, could be distinguished using the knowledge based visual interpretation. In the end the final land cover map was converted into a C-factor map. C-factors for the different land cover types were obtained from literature.

3.2. C-Factor Mapping using Spectral Indices

Three features have an important role on the reflection properties of vegetation: pigmentation, physiological structure and water content. In the visible portion of the spectrum the radiation is rather low, but due to higher absorption of red and blue light by mainly chlorophyll the vegetation reflects comparably more in green light. The reflectance in the near infrared is highest but the amount is proportional to the leaf development or the cell structure of the leaves. In the middle infrared the free water content in the leaves mainly determines the reflection properties. Low water contents result in high reflection and high water content result in low reflection.

Figure 2: Examples of spectral curves for healthy vegetation bare soil and water



Extracted from DE JONG (1994)

Different band combinations enable us to differentiate between bare soil, water and vegetation. These arithmetical band combinations can be referred to as "spectral vegetation indices".

3.2.1. NDVI

The Normalised Difference Vegetation Index is one of various mathematical combinations of satellite bands, which have been found to be sensitive indicators of the presence and condition of green vegetation. It is based on the reflectance properties of vegetation in comparison with water, snow and clouds on the one hand and rocks and bare soil on the other hand. As mentioned before vegetated areas have high reflectance in the near infrared and low reflectance in the visible red. Water, snow and clouds have larger visual than near-infrared reflectance and bare soil and rocks have similar reflectance in both spectral regions. As a consequence green vegetation yields high values for the index, water has negative values and bare soil gives indices around 0. The intermediate values give an indication for differences in coverage with green vegetation. The NDVI, as a normalised index, is compensating changes in illumination conditions, surface slopes and aspect (LILLESAND and KIEFER 1999)

$$NDVI = ((TM4 - TM3) / (TM4 + TM3) * c1) + c1$$

Where:

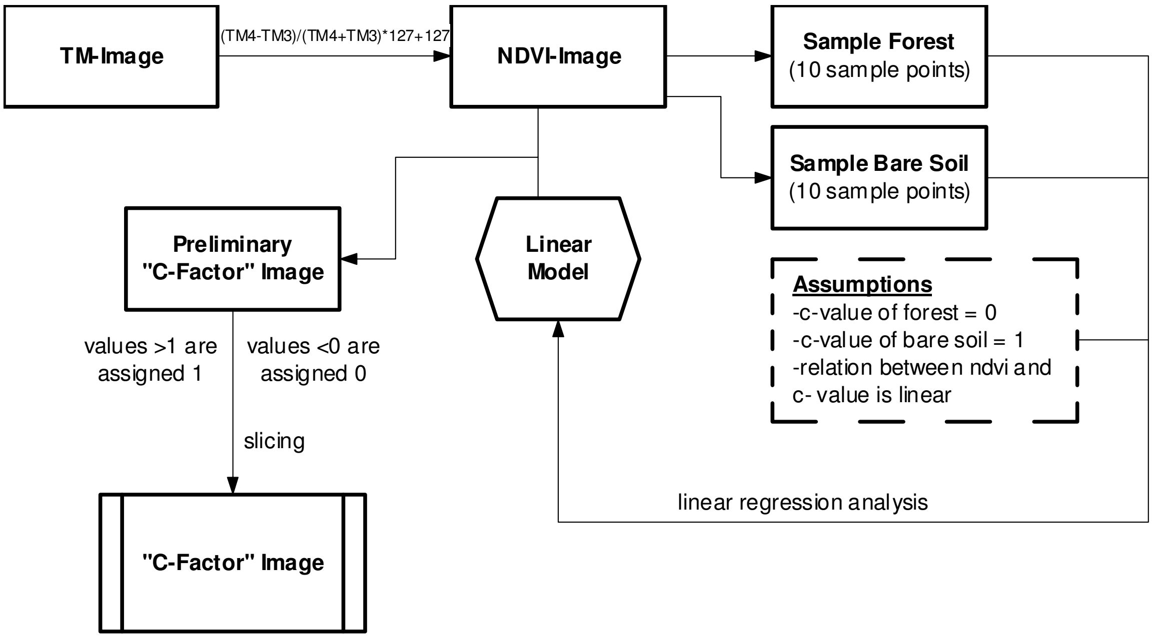
NDVI: Normalised Difference Vegetation Index
TM4: TM spectral band 4 (0.76 - 0.90 µm)
TM3: TM spectral band 3 (0.63 - 0.69 µm)
c1, c2: Scaling factors

In his PhD thesis on Remote Sensing Applications in Mediterranean areas DE JONG (1994) describes the use of vegetation indices in order to extract vegetation parameters for erosion models. Using field data of 33 plots for statistical analysis he describes a linear relation between NDVI and USLE C-Factor with a correlation factor of -0.67. Based on these results the following statements are assumed to be valid.

- NDVI and USLE-C are correlating
- There is a linear relation between NDVI and USLE-C

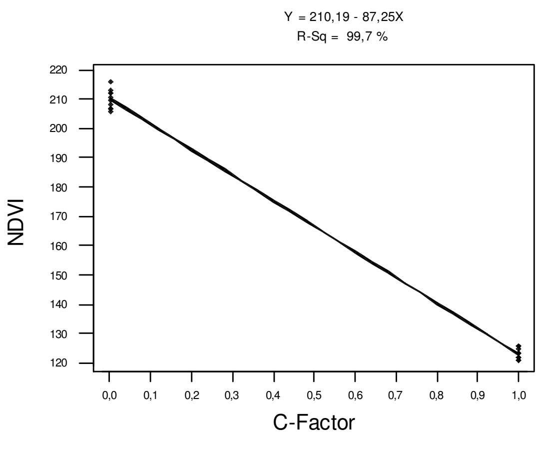
However, it has to be pointed out that NDVI mainly shows high correlation with ecological variables as leaf-area-index, total vegetation cover or above ground biomass (LAWRENCE and RIPPLE 1998, RONDEAUX et al. 1996). On the other hand NDVI has only limited or no capabilities to detect variables as ground cover density in forests, canopy structure, litter layer or management practices, which are from crucial importance for the determination of C-factor values. Thus, the correlation between NDVI and C-factor in the study area is not expected to be decidedly higher than the correlation factor detected in the work of DE JONG (1994).

Figure 3: Flowchart outlining the procedure of C-factor mapping using NDVI



Using the above quoted formula an NDVI-Image was created. C-values for bare soil (1) and forest areas (0) where derived from literature (KOOIMAN 1987, MORGAN 1996). In a next step NDVI values for forest and bare land were taken from each image. These sample points were used for a linear regression analysis. As a result a linear model was inverted.

Figure 4: Linear regression of NDVI and C-Factor values

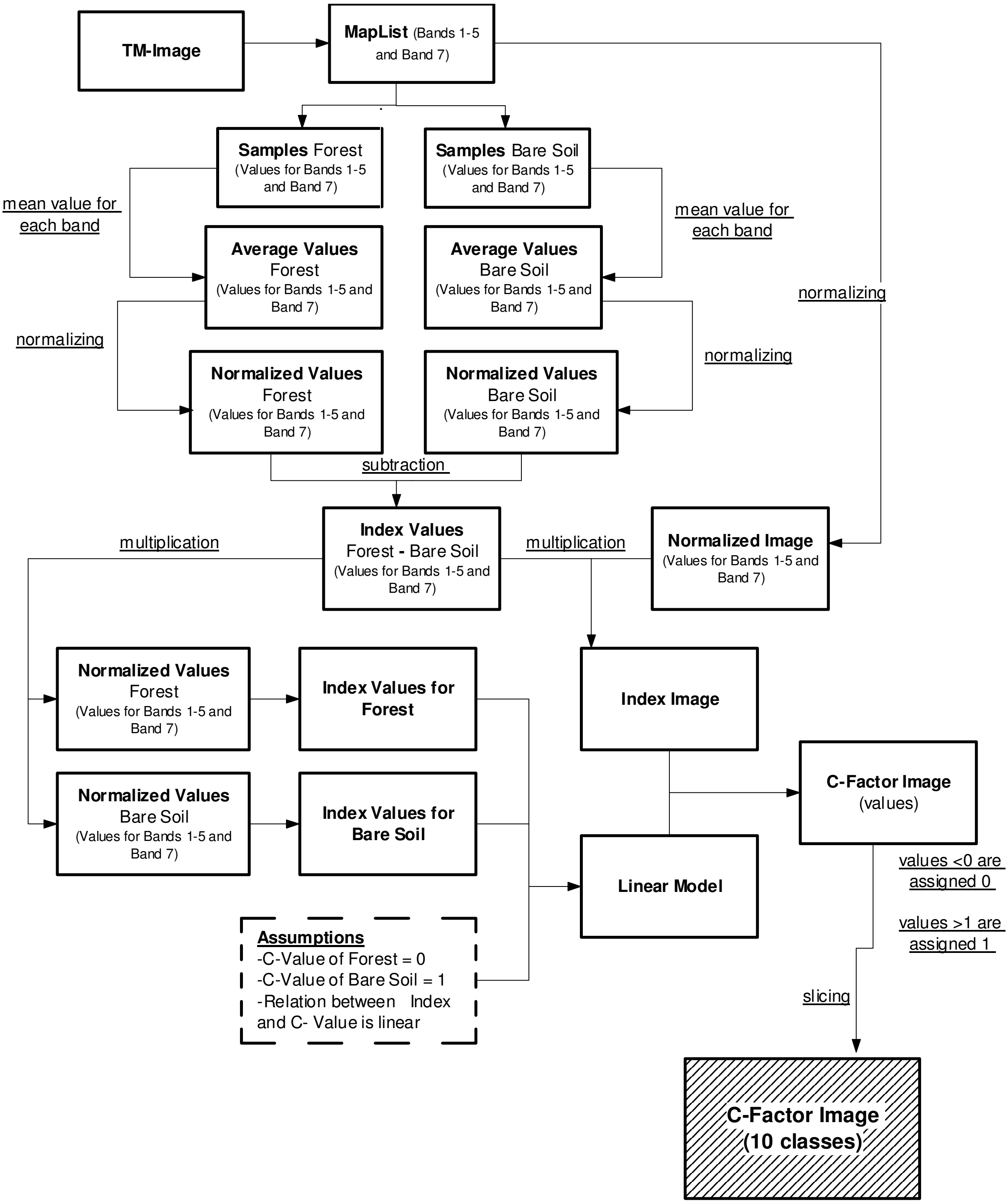


Using this model a C-value image was calculated. Pixels with values > 1 were classified as 1 and pixels with values < 0 were classified as 0. In a next step a group domain containing 10 equal classes was created and applied in the slicing operation of the ILWIS software. As a result a C-factor map with 10 classes was obtained.

3.2.2. Transformation Index

Knowing that the NDVI is only based on reflection differences in Bands 4 and 3 one can think in design of other indices using more of the seven available bands of Landsat TM images.

Figure 5: Flowchart outlining the procedure of C-factor mapping using the transformation index



For the following approach TM Bands 2-5 and Band 7 were used. Band 1 and Band 6 were excluded. Band 1 is mostly affected by haze, which results in higher DN values. Due to lack of complete shadowed areas in the TM-Image it was difficult to obtain an exact haze correction for Band 1. In view of the fact that the values of Band 1 and Band 2 were highly correlating (correlation coefficient = 0.94) it was decided to exclude Band 1 from the process. The thermal infrared Band 6 has a spatial resolution of 120 m compared to 30 m of the other bands and was not used in this process.

This approach is based on the assumption that 0 and 1 are C-factor values for pure vegetation (dense forest) and for bare soil respectively and that all other land cover types will have C-values between 0 and 1. After creating a maplist with the ILWIS-Software (Bands 2-5 and 7) 10 pixel values for dense forest and for bare land were taken. The sampling was done using information on land cover collected during the fieldwork.
The mean values are given below in vector notations.

F	=	[35, 35, 139, 104, 30]	F = Forest
S	=	[45, 73, 71, 130, 58]	S = Soil

The variation of illumination in sunlit and shadow areas caused by uneven topography results in different reflectance values of similar objects. One possible way for removing this effect is to normalise the data by the total intensity (SHRESTHA 1984). Thus the reflectance values of each band were normalised by the sum of all band values for that particular pixel.

Intensity for F = 35 + 35 + 139 + 104 + 30 = 343
Intensity for S = 45 + 73 + 71 + 130 + 58= 377

NF = F / 343 = [0.1020, 0.1020, 0.4053, 0.3032, 0.0875]
NS = S / 377 = [0.1194, 0.1936, 0.1883, 0.3448, 0.1539]

In a next step the intensity normalised soil sample (NS) was subtracted from the intensity normalised forest sample (NF). Thus a transformation vector (NFS) was obtained which served as a weight function in the data transformation from the five bands into one index value. In other words the transformation vector was used in order to emphasise reflection differences of the whole image based on the reflection characteristics of bare soil and pure vegetation.

NFS = NF - NS = [-0.0174, -0.0916, 0.2170, -0.0416, -0.0664]

The transformation vector (NFS) was used to transform the whole image into an index image. In first place an intensity normalized image (NTM) was produced. Subsequently multiplication of the normalised Image with the transformation vector performed the transformation of each pixel.

NTM2 = TM2 / TM2+TM3+TM4+TM5+TM7
NTM3 = TM3 / TM2+TM3+TM4+TM5+TM7
NTM4 = TM4 / TM2+TM3+TM4+TM5+TM7
NTM5 = TM5 / TM2+TM3+TM4+TM5+TM7
NTM6 = TM7 / TM2+TM3+TM4+TM5+TM7

$$NTM = [NTM2, NTM3, NTM4, NTM5, NTM7]$$

$$IndexImage = NFS * NTM = [-0.0174, -0.0916, 0.2170, -0.0416, -0.0664] * \begin{pmatrix} NTM2 \\ NTM3 \\ NTM4 \\ NTM5 \\ NTM7 \end{pmatrix}$$

The numerical extremes of the index scale were found from the two index values for bare soil and forest. In order to obtain these values the transformation vector (NFS) was multiplied with the intensity normalised samples of forest (NF) and bare soil (NS).

$$IndexForest = NFS * NF = 0.0585$$
$$IndexSoil = NFS * NS = -0.0034$$

Using the calculated index values and the assumed C-factor values for bare soil and forest a linear model was obtained. This model was used to convert the index image into a C-factor image. Pixels with index values higher than 1 were assigned the value 1 and pixels with values lower than 0 were assigned the value 0.

$$Y = -0.0619X + 0.0585$$

Y : Index
X : C-factor

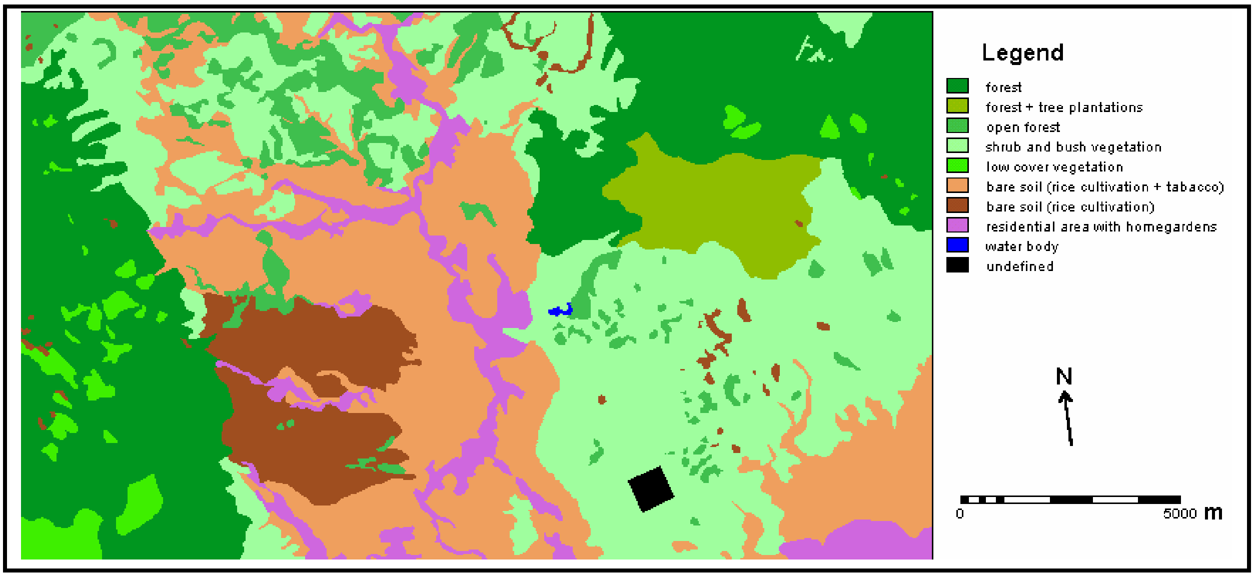
In the final step the C-factor image was classified in ten equal classes using the slicing operation of ILWIS.

4. Results and Discussion

4.1. C-Factor Mapping by Land Cover Mapping

The visual interpretation of the satellite image made by screen-digitising is highly generalised. It is considered to be a preliminary land cover map in order to improve the digital classification.

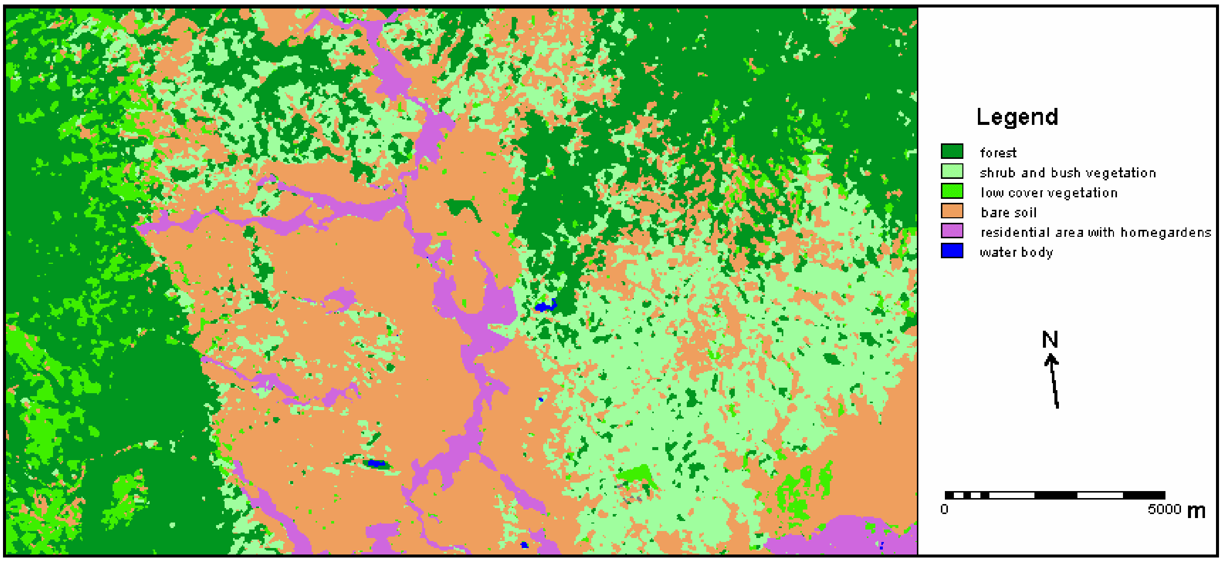
Figure 6: Preliminary land cover map produced by visual interpretation



It was difficult to classify inhomogeneous areas such as areas where small patches of natural vegetation occurred next to cultivated fields and fallow fields. In contrast to this it was rather simple to recognize more homogeneous areas such as the Pasak valley or most parts of the piedmont, which were mainly classified as bare land. Residential areas and home gardens, which had similar reflectance values as forested areas, could be distinguished based on the knowledge obtained in the field and additional information as topographic maps and aerial photographs. Depending on the homogeneity of the area and on the amount of data, visual interpretation can be difficult and time consuming. However, since not all required information for a classification is related to spectral characteristics of the image, this method is still indispensable and gives good results in the combination with digital image classification methods.

Applying the maximum likelihood classifier resulted in the best digital classification results for the Lom Sak image. Using this method the different cover types of inhomogeneous areas as hillands or mountains came out very clearly. In contrast similar reflectance characteristics of forests and home gardens caused wrong classifications. In order to combine the results of the visual interpretation and the digital classification GIS overlay operations were applied. As a result, the wrong classifications of the classes "forest" and "residential areas with home gardens" could be corrected.

Figure 7: Final land cover classification map (digital classification + visual interpretation)



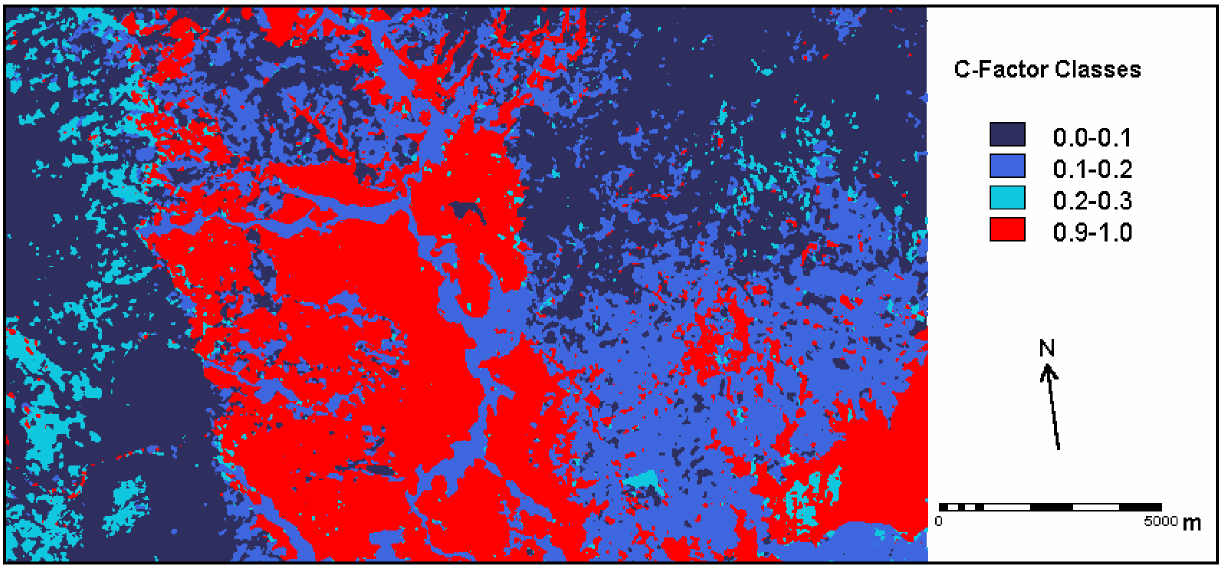
The assigned C-factors values for the different land cover classes were obtained from literature. C-factor values for the same land cover types vary depending on the geographical location of the area. In order to obtain best possible results, data from similar geographical settings were chosen.

Table 1: C-factor values from literature review

Land Cover Class	C-Factor	Location	Author/Source
Dense forest	0.001	Sumatra	KOOIMAN (1987)
Open forest	0.001	Sumatra	KOOIMAN (1987)
Shrubs and bush vegetation	0.1	Java	HAMER (1981), quoted in KOOIMAN (1987)
Low cover vegetation (fallow)	0.2	Java	HAMER (1981), quoted in KOOIMAN (1987)
Bare soil	1	Sumatra	KOOIMAN (1987)
Residential areas and home gardens	0.14	Sumatra	KOOIMAN (1987)

It was difficult to find any C-factor values for settlement areas. Taken into account that the spectral reflectance of this unit was mainly determined by the vegetation cover of home gardens, it was decided to refer to this cover type. The resulting C-factor map is shown in Figure 8.

Figure 8: C-factor map by land cover classification



One of the major limitations in applying this method for the Lom Sak case was the limited availability of field data. In order to obtain a detailed land cover map more ground information was needed. Therefore the result of the classification was rather general which again resulted in a generalised C-factor map.

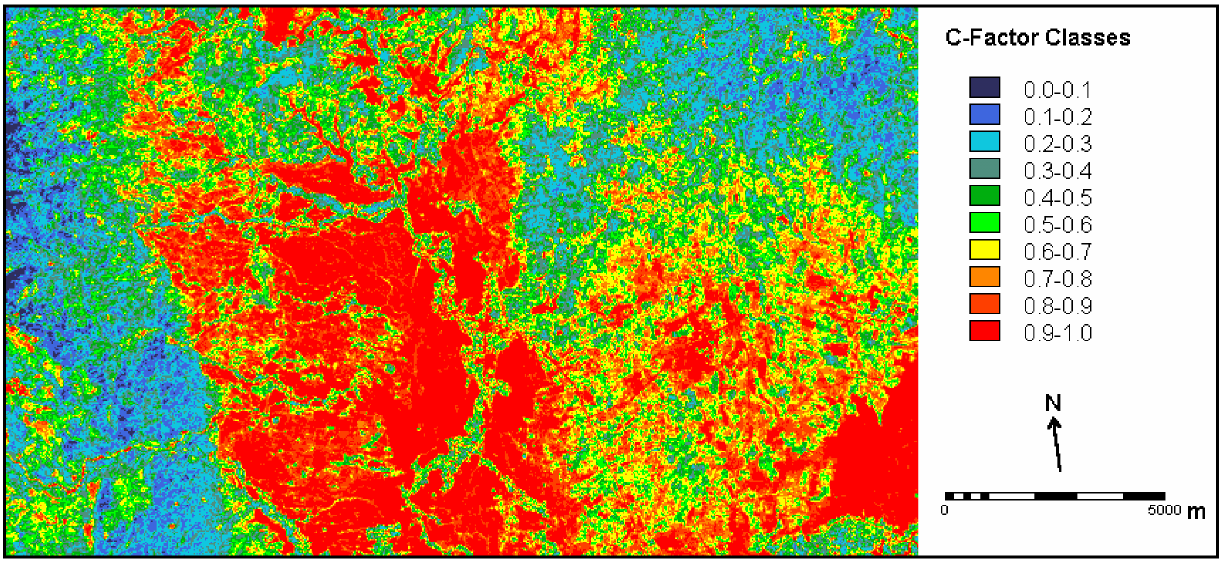
4.2. C-Factor Mapping using Spectral Indices

4.2.1. NDVI

In order to use NDVI for the extraction of information on land cover it was assumed, that NDVI and USLE-C are correlating and that there is a linear relation between NDVI and USLE-C and (DE JONG 1994). This approach is based on NDVI values of forest and bare soil areas as reference samples. This can be seen as a limitation. Ten pixels of forest and bare soil areas were used in order to obtain a linear model by linear regression analysis. Subsequently this model was used for deriving C-factor values for all other land cover types. Additional C-factor values from different land cover types, which have to be derived from field data, would improve the linear model and the result of the transformation of NDVI values into C-factor values.

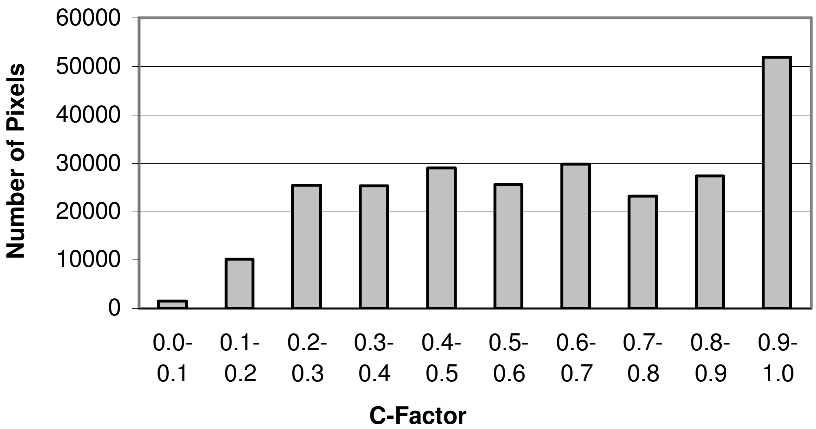
The result of the NDVI based approach is shown in Figure 9 form of C-factor map. C-factor values are shown in 10 different classes, whereby classes range from C-factor 0-0.1 (forest) to C-factor 0.9-1.0 (bare soil). The relative distribution of the C-factor values in regard to the main land cover units of the study area is satisfactory.

Figure 9: C-factor map based on NDVI



However, looking closer to the number of pixels assigned to certain classes gives a more detailed picture. The highest number of pixels was classified as C-factor class 0.9-1.0 (bare land). Knowing that in December most of the Pasak valley and the low and middle glacies are bare, this result seems to be feasible. In contrast the number of pixels classified, as class 0-0.1 (forest) was very low, since the samples used for forest were only taken from dense, natural forest.

Figure 10: Pixel distribution of the C-factor map based on NDVI

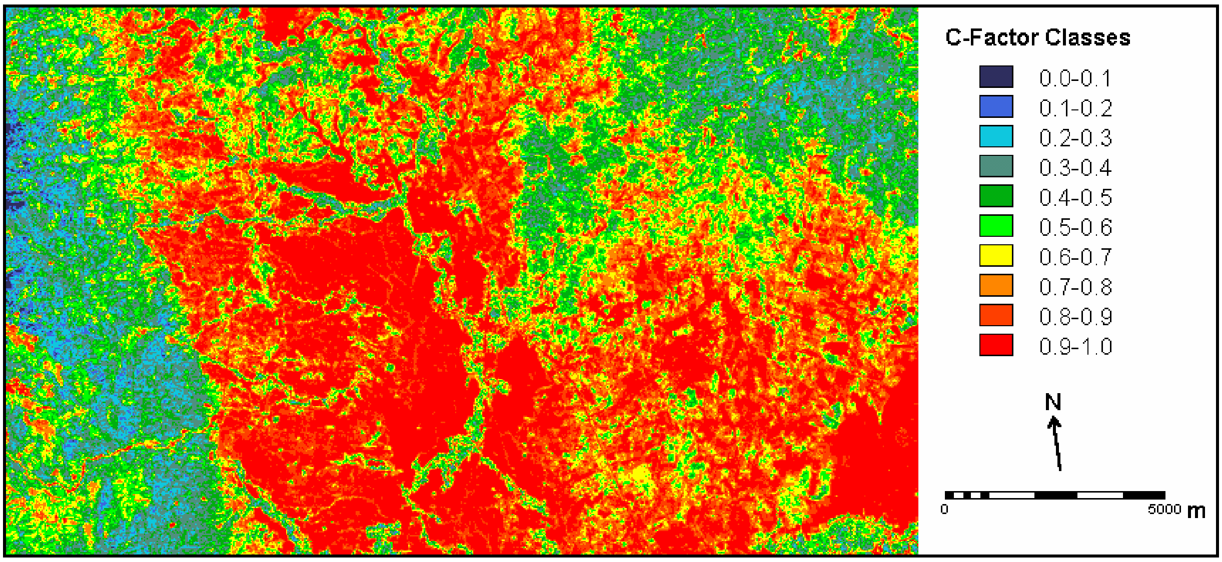


At this point the limitations of NDVI for the extraction of C-factor values become apparent. As mentioned earlier some variables as density of undergrowth, litter layer or management practices, which influence the C-factor, cannot be detected from a NDVI image. Another limitation of the NDVI based approach is an underestimation of C-values for vegetation under certain conditions (DE JONG 1994). Vegetation under stress shows an increased reflection in red wavelength and a decrease of the near infrared reflection resulting in a small NDVI value. This means for areas having a dense cover of vegetation under stress, the NDVI will be low and consequently the C-factor value will be high. The image used for the present study was taken in December, the moth with the lowest rainfall in the year. Therefore it can be assumed that parts of the vegetation cover were under stress. For the erosion process the condition of the vegetation is of minor importance. Hence, C-factor values of vegetation under stress are expected to be similar to the values of healthy vegetation.

4.2.2. Transformation index

Similar to the NDVI based approach, this method is based on two reference samples of bare soil and pure vegetation (forest). The contrasting point is that more of the available TM bands are used in order to distinguish between these two land cover forms.

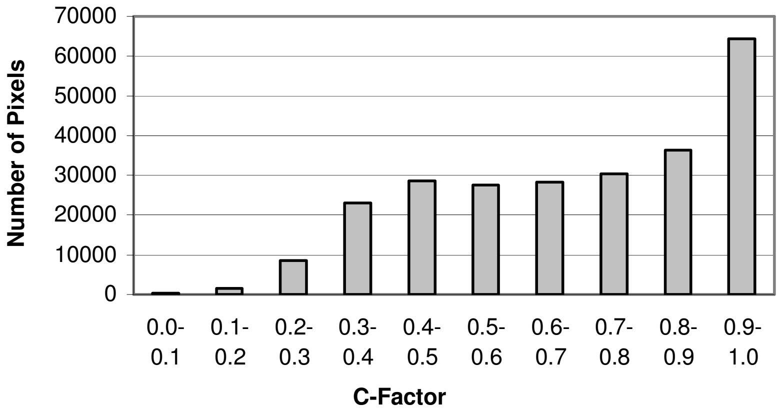
Figure 11: C-factor map based on transformation index



Similar to the NDVI based method bare lands in the valley and large parts of the piedmont were assigned to C-factor class 0.9-1.0. Areas with high vegetation cover as forest, shrub and bush land were to a large extent assigned to C-factor values higher than 0.3. Referring to C-factor values for natural vegetation obtained from literature study (see Table 1) these results can be considered as far too high. This is most likely caused by the high sensitivity of the transformation index to the soil reflection characteristics. In order to correct this error adjustment factors could be developed.

As shown in Figure 12 about 25% of the total pixels were classified as C-factor class 0.9-1.0 whereas only 4% were classified as C-factors < 0.3.

Figure 12: Pixel distribution of the C-factor map based on the transformation index



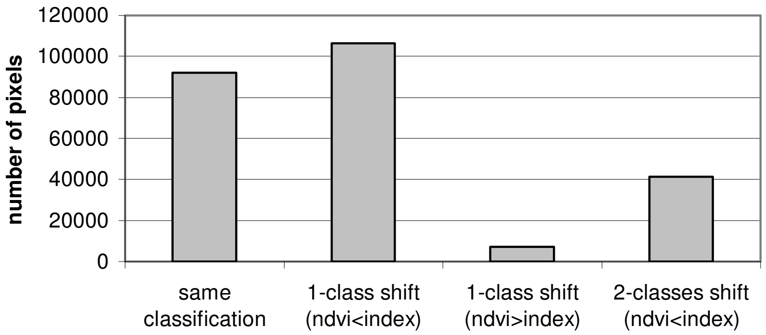
4.3. Comparison of the results obtained by different methods

Table 2: Correlation Matrix of the three resulting C-factor maps

	Transformation Index based method	NDVI based method	Land Cover Classification based method
Transformation Index based method	**1**	**0.97**	**0.69**
NDVI based method	**0.97**	**1**	**0.76**
Land Cover Classification based method	**0.69**	**0.76**	**1**

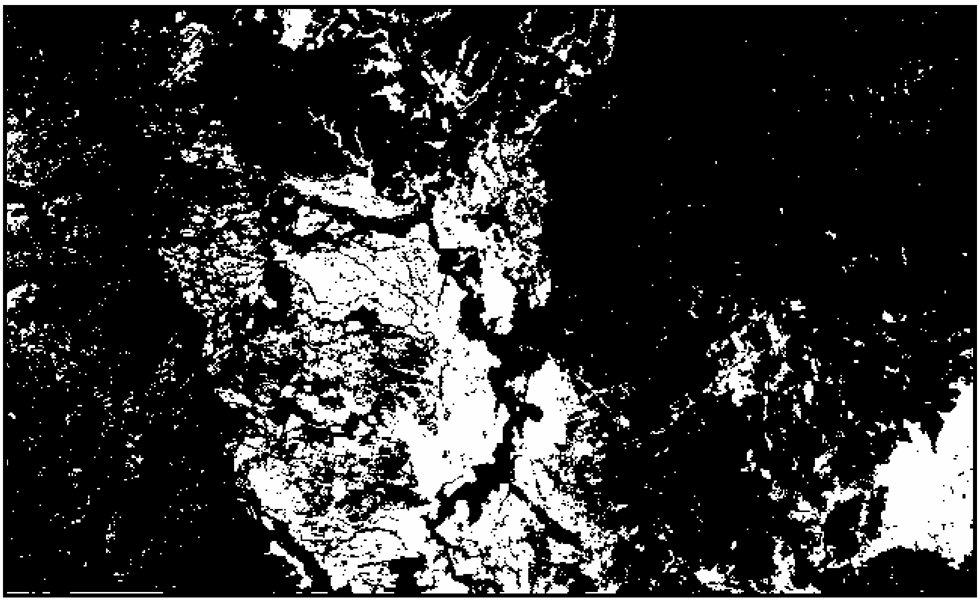
The results of both methods based on spectral indices were highly correlated (correlation coefficient 0.97). However, the values of the transformation index based method were more shifted towards higher C-factor values. Using the CROSS function of ILWIS a cross table of the two C-factor maps was produced. The most relevant information of the cross table is summarised in Figure 14. It shows that more then 40% of all pixels of the index based C-factor map were classified one class higher then the corresponding pixels in the NDVI based approach. However, the difference in classification has to be analysed with regard to land cover types. Using both techniques bare soil areas were mostly classified into the same class. On the contrary vegetated areas as forests and shrub and bush vegetation were predominantly assigned higher C-factors by using the transformation index. This phenomenon can be explained by the fact that the transformation index gives more emphasise to the reflectance properties of soil then the NDVI does.

Figure 13: Selected results of the cross tabulation between the two indices based methods



The correlation between the C-factor map produced by land cover classification and the C-factor maps based on spectral indices is not high (Table 2). Whereby the NDVI based approach shows with r=0.76 a higher correlation then the transformation index (r=0.69). In order to get information on the spatial distribution patterns of the different C-factor classifications cross maps were produced.

Figure 14: Map showing the variation in C-factor classification between the NDVI and the land cover based methods



Pixels are assigned to the same class

Pixels are assigned to different classes

The results show that large parts of areas with bare soil were in all three methods assigned to the same class (high correlation). In contrary vegetated areas, especially the forests, shrub and bush lands were assigned different C-factor classes (low correlation). However, this should not lead to the conclusion that spectral indices are not suitable for the extraction of information on C-factor values. It can rather be stated that the different techniques can not really be compared. It was mentioned earlier that the land cover classification was based on limited field data, which resulted in a generalised classification with large areas, classified as the same land cover class. Thus, large units were assigned the same C-factor values and variations within the units were not considered. On the other hand side using the indices based approaches each pixel was classified according to its reflectance values, which resulted in a higher variation. The fact that the land cover classes were assigned C-factor values from literature, which were not from the study area, also influenced the quality of the land cover classification based approach. Further more it has to be considered that C-factors obtained from literature were annual basis, referring to the vegetation cover of a whole year. In contrast the C-factor values determined by spectral indices were only referring to the December image.

Hence, we conclude that the validity of the NDVI and transformation index based C-factor mapping can not be assessed only by comparison with the C-factor map produced by land cover classification. In order to assess the quality of these methods detailed field data on C-factor of the different land cover types of the area is needed. The validity of the land cover classification based C-factor mapping has been proven in previous studies (FOLLY 1996, JUERGENS and FANDER 1993).

5. Summary and Conclusion

The present study tried to investigate the use of digital satellite maps for obtaining quantitative information parameters for the use of erosion modelling. The study area is located in the Lom Sak and Lom Kau districts in the north of Thailand. For the fieldwork area Landsat TM data (all 7 bands) dated 9/12/1987 was available.

Different methods to C-factor mapping using remote sensing have been attempted of which three were applied in this study. The first approach considers C-factor mapping as a special type of land cover mapping. It is based on the assumption that all information needed for the determination of C-factors cannot be extracted directly from the image (FOLLY et al. 1996). Therefore a land cover classification map is produced first and corresponding C-factors to the identified land cover are taken from literature. The final land cover map for the study area was obtained by a combination of a visual interpretation and a supervised classification using the maximum likelihood algorithm.

The second and third applied methods are following a completely different approach, where spectral indices are used in order to obtain direct information on C-factors from digital images. For the Lom Sak case the NDVI and the transformation index were applied. Both methods are based on two reference samples of pure vegetation (forest) and bare soil. Based on the assumption that there is a linear relation between the indices and the C-factor linear models were created and used to assess the C-factors for each pixel of the image. The contrasting point between these two methods is that in order to distinguish between the reflectance parameters of pure vegetation and bare soil different TM band combinations are used.

The correlation between the two indices based C-factor maps was large (0.97). Hence, the different methods of combining spectral information to optimise the contrast between green vegetation from bare soil yielded in very similar results. The comparison between the C-factor map produced by land cover mapping and the indices based C-factor maps showed lower correlation. However, analysing the spatial variation within the image showed that all three methods classified bare land into the same class (0.9-1.0). Conversely vegetated areas as forests, shrubs and bush land were assigned different C-factors.

These results should not lead to the conclusion that one or the other approach is not useful for the extraction of vegetation parameters for erosion modelling. In order to assess each of the here applied methods detailed ground information is needed, which was not available for this study.

The main advantages and disadvantages of the different methods for C-factor mapping are summarised in Table 3.

Table 3: Advantage and Disadvantage of the different methods for C-factor mapping

	Advantage	**Disadvantage**
land cover classification based method	• Gives most accurate results	• Difficult to classify heterogeneous areas of natural vegetation • Need of high amounts of field data, time and cost consuming • Depending on other information (literature)
spectral indices based methods	• Limited need for field surveys • Can cover large areas without the need of additional field data	• Limited detection of some variables which determine the C-factor (canopy structure, ground growth density, litter layer, management practices) • The vitality of the vegetation is a major source of uncertainty, since the condition of the vegetation is not always related to its soil protective function

However, the C-factor mapping methods based on the use of spectral indices meet the requirements to reduce the necessity of time and cost consuming field surveys. In spite of the somewhat poor correlation this method could be used to collect and prepare vegetation data for erosion models for large areas. Therefore it is recommended to carry out further research in this field, in order to improve the existing methods or to develop new spectral indices based approaches.

6. References

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ERKLÄRUNG

Seit Mitte der 90iger Jahre haben über 10 Absolventen des Geographischen Instituts der JLU Gießen ein Aufbaustudium am *International Institute for Aerospace Survey and Earth Sciences* in den Niederlanden Holland erfolgreich durchlaufen. In diesem Zusammenhang haben die beiden Institute ein Kooperationsabkommen abgeschlossen, dass es den Gießener Studenten/Absolventen erleichtert einen Studienplatz am ITC zu bekommen. Das ITC ist eines der europaweit führenden Forschungsanstalten für die Anwendung von geographischen Informationssystemen (GIS) und Fernerkundung im Bereich von Ressourcen- und Umweltmanagement.

Die vorliegende Arbeit wurde als Abschlussarbeit im Rahmen des *Professional Master Course in Geoinformation Science and Earth Observation* von Zihni Erencin im August 2000 eingereicht. Das Thema hat einen unmittelbaren Bezug zu den Forschungsinhalten der Abteilung Geoinformatik und Fernerkundung des Geographischen Instituts der JLU.

Hiermit versichere ich, dass ich die vorliegende Arbeit selbstständig verfasst und keine anderen als die abgegebenen Hilfsmittel verwendet habe.

Essen den, 24.05.2004

Zihni Erencin