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ADDITIVE APPROACH TO SOIL WATER EROSION RISK ASSESSMENT USING PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

The paper presents additive approach as an alternative to known methodology (factorial scoring) of soil water erosion risk assessment. The study is performed for agricultural land of a test site located in Lower Silesia, Poland. Proposed algorithm is based on Principal Component Analysis (PCA) of three environmental factors: soil susceptibility to water erosion, slope and vegetation cover. The interpretation of PCA components leads to conclusion that two of them (component 2 and component 3) are suitable to describe the erosion risk and their simultaneous analysis – which Authors called additive approach – is sufficient to assess the soil water erosion hazard. For this purpose models with different assumptions were created: PCA Model I, in which component 3 values are negative, is assumed to indicate areas less endangered with potential soil water erosion risk, whereas PCA Model II with the component 3 values being greater or equal to 0 demonstrates more endangered areas. In both cases the diversification of actual soil water erosion hazard is a result of component 2 values. The results of the study lead to the conclusion that the proper interpretation of principal components and their spatial distribution provides detailed and comprehensive information on actual soil water erosion risk, especially on the areas facing the same degree of potential erosion.

Key words: soil water erosion, Principal Component Analysis (PCA), factorial scoring, remote sensing, Geographical Information System (GIS).

INTRODUCTION

Soil water erosion is considered one of the major and most widespread forms of land degradation. As stated by Van Lynden [23], soil water erosion is regarded as the main cause of soil degradation in Europe. It reduces soil productivity and soil ecological functions, such as biomass production and filtering capacity, as well as it affects water quality, causing accumulation of sediments and agrochemicals [6]. Soil water erosion has accelerated, especially in developing countries, due to climate change and various socio-economic and demographic factors [15]. Manmade activities such as deforestation, land cultivation, inefficient farming and uncontrolled grazing increase the erosion effect in a large extent. Soil may be regarded as a non-renewable natural resource that takes long to regenerate. Therefore protection of soil plays a very important role in the European and regional policy [2].

Soil erosion by water is a complex phenomenon depending on many environmental and anthropogenic factors, including soil properties, vegetation coverage, land cultivation, relief and weather conditions. Various approaches and models – modified and improved within years of research – for evaluation of soil erosion by water are presented in literature [5, 7, 16, 17, 24–26]. When assessing the erosion risk, a distinction is made between expert-based methods and model-based methods [22]. The methodology used in this paper belongs to expert-based methods, and the authors present two approaches: indicator – where the factorial scoring is used, and additive – where the Principal Component Analysis is proposed to model the soil water erosion risk. The factorial scoring method has several limitations, among others: the results are affected by a defined classification and scoring system [14]. Hence, in this paper the ranges of classes for input data, i.e. soil susceptibility to water erosion, slope and Normalized Differential Vegetation Index (NDVI), are determined based on long-term studies and literature: [4, 10, 11, 19].

Another difficulty associated with this method is that each factor is treated independently, whereas there is often interaction between the factors [14]. In multi-criteria analysis, such as assessment of soil water erosion risk, these relationships are significant. The authors use the factorial scoring carefully, aware of the limitations of this method, to obtain a general assessment of soil water erosion risk and indicate the areas where more detailed analysis should be done. This is performed as part of the additive approach where the Principal Components Analysis (PCA) is applied. PCA is used to generate a new set of independent variables from the set of highly correlated variables carrying a lot of redundant information. The method is usually used to reduce the set of bands in multispectral imagery to a set of bands in which the information content is concentrated and has little correlation [9]. In this study the authors performed PCA on a set of three variables: slope, NDVI and soil sensitivity. While PCA did not reduce the number of variables, it revealed the actual relationships between the input data.

In the literature the distinction is made between the potential erosion risk – reflecting the local conditions of soil, climate and slope - and actual erosion risk which combines the former with the land cover factor. It is therefore possible to recognize areas of high potential risk but low actual risk as a result of the protection afforded by vegetation [14]. In Poland, the potential erosion risk is usually estimated based on the procedure proposed by Jozefaciuk and Jozefeciuk [10,11]. In this method the soil water erosion hazard is assessed on the basis of soil type, slope classes and the annual precipitation. With the addition of the vegetation cover factor, the actual erosion risk may be estimated. The aim of the study is to recognize the spatial variability of the actual soil water erosion hazard, especially within the areas of low and high potential erosion risk. Moreover, the emphasis is laid on more detailed analyses (additive approach) performed within areas determined using indicator approach.

STUDY AREA AND SOURCE DATA

The research area is located in the province of Lower Silesia, to the north of the city of Wrocław, Poland (Fig. 1). It covers a part of Trzebnickie Hills dominated by fertile loess formations which are highly endangered with the degradation process. In this region the thickness of loess soils ranges from 3 to 25 m [20]. The area under study embraces terrains of agricultural use located on the southern slopes of Trzebnickie Hills. In consequence, soil water erosion in this area is mainly a result of a combination of the high vulnerability of the local loess soils to water erosion and inappropriate farming. However, this area is classified as low potential risk of water erosion according to the official map of soil water erosion hazard elaborated for Lower Silesia by the Institute of Soil Science and Plant Cultivation, State Research Institute [19] (Fig.1).The potential erosion risk presented on the map was estimated using the aforementioned algorithm proposed by Jozefaciuk and Jozefaciuk [10,11]. According to this map, the largest areas of medium and high soil water erosion risk occur in the mountainous region located in the southern part of Lower Silesia, while the vast majority of the province (62.5% of agricultural lands) is classified with low degree of soil water erosion. Particularly, within the study area low risk of soil water erosion characterizes almost 70% of arable lands, while only 0.1% of areas are highly endangered with erosion processes and around 7% are of medium soil water erosion risk degree (Fig.1). On the map by Stuczyński [19] the degree of soil water erosion risk is determined only on arable land considered the most endangered with soil degradation processes. The authors propose to widen the analysis to include meadows and pastures, therefore the advancing soil degradation caused by the inefficient farming, inappropriate tilling methods and uncontrolled grazing may be investigated within all agricultural lands.

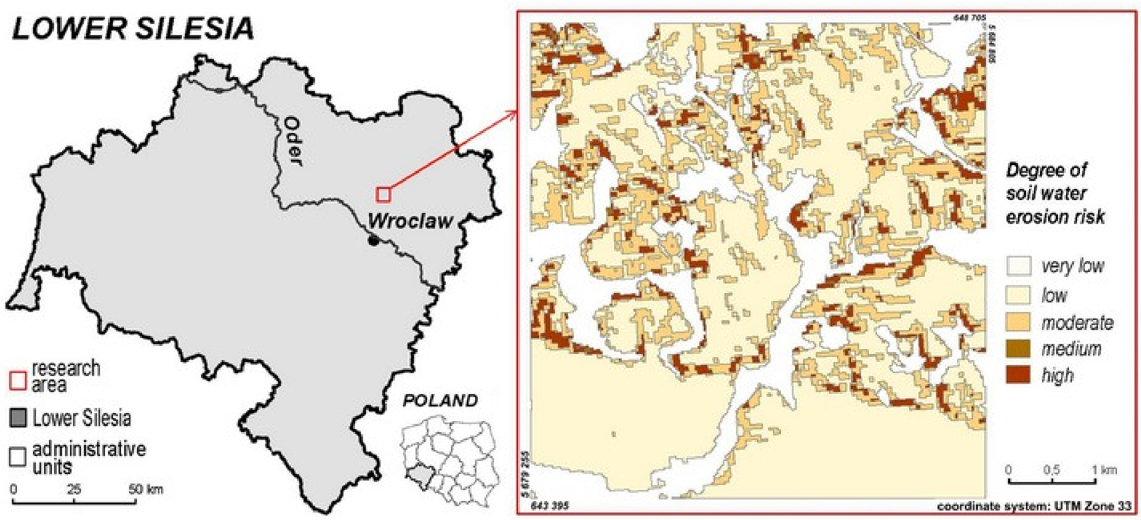

Fig. 1. Research area and potential soil water erosion hazard within the area by Stuczynski [19]

It is known that in areas of low potential erosion risk, the actual erosion may vary significantly. On the other hand, areas of high potential risk may be characterized by low actual risk as a result of the protection afforded by vegetation. As mentioned above, nearly 70% of the study area is classified with low risk of potential soil water erosion. However, considering the type of soil, vegetation coverage and intensive agricultural use in these areas, it may be assumed that the intensity of erosion processes is higher. In the study three environmental factors regarded as the most significant for soil water erosion are used: soil susceptibility to water erosion, slope and vegetation coverage. Weather conditions are assumed to be constant throughout the study area based on meteorological measurements. The average annual precipitation is around 650 mm and specifically the monthly rainfall in April 2011 is 17.9 mm. The date of the rainfall measurement is consistent with the acquisition date of the rest of the source data.

The complexity of the studied phenomenon entails a variety of data sources: satellite images, digital elevation models (DEM), vector databases (Fig. 2). Multispectral Landsat TM satellite imagery (USGS product Level1T- geometric and radiometric corrections applied) acquired on 10.04.2011 is used to determine the land cover characteristics and the vegetation coverage of the study area. A DEM with 10m resolution, which is used as the data source of the relief, was derived from aerial photography in the scale of 1:26 000. The soil characteristics are extracted from the vector soil map of Lower Silesia in the scale of 1:25 000 (source: Regional Centre of Geodetic and Cartographic Documentation (WODGIK)). Additionally, current orthophotos with 0.25 m resolution were considered as the ground truth data together with the geodetic and cartographic documentation (source: Main Centre of Geodetic and Cartographic Documentation (CODGiK)).

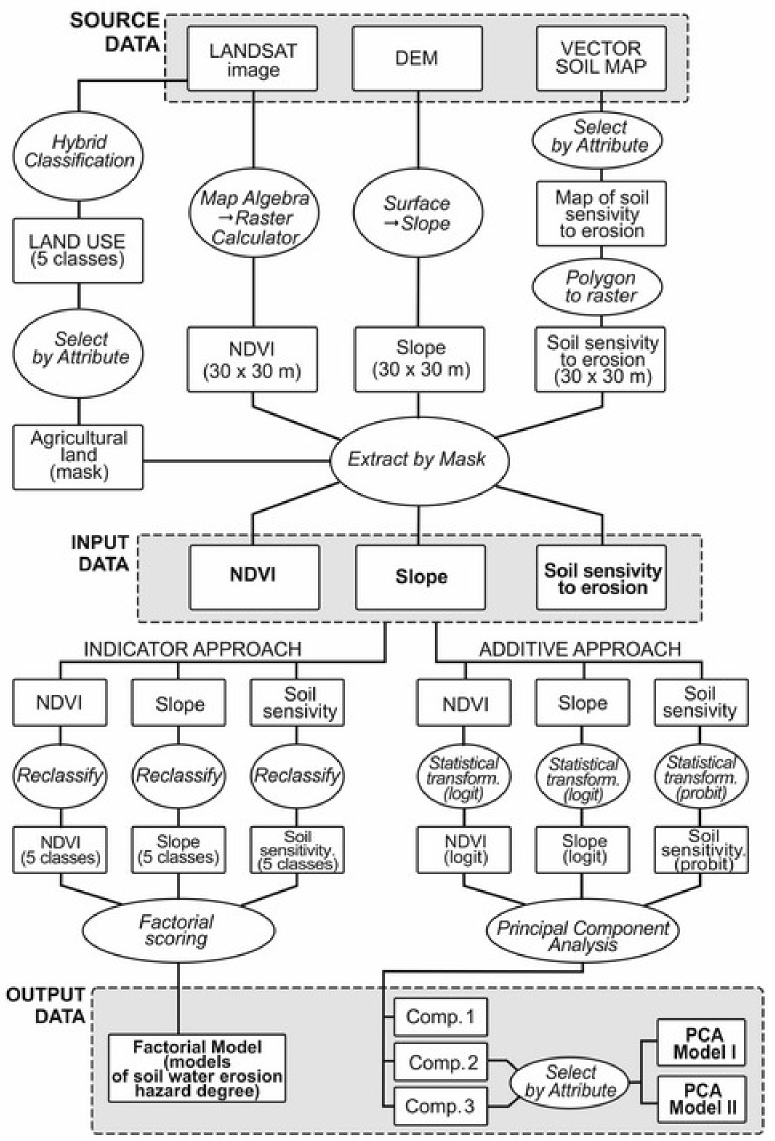

Fig. 2. Data processing scheme

DATA MINING

Classification

The first step of the study is the selection of agricultural lands within the research area through the Landsat image classification. Due to the dense cloud cover of the Landsat scene, the representative 50×50 km area was chosen for classification. A hybrid classification process was carried out in two stages: unsupervised and supervised classification – both conducted on all bands of Landsat image, excluding thermal band (band 6) due to its lower acquisition resolution.

For the unsupervised classification the ISODATA method was chosen with the number of iterations set at 20, convergence threshold of 95% and cluster number of 40. The results of unsupervised classification were improved by modifying classes containing mixed pixels belonging to different land cover classes. The resultant 51 clusters were used as training set in Gaussian maximum likelihood supervised classification. Based on ground true data (geodetic site measurements performed on 9–10.04.2011) and the actual orthophoto map the number of obtained clusters was reduced to five main classes which are: arable lands, meadows and pastures, water, forest and urban areas. The hybrid classification results were limited to the study area and yielded the following results: arable areas comprise 42.70%, meadows and pastures – 38.85%, water – 0.28%, forest – 15.19% and urban – 2.98% of the study area. Only classes representing arable lands, meadows and pastures were analyzed. The areas of other classes are beyond the scope of this research, thus they are designated as unclassified in the following parts of the study. The overall classification accuracy was 84% for the determined classes. For the accuracy assessment of the hybrid classification, an error matrix was constituted and kappa coefficients for each class were calculated (see Tab. 1).

Table 1. Accuracy assessment results and error matrix

Classification \ Reference	Arable	Meadows and Pastures	Water	Forest	Urban	*Row Total*
Arable	36	11	0	0	0	*47*
Meadow and pastures	6	31	0	0	0	*37*
Water	0	0	5	0	0	*5*
Forest	1	0	0	15	0	*16*
Urban	0	0	0	0	5	*5*
Column Total	*43*	*42*	*5*	*15*	*5*	*110*

	Arable	Meadow	Water	Forest	Urban	*Total*
User's Accuracy	0.77	0.84	1.00	0.94	1.00	0.91
Producer's Accuracy	0.86	0.74	1.00	1.00	1.00	0.92
Overall accuracy:	0.84					

K_{arable}	0.62
K_{meadow}	0.74
K_{water}	1.00
K_{forest}	0.93
K_{urban}	1.00
Overall Kappa	0.86

Input data

As was mentioned before, out of the environmental factors influencing the soil water erosion, the following were chosen: soil susceptibility to water erosion, vegetation coverage and slope. These input data were obtained through processing of the source data (Fig. 2).

Soil susceptibility to water erosion was obtained from a vector soil map based on the type of soil and its subsoil. According to Jozefaciuk [10, 11], there are five degrees of soil susceptibility to water erosion: very low (e.g. skeletal soil, clay), low (e.g. sandy clay loam), medium (e.g. sandy loam), high (silt soil with loam fraction) and very high (e.g. loess, silt soil). The study area is characterized by high and very high soil susceptibility to water erosion (Fig. 3). It can be observed that over 80% of the entire study area is highly susceptible to water erosion and in the southern part the degree becomes very high. It should be noted that the vector map is converted to 30-meter resolution raster data. The assumed cell size is a result of the Landsat image resolution.

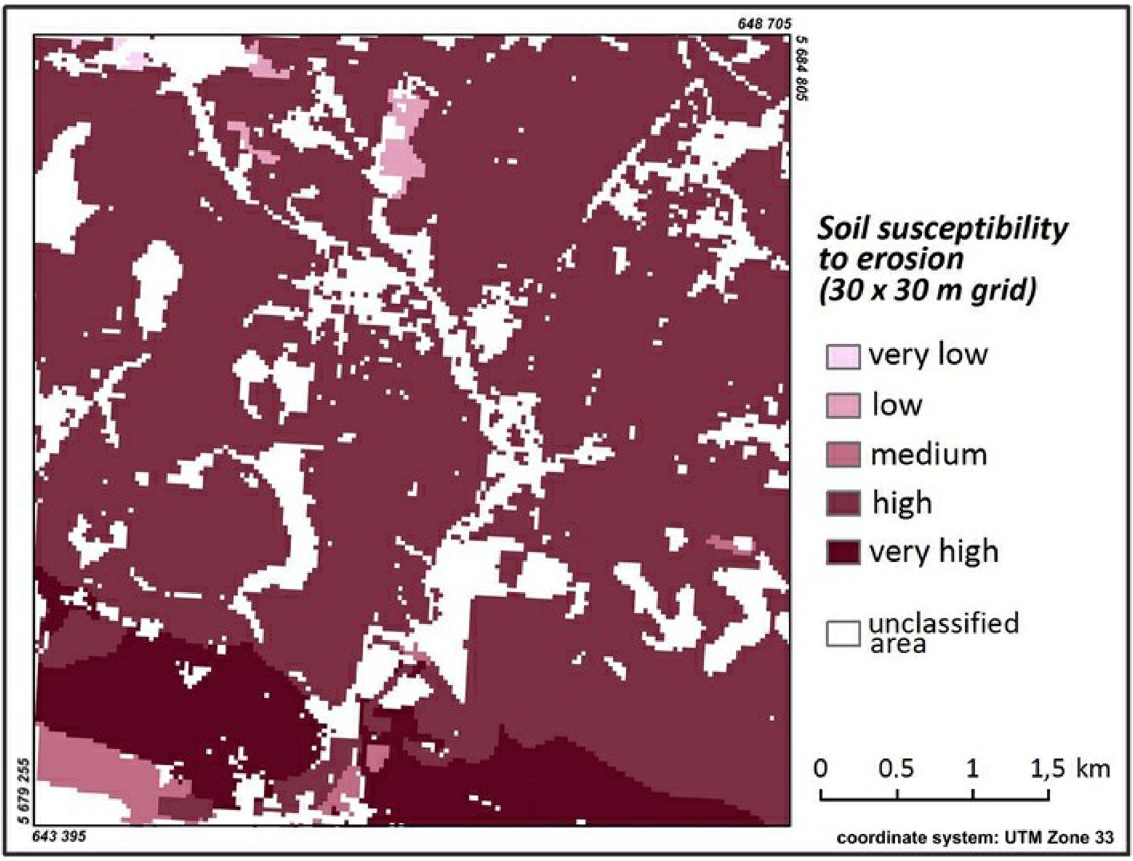

Fig. 3. Spatial distribution of soil susceptibility to erosion within research area

The vegetation cover, as an important biophysical determinant of soil water erosion, may be estimated by vegetation indices [3, 13, 21, 22]. In this study, the Normalized Differential Vegetation Index (NDVI) is used as an indicator of vegetation type and its condition. The NDVI formula is as follows (Jensen, 2000):

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

where:
NIR – spectral reflectance measurements acquired in near-infrared band
RED – spectral reflectance measurements acquired in red band

As the NDVI is a normalized index, its values range from -1.0 to 1.0. High values of NDVI indicate dense and fresh vegetation which, in terms of soil water erosion risk, prevents the runoff and preserves the top soil layer even during heavy rainfall. NDVI values close to 0 are interpreted as bad plant condition, very sparse vegetation or bare soil. Negative values of the index generally correspond to water. Based on the literature [4], the values are divided into five classes: 0.01–0.20 (bare soil), 0.21–0.30 (mixed of bare soil and vegetation), 0.31–0.40 (weak vegetation), 0.41–0.80 (fresh vegetation), 0.81–1.0 (very fresh vegetation). For the area under study, NDVI values range from 0.01 to 0.64 (Fig. 4).

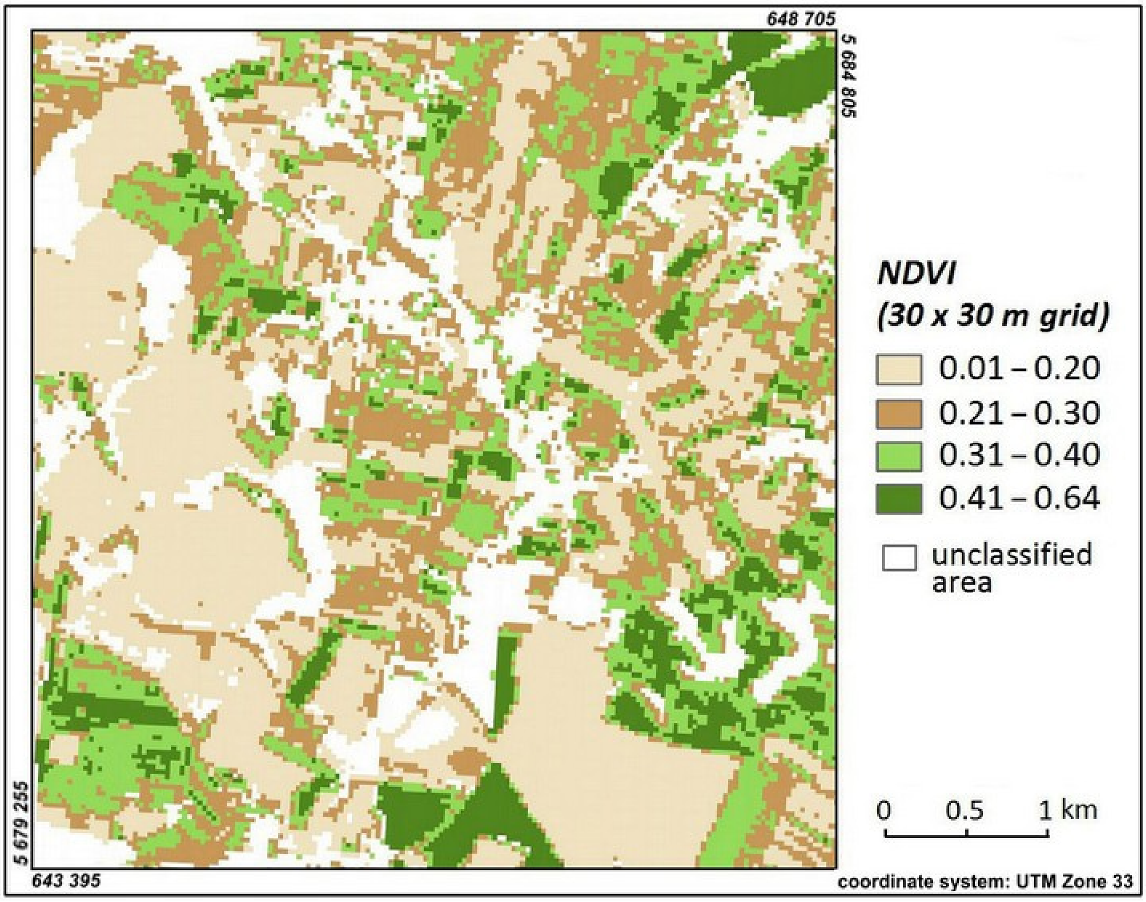

Fig. 4. Spatial distribution of NDVI within research area

The topography affects the erosion especially in terms of steepness of slope. The slope value is computed with respect to a plane fitted to the height-values of a 3×3 cell neighbourhood around the centre cell using the average maximum technique [1]. The maximum rate of change between each cell and its eight neighbours is calculated based on the 10-meter resolution digital elevation model (DEM) and generalized to 30-meter raster. Figure 5 depicts the spatial distribution of slope within the research area: most common are slopes below 5%, concentrated in the southern part, although there are some regions of medium (11–18%) and high (19–25%) slope values.

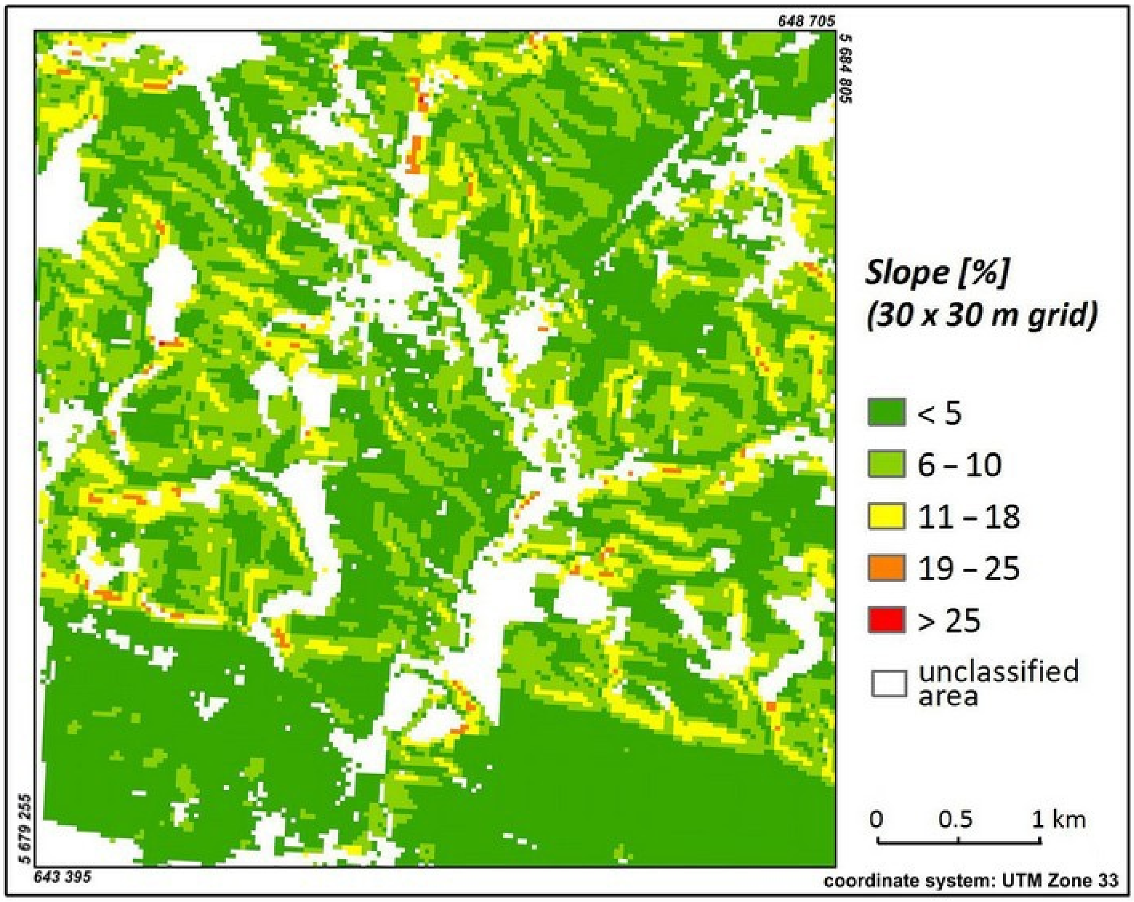

Fig. 5. Spatial distribution of slope within research area

Integrating data acquired from various sources (satellite images, orthophotosand vector databases) requires consideration of their accuracy and consistency. In this study the data of higher accuracy (DEM) was generalized to 30×30 m grid which is a resolution provided by Landsat image, and the vector soil map was converted into a raster with the same resolution.

INDICATOR APPROACH

Factorial scoring

Factorial scoring is a technique used in indicator modeling that consists in applying a common scale of values to diverse and distinct inputs in order to conduct an integrated study. The analysis is based on the assignment of factorial scores to each class of input data. In this study, the ranges of values in each class are determined based on the literature as described in previous section [4, 10, 11, 19]. Table 2 presents the score values corresponding to each class of input data.

Table 2. Ranges of values in each class of input data and corresponding score values

Factor scores (Class)	NDVI	Slope [%]	Soil susceptibility to water erosion
1	0.81 – 1.00	< 5	very low
2	0.41 – 0.80	6 – 10	low
3	0.31 – 0.40	11 – 18	medium
4	0.21 – 0.30	19 – 25	high
5	0.00 – 0.20	>25	very high

These factor scores are summed to give a total score, which in the following step is classified using an arbitrarily chosen classification system. In this research, five ranges of values corresponding to classes of soil water erosion risk were distinguished. As a result the study area is categorized into five classes: areas of very low, low, medium, high and very high soil water erosion risk (Tab. 3).

Table 3. Factor score values and corresponding erosion risk degree

Erosion risk degree	Factor scores' sum
very low	≤ 4
low	5 – 7
medium	8 – 10
high	11 – 13
very high	≥ 13

It is noticed that within the study area the 1st class of NDVI (0.81–1.0) does not occur, the highest value of the vegetation index is 0.64. Therefore the very low degree of soil water erosion risk (factor score≤ 4) may only be a combination of very low soil susceptibility to erosion (1), slopes below 5% (1) and the highest NDVI within the research area (2). These conditions do not occur within the study area. Similar situation refers to the highest degree of soil water erosion (factor score ≥ 13): such areas embrace only 0.4% of the study area. The degree of soil water erosion risk within the study area is presented in the Figure 6. It is shown that the largest area is characterized by medium degree of soil water erosion risk (over 65% of studied area) and high erosion risk refers to almost 30% of agricultural lands.

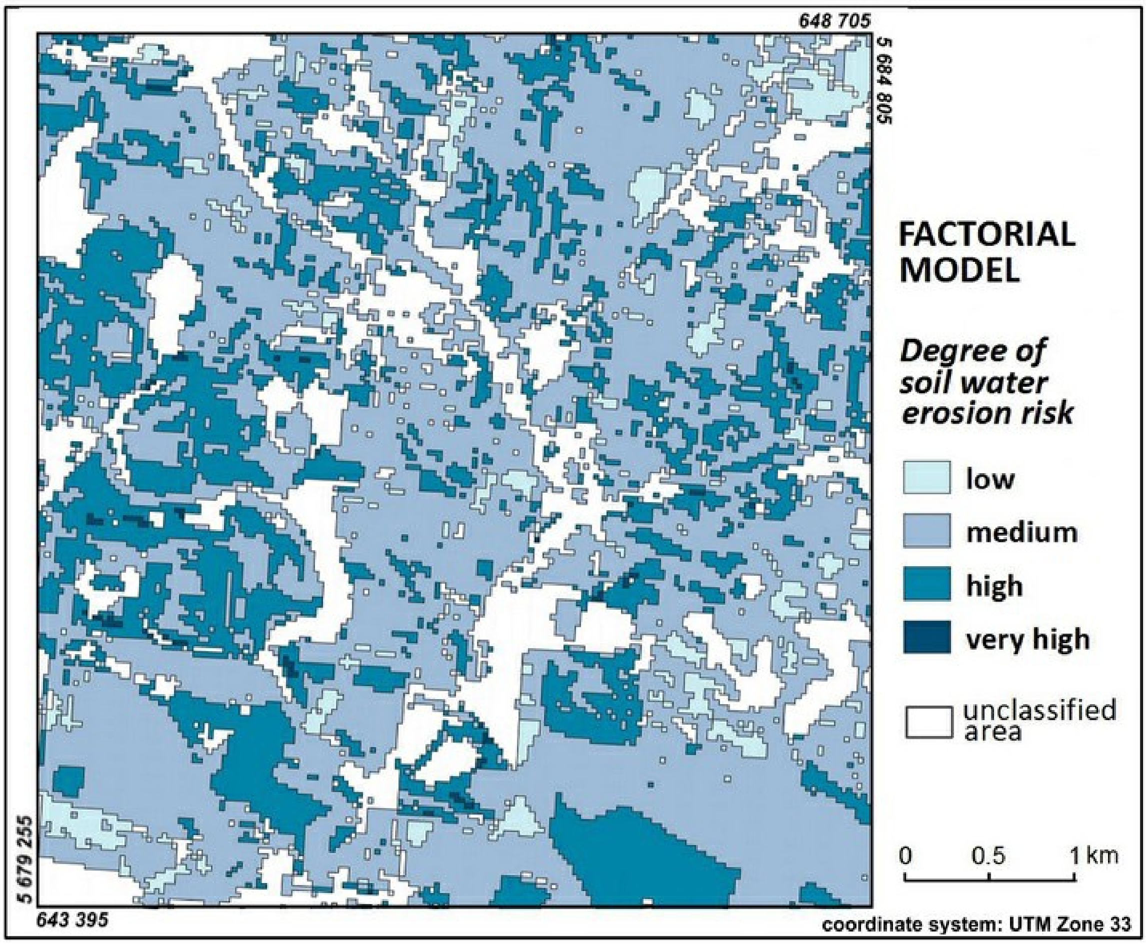

Fig. 6. Degree of actual soil water erosion risk based on factorial scoring

Assessment of the actual erosion risk reveals that most of the area faces medium degree of soil water erosion hazard. Within these areas more detailed analysis that allows for profound spatial differentiation of erosion risk is required.

ADDITIVE APPROACH

Principal Component Analysis

In the additive approach, the same set of input data as for the factorial scoring is used. Before they could be used for modeling, all spatial datasets which are originally diversified – in continuous or ordinal scale (soil susceptibility), dimensionless (NDVI), percentage (slope) – have to be converted in order to provide data homogeneity. This conversion should ensure normal or at least symmetric distribution of the data in order to apply data standardization and evaluate basic statistics. It can be performed using two transformed equations of linear regression, namely logit and probit. Both of them are based on the assumption that estimated random variable has the logistic distribution for logit and the Gaussian distribution for probit [12]. Using the abovementioned equations, the NDVI and slope values were recalculated using logit function, whereas the soil susceptibility to erosion for each pixel was transformed from ordinal to continuous scale using probit function. The transformations were followed by standardization.

Once the data are transformed and their homogeneity is ensured, the modeling can be performed. Assessment of erosion risk is a complex issue requiring data exploration in terms of mutual dependencies between the input data. Additionally, the reduction of the number of explanatory variables can be required in order to prevent over-fitting [12]. In this case the relation between the three input variables (slope, NDVI, soil susceptibility) was investigated using the Principal Component Analysis. With PCA one can generate a new set of uncorrelated variables (PCA components) from the set of correlated explanatory variables carrying a lot of redundant information. The Principal Component Analysis consists of the following steps:

- Generating the covariance matrix of the data in the coordinates of the original input dataset,
- Calculating the eigenvalues and eigenvectors of the covariance matrix,
- Ranking the eigenvalues to identify the first, second and subsequent principal axes (components),
- Calculating the new pixel values in each of the principal axes [18].

The analysis of variance shows how much information of the input data is explained with the new components. One of the crucial steps is the interpretation of PCA outcomes which is based on the values of correlation coefficients between components and input data.

In this study PCA was performed on the set of three variables: NDVI, soil susceptibility to erosion and slope (Fig.2). Eigenvalues and variance of principal components are shown in Table 4. The value of the cumulative percent of variance shows that the first and second components explain nearly 77% of input dataset variability. At this stage, the interpretation of components will show whether the first two components are suitable for the analysis of soil water erosion risk. Interpretation of the PCA results is based on the values of correlation coefficients between components and independent variables (see Tab. 5).

Table 4. Eigenvalues and variance of principal components

Component	Eigenvalues	% of total variance	Cumulative % of variance
1	1.300636	43.35	43.35
2	1.005791	33.53	76.88
3	0.693583	23.12	100.00

Table 5. Correlation coefficients between components and independent variables

		Components		
		Component 1	Component 2	Component 3
Variables	Slope	**-0.81**	0.06	**0.58**
	NDVI	0.05	**0.99**	0.12
	Susceptibility to erosion	**0.81**	0.14	**0.58**

Based on the correlation coefficients between components and independent variables the interpretation of components is as follows:

- Component 1 introduces a balance between slope and susceptibility to erosion; the slope is inversely correlated with the type of soil (e.g. skeletal soils which are very low susceptible to erosion occur on steeper slopes),
- Component 2 refers to vegetation index (NDVI),
- Component 3 describes the summarized relationship between the slope and the susceptibility to erosion.

Analysis of component 1 is not suitable for modeling of erosion risk due to its ambiguous interpretation, e.g. values close to 0 refer to areas of high susceptibility to erosion and high slopes, while at the same time they also correspond to areas of low susceptibility and low slopes. By contrast, the values of component 3 provide more definite information on erosion hazard: high values of the component indicate the areas of steep slope and high susceptibility to erosion whereas low values refer to areas of small slope and small soil susceptibility. Spatial variability of component 3 presented in Figure 7 confirms that the analysis of components in the additive approach can provide more specific information on the soil water erosion degree.

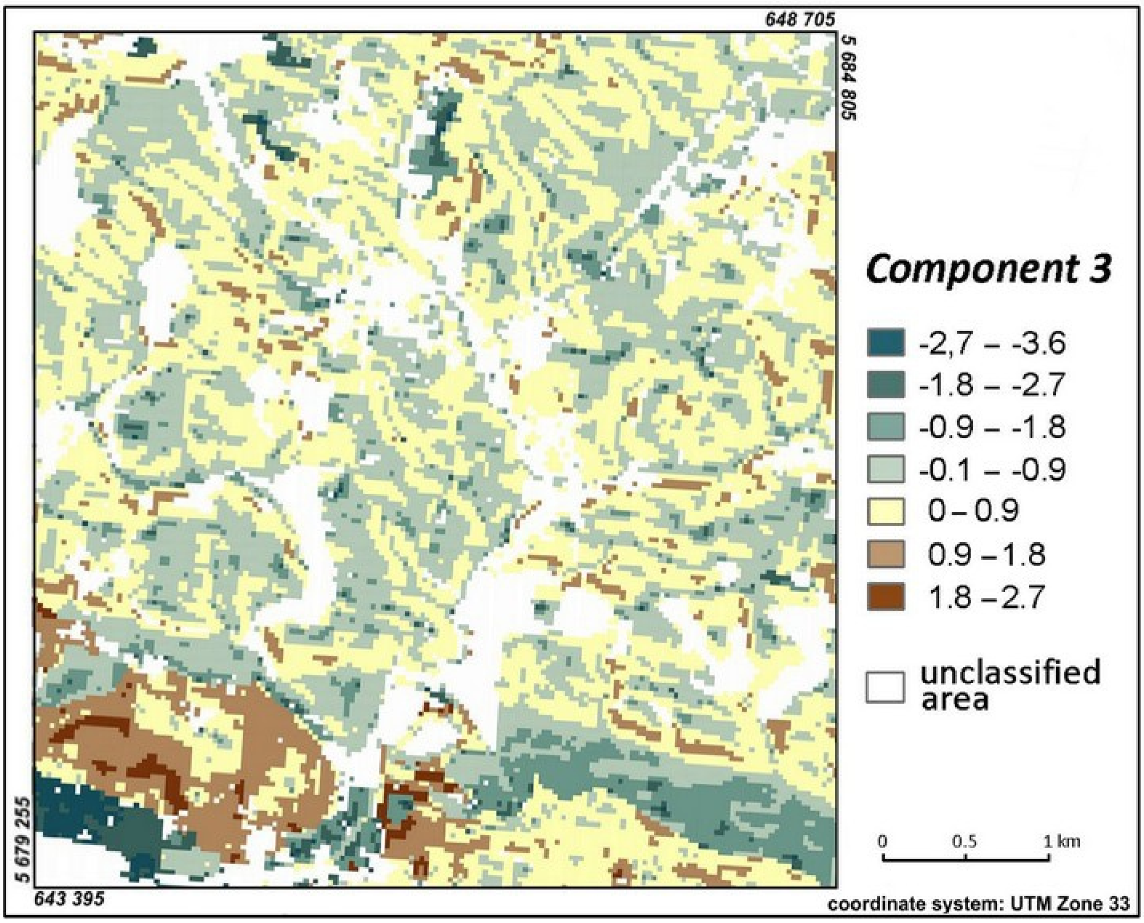

Fig. 7. Spatial distribution of component 3 within research area

The outcomes of the PCA lead to the conclusion that the simultaneous analysis of component 2 and component 3 is sufficient to describe the investigated phenomenon.

RESULTS

In order to assess soil water erosion hazard in terms of component 3 and component 2 (NDVI), models with different assumptions were created (Tab. 6). PCA Model I, in which component 3 values are negative (low slope and low soil susceptibility), is assumed to indicate areas less endangered with potential soil water erosion risk, whereas PCA Model II with the component 3 values being greater or equal to 0 (i.e. steep slope and high soil susceptibility) demonstrates more endangered areas. In both cases the diversification of actual soil water erosion hazard is a result of component 2 values.

Table 6. PCA models assumptions in additive approach

PCA Model I Component 3 < 0 (less endangered areas with potential erosion risk)		PCA Model II Component 3 ≥ 0 (more endangered areas with potential erosion risk)	
NDVI (Component 2)	**Degree of actual soil water erosion hazard**	**NDVI (Component 2)**	**Degree of actual soil water erosion hazard**
0.41 – 0.80	low	0.41 – 0.80	low
0.31 – 0.40	moderate	0.31 – 0.40	moderate
0.21 – 0.30	medium	0.21 – 0.30	medium
0.00 – 0.20	high	0.00 – 0.20	high

PCA Model I (Fig. 8) depicts the spatial variability of actual soil water erosion risk in the areas of low soil susceptibility to water erosion and flat terrain. Over 50% of these areas faces high actual erosion risk, and around 42% - moderate and medium degree. It means that despite the favourable soil and relief conditions, attention to anti-erosion protection should be paid, depending on vegetation cover.

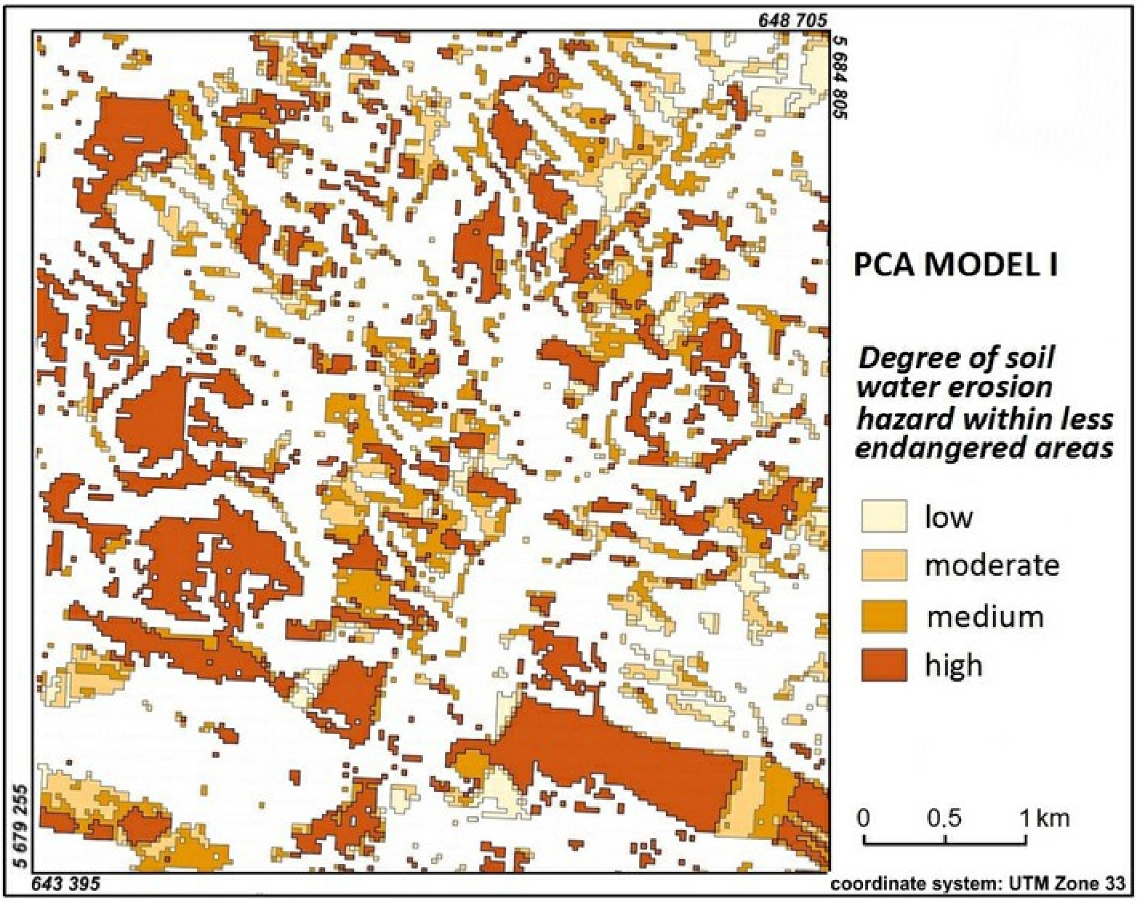

Fig. 8. Degree of actual soil water erosion hazard within less endangered areas with potential erosion

PCA Model II (Fig. 9) presents the diversification of actual erosion risk in the areas of high soil susceptibility and steep slopes. Only 10% of these areas ("low" class) is covered with the vegetation that protects it from the severe soil degradation. This model also shows areas most endangered with actual soil water erosion ("high" class), that make up around 40% of the total area.

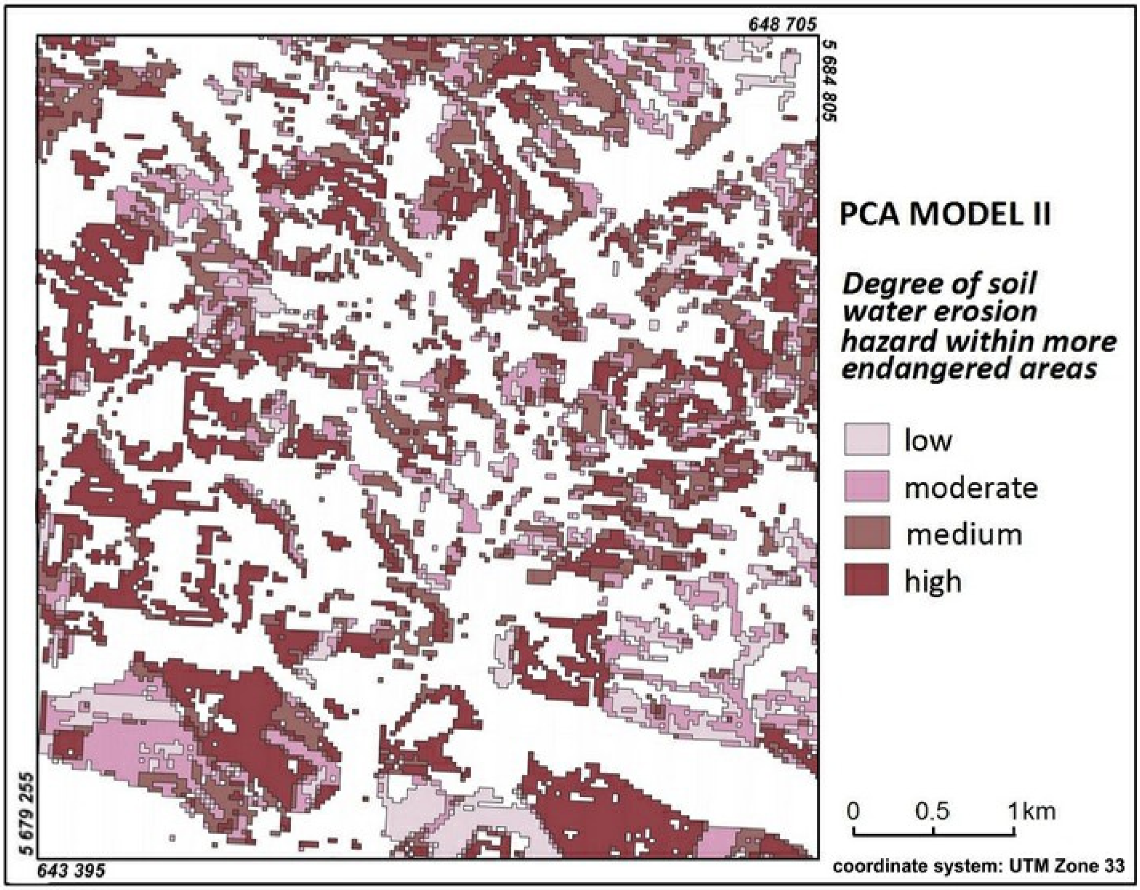

Fig. 9. Degree of actual soil water erosion hazard within more endangered areas with potential erosion

The additive approach conducted in the study provides more accurate information on soil water erosion risk than the indicator approach. This can be analyzed by superimposing the PCA models on chosen classes of the factorial model. The example of spatial diversification of actual soil water erosion degree within the areas of 3rd class of the factorial model is presented below (Fig. 10).

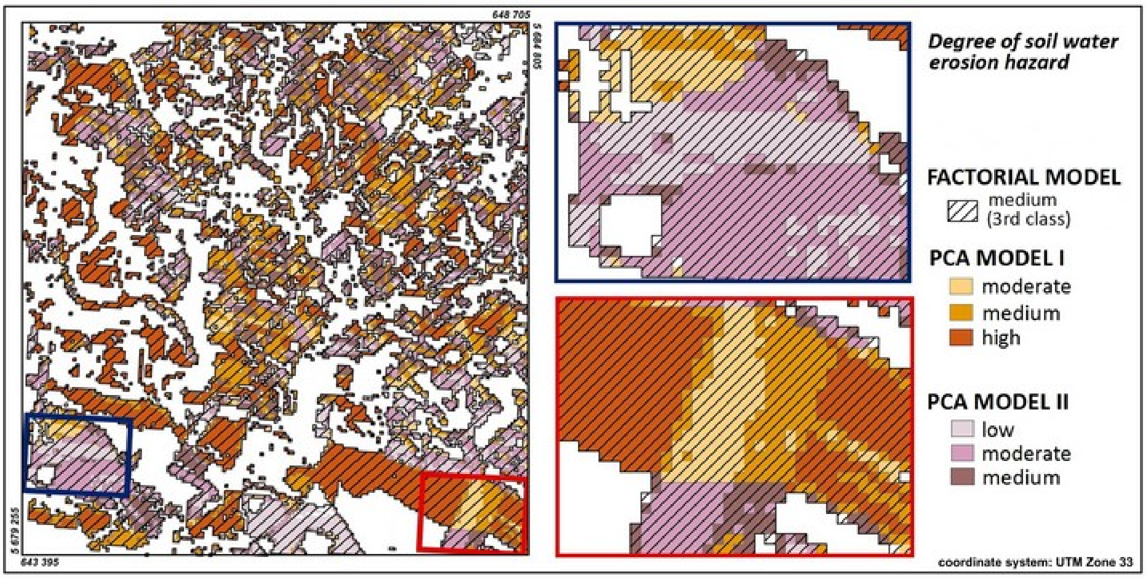

Fig. 10. Diversification of actual soil water erosion degree resulted in additive approach within the areas of medium class of factorial model

Although in the factorial model over 65% of agricultural land is classified as medium degree of erosion risk, the additive approach indicates that this area is not homogenous. It can be observed that there are areas of different potential erosion risk: less endangered areas cover 45.3% and areas more threatened with soil water erosion – 54.7%.

Nearly 30% of the areas of low soil susceptibility to erosion and flat relief is highly endangered with erosion, while on the terrains of high potential risk the largest area (over 35%) is characterized by medium and moderate actual soil erosion risk. The above analysis confirms that more detailed and comprehensive assessment of soil water erosion risk is possible with the use of components derived by PCA as the input data.

SUMMARY AND CONCLUSION

In this study assessment of soil water erosion risk is performed involving three environmental factors: soil susceptibility to water erosion, slope and vegetation coverage. The paper presents two approaches to estimate soil water erosion hazard on agricultural lands: indicator and additive approach for which factorial scoring and Principal Component Analysis are used, respectively. In the first method initial datasets of values are classified into five classes with factorial scores assigned. Scores are summed to give a total score which in turn is again classified into five classes representing erosion risk from the lowest (1st class) to the highest degree (5th class). Using the abovementioned method, the majority of the study area is found to be of medium degree of soil water erosion risk. Knowing the local environmental conditions and characteristics of agricultural use of the study area, one may assume that more degrees of erosion risk can be identified within the medium class of the factorial model. To obtain this diversification, principal component analysis is proposed for the additive approach. The PCA is preceded with the input data transformation which guarantees data homogeneity. These conversions are performed using logit and probit functions. The PCA changes the original set of values into a new set of uncorrelated variables representing the investigated phenomenon through three components. Interpretation of these components leads to conclusion that two of them (component 2 and component 3) are suitable and sufficient to model erosion risk. Component 3 provides information on potential erosion risk and the analysis of its spatial distribution shows areas of lower (where the component has negative values) and higher (where the component values are greater or equal 0) degree of potential erosion hazard within medium class of the factorial model mentioned above. Each of these areas covers approximately half of the agricultural land, with the less endangered areas comprising 45.3% of it and the more threatened ones – 54.7%. Component 2, which in the study is considered equivalent to the NDVI (correlation coefficient 0.99), conveys additional information on the variety of vegetation coverage, thus the additive approach enables identifying the degree of actual soil water erosion risk in the regions of homogenous potential erosion risk. PCA Model I represents the diversity of actual soil water erosion degree in areas of low soil susceptibility and flat terrain (less endangered areas), whereas PCA Model II shows the variability of actual erosion in areas of steep slope and high soil susceptibility (more endangered areas). Detailed analysis of the maps of actual soil water erosion risk shows its substantial spatial diversity in the study area.

The outcomes of the soil water erosion assessment in additive approach reveal that this phenomenon is much more heterogeneous than it appears from the indicator model. Moreover, the interpretation of the PCA components and the visual analysis of their spatial distribution provide comprehensive information on actual soil water erosion risk. Hence, the proposed methodology applied to the whole of Lower Silesia would bring a wide and complete cognition of soil water erosion degree in this region of Poland.

Acknowledgements

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