MULTI-TEMPORAL SOIL EROSION RISK ASSESSMENT IN N. CHALKIDIKI USING A MODIFIED USLE RASTER MODEL

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ABSTRACT

The aim of this work was to test a modified version of the Universal Soil Loss Equation (USLE) for assessing the risks of erosion in N. Chalkidiki, Greece. USLE estimates the severity of erosion, thus assisting the decision process in selecting erosion control measures. Although USLE has several limitations, it was selected because it is the simplest approach while remaining robust, and it partially solves the problem of data availability. Modifications referred to here concerned the estimation of factors *C* and *k* (representing land management and soil vulnerability, respectively). More specifically, the *C*-factor was estimated using multi-temporal *NDVI* layers derived from LANDSAT images, while the *k*-factor was estimated based on the geological map. All USLE factors were calculated as grid layers after processing the original data, then they were multiplied together (according to the USLE) in order to derive the final risk map for three different seasons. A scale of 1:100 000 was selected and the mapping unit was set at 1 ha. The results, assessed for their accuracy by experts, showed that the use of multi-temporal *NDVI* gave a better insight than a single date approach in understanding the erosion procedures in the study area and facilitated the comparison between seasons and areas.

INTRODUCTION

About soil erosion

Erosion is a natural geological phenomenon resulting from the removal of soil particles by water or wind, transporting them elsewhere, while some human activities can significantly increase erosion rates. Erosion is triggered by a combination of factors such as steep slopes, climate (e.g. long dry periods followed by heavy rainfall), inappropriate land use, land cover patterns (e.g. sparse vegetation) and ecological disasters (e.g. forest fires) (1). Moreover, some intrinsic features of a soil can make it more prone to erosion (e.g. a thin layer of topsoil, silty texture or low organic matter content) (2). The Mediterranean region is particularly prone to water erosion due to its physical factors: climate, topography and soil characteristics (3,4). Serious erosion is generally irreversible.

Different indicators of soil erosion have been identified and it is a common opinion that the area actually affected by erosion is in fact the best indicator for soil erosion. Equally interesting to the actual erosion rate is the risk of future erosion in a specific area. The area at risk can be estimated using an appropriate model of soil erosion. Effective modelling can provide information about current erosion, its trends and allow scenario analysis. The integration of existing soil erosion models, field data and data provided by remote sensing technologies, through the use of geographic information systems (GIS), appears to be an asset to further exploit (5). From this perspective, it is not surprising that the European Commission adopted an action plan on GMES - Global Monitoring for the Environment and Security - in 2004. The plan outlines firm steps towards the establishment of a system that will harness, co-ordinate, and enhance existing Earth Observation (EO) data and monitoring information from satellites and Earth-based sensors, in order to support decision making for the environment and security.

The awareness of the fact that EO data have not been used to their maximum capability for policy support in the EU has produced a considerable effort to correct this situation (6). This is true for many areas of application including land use, land cover, terrestrial ecology, geology and soils. Considering EO data (i.e. data acquired with Remote Sensing), scale and spatial resolution are two of the most important factors, especially in the land resource area, because of the spatial heterogeneity of some complex mosaic of patches and transitional forms, typical of the Euro-Mediterranean region (7). In many cases, problems with the availability of multi-temporal EO data also create obstacles. Multi-temporal data are needed both to aid classification (e.g. of land cover) and to detect changes. However, gaps in time series data often occur because of cloud cover and sensor failure. These add to the cost and difficulty of data acquisition and may limit data use.

Soil erosion risk models and USLE

A large variety of models can be found in the literature that could be used in soil erosion risk assessment. These models can be classified as follows:

- Empirical and mechanistic models: The empirical models describe a process based on empiricism. In contrast, mechanistic models attempt to represent the physical causes of responses to conditions.
- Static and dynamic models: the difference between static and dynamic models is that dynamic models take into account time as an extra variable.
- Deterministic and stochastic models: Deterministic models make definite predictions for quantities without any associated probability distribution. Stochastic models, on the other hand, contain some random elements or probability distributions. Except for the predicted value, stochastic models can also predict the variance.
- Spatial dimensions in models: Any model can be distinguished between one-dimensional (1D), two-dimensional (2D) and three-dimensional (3D) models.
- Qualitative and quantitative models: Qualitative models predict values on quality levels such as not risky, risky or highly risky. The input data for a qualitative model can be both qualitative and quantitative. On the other hand, a quantitative model produces a numerical output.
- Long-term or event-based models (temporal scale).
- Single point or spatially distributed models (spatial scale).

Because of the complexity of real world processes, the models which try to simulate these processes often contain combinations of the aforementioned model types; as an example, the model "ANSWERS" is a dynamic two-dimensional (2D) model.

The main criteria in order to choose one of the above models are: the purpose of use, the available data, the available time, and the cost. Most erosion models have been designed to predict point soil loss, because they were developed on a field scale. As a result, this kind of models cannot estimate accurate soil erosion loss values when they are applied over large geographic scales. Besides, most models have been developed to predict a specific type of soil erosion (e.g. rill-, inter-rill erosion, gully erosion, etc). As a result, a model cannot perform well in an area where the dominant type of erosion is not the one for which the model was designed. The main problem in relation to the erosion risk models is the validation of their estimates, because there are not always reliable data for comparing the calculations of the models with actual soil losses.

One of the most widely applied empirical models for assessing the sheet and rill erosion is the Universal Soil Loss Equation (USLE), developed by Wischmeier and Smith in 1978 (8). This model takes into consideration several determining factors, such as the soil erodibility factor, rainfall intensity factor, slope length and steepness factor, cover and management factor and support practice factor. USLE was developed mainly for soil erosion estimation in croplands or gently sloping topography. USLE estimates soil loss from a hillslope caused by raindrop impact and overland flow (commonly termed "interrill" erosion), plus rill erosion. It does not estimate gully or stream-channel erosion. Although USLE has many shortcomings and limitations, it is widely used, especially at regional and national level, because of its relative simplicity and robustness (9) and because it represents a standardised approach. USLE has not been designed to operate at field scale, however, it was noted that there is room for improving the accuracy of results by using more detailed digital elevation models, satellite data, with enhanced geometric characteristics, and more detailed soil information. A Revised Universal Soil Loss Equation (RUSLE) followed the same formula as USLE, but got several improvements in the determining factors and a broader application to different situations, including forests, rangelands and disturbed areas compared to USLE (10). RUSLE is a computation method that may be used for site evaluation and planning purposes and also for assisting in the decision process of selecting erosion control measures. It provides an estimate of the severity of erosion and also numerical results that can validate the benefits of planned erosion control measures in the risky areas (11).

Aim and objectives

In many countries including Greece, data availability plays a crucial role in selecting an appropriate erosion prediction model. Especially, the lack of reliable soil and climatic data is the main obstacle in implementing most models. Detailed soil properties maps are missing or they are not available in Greece, while the meteorological stations are not as dense as needed for a mountainous country. Additionally, as erosion is a multi-temporal procedure, seasonal land cover and use affect the accuracy of any mapping results. Therefore, land cover maps of static nature, such as CORINE, are not enough for deriving multi-temporal information. As a result of all the above, several potential data sources for obtaining seasonal land cover, soil characteristics, and rainfall estimations should be considered for any specific case.

The main aim of this work was to test a modified version of the Universal Soil Loss Equation (USLE) for assessing the risk of soil erosion in N. Chalkidiki, Greece. For this purpose, the *C*-factor was calculated using multi-temporal vegetation indices (namely *NDVI*) derived from satellite images, whereas it is originally estimated by expertise. The *k*-factor was calculated based on the geological map, while it is originally based on soil analysis data. The *NDVI* was selected for estimating the *C*-factor because *NDVI* can express the condition of vegetation in different seasons (seasonal land cover), thus providing a reliable temporal dimension in soil erosion risk assessment. This is of great importance in Mediterranean regions, such as the studied one, where dry summers are followed by heavy winter rainfalls. The reason for calculating the *k*-factor from geological data was the lack of precise and reliable soil datasets in the study area. The testing hypothesis of the work was that the above modifications of *C* and *k*-factors were necessary and efficient for improving insight in understanding the erosion procedures in the study area.

Study area

The study area is located in the north part of Chalkidiki prefecture, Greece (Figure 1). Chalkidiki is a peninsula in the Aegean Sea, made up of three smaller peninsulas which from west to east are: Kassandra, Sithonia and Athos. Cholomon Mountain dominates the landscape. The region has very warm and dry summers: average temperature is between 23°C and 34°C during summertime; and between 4°C to 19°C during the winter. The area's population is 110 000, and its capital city is Polygyros. The lowlands are covered by crop patterns of arable land, olive trees, grapes, and vegetables (mainly tomato and cucumber), while on the mountainous areas coniferous, broad-leaved, and mixed forests are altered with bushes and pastures.

DATASET AND METHODS

Dataset

The data that was available for the implementation of this work comprised the following:

- A set of three (diachronic) LANDSAT-7 images acquired on 24 August 2000, 5 April 2001, and 2 November 2002 (Figure 2).
- A representation of the relief in terms of Digital Terrain Model (DTM) derived from the Greek Ministry of Agriculture, on a scale of 1:50 000.

- A geological map derived from the Greek Institute of Geological Surveys (IGME), on a scale of 1:50 000.
- A land cover/use map based on the CORINE nomenclature, used for assisting interpretation of the satellite images (Figure 3).
- Monthly climatic average observations derived from three meteorological stations of the Greek Institute of Forest Surveys.

Figure 1: The study area is located in Chalkidiki, Greece and comprises forest and agricultural patterns.

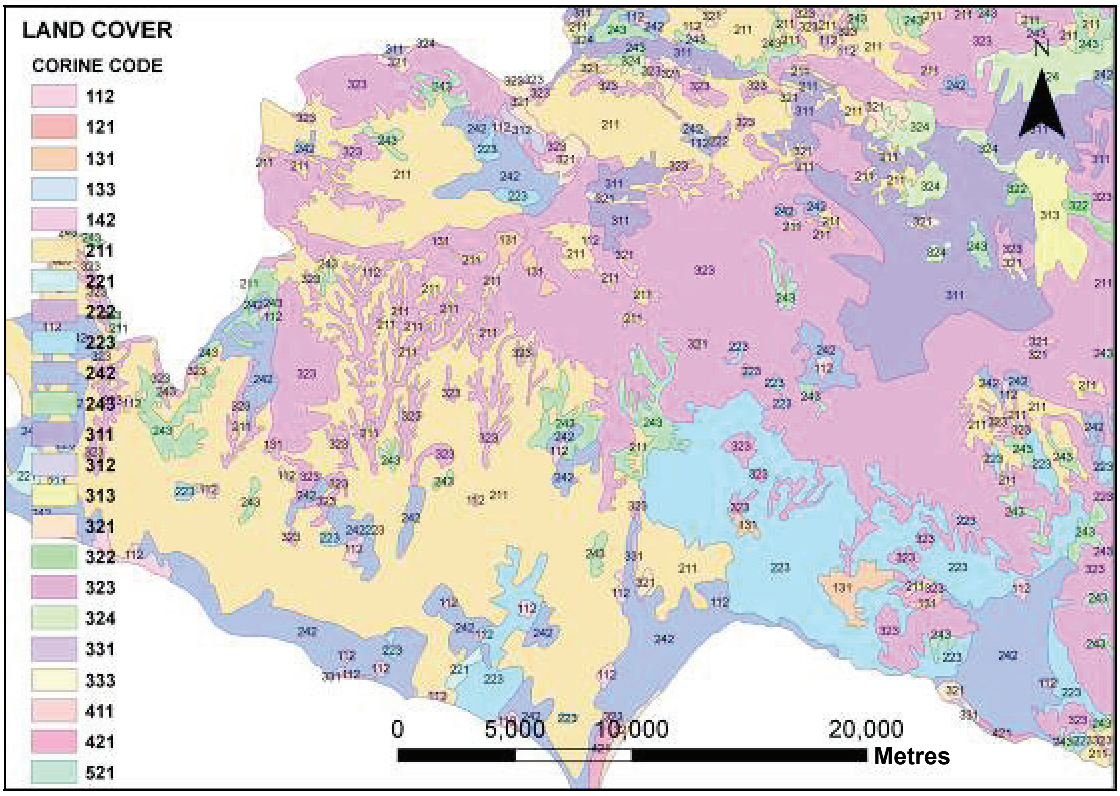

Figure 3: The CORINE 2000 land cover map of the study area used for image photo-interpretation.

Figure 2: The multi-temporal set of LANDSAT-7 images used for soil erosion risk assessment (from top to bottom: 24 Aug 2000, 5 Apr 2001, and 2 Nov 2002).

Methodology

The methodology used in this work was the implementation of the Universal Soil Loss Equation (USLE) in a raster GIS environment (or grid-based approach) after some modifications in the calculation of specific factors. USLE was developed as an equation of the main factors controlling soil erosion, namely climate, soil characteristics, topography and land cover management. More specifically, USLE is expressed by the following formula:

$$A = R \cdot k \cdot LS \cdot C \cdot P \tag{1}$$

where *A*: mean annual soil loss in tonnes per ha and year, *R*: rainfall erosivity, *k*: soil erodibility, *S*: slope steepness, *L*: slope length, *C*: cover and management, *P*: support practices.

USLE was applied in N. Chalkidiki in the spatial domain using GIS, i.e., all USLE factors were derived as raster (grid) geographic layers after processing the original data, then they were multiplied together for calculating the final risk map (an overview of all the methodological steps is given in Figure 4). For a grid-based approach (i.e., use of raster data), the scale of application is related to the cell size of the produced maps. In this work, where a scale of 1:100 000 was selected, the appropriate cell size or pixel was 100 m (area of 1 ha). Consequently, the mapping unit of the results was of the same resolution.

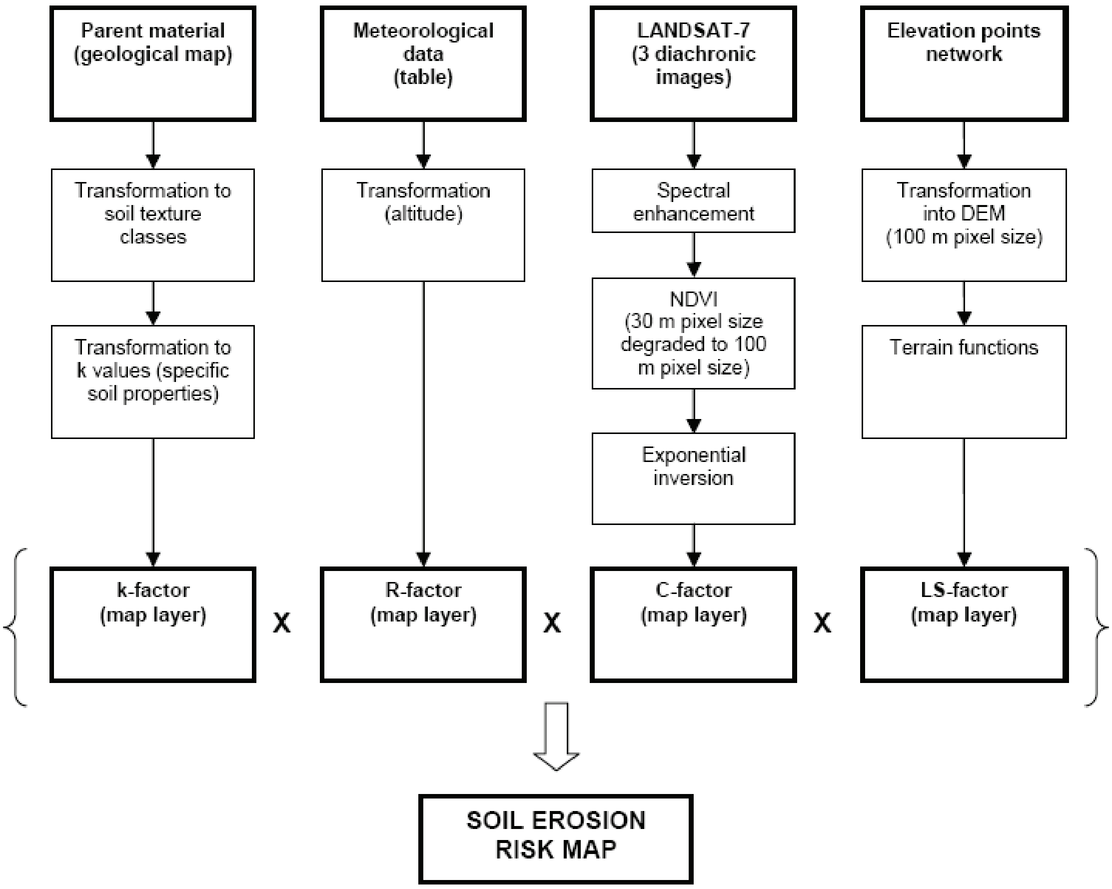

Figure 4: The scheme of the methodological steps.

***R*-factor calculation.**

In USLE, the *R*-factor is derived from the following equation:

$$\log R = 1.93 \log \sum \frac{p_i^2}{P} - 1.52 \tag{2}$$

where p_i is the monthly and P is the annual precipitation. In this application, the lack of a dense meteorological network in the study area made us use a linear equation between precipitation and altitude for calculating the *R*-factor (12). The equations were derived using the mean monthly precipitation data from three stations, namely Vasilika, Arnaia, and Thermi. Finally, for each month the following equations were derived respectively:

for April: $$R = 0.016H + 41.84 \tag{3}$$

for August: $$R = 0.029H + 21.71 \tag{4}$$

for November: $$R = 0.052H + 54.48 \tag{5}$$

where *R*: precipitation and *H*: altitude. The rainfall erosivity map for each month was derived from the above equations which were implemented in "ArcGIS 9.0" software using the "Raster Calculator" tool of the "Spatial Analyst" extension.

K-factor calculation

The *k*-factor (soil erodibility factor) depends on the following soil parameters in combination:

- Percentage of silt, very fine sand, clay and organic matter.
- Structure (codes between 1 and 4 are given to different common structures).
- Drainage (codes between 1 and 6 are given from fast to very slow drainage respectively).

Lal and Elliot in 1994 (13) proposed the following formula for *k*-erodibility factor calculation:

$$k = 2.8 \cdot 10^{-7} \cdot M^{1.14}\left(1.2 - a\right) + 4.3 \cdot 10^{-3}\left(b - 2\right) + 3.3\left(c - 3\right) \tag{6}$$

where *M* is the size of soil particles (% silt + % very fine sand)·(100 - % clay), *a* is the percentage of organic matter, *b* is the code number defining the soil structure (very fine granular = 1, fine granular = 2, coarse granular = 3, lattice or massive = 4), and *c* is the soil drainage class (fast = 1, fast to moderately fast = 2, moderately fast= 3, moderately fast to slow = 4, slow = 5, very slow = 6).

Generally, the above values of the *k*-factor are applied on scales of 1:50 000 and 1:10 000 when a soil map is available. However, in this work, the *k*-factor was derived from the geological map due to unavailability of soil maps for the study area, following the steps:

- Conversion of the geologic map from vector to raster format; this is a common GIS function.
- Determination of the soil texture class for each type of parent material of the geological map; this procedure was based on soil genesis rules (14) (Table 1). Note that different geologic parent material may result in the same or different soil texture.
- Reclassification of the raster geological map into a soil texture map according to the soil texture class and parent material relationship (previous step).
- Reclassification of the raster soil texture map into k values according to the specific soil parameters and domain expertise (Table 2).

Table 1: The k-values as they were assigned to soil textural classes derived from the respective parent geologic material.

Parent geologic material	soil texture*	*k*-values
Alluvial deposits	SL-L	0.15
Limestone	C or SiC	0.4
Peridotid	CL-C	0.5
Granite	S-SL	0.2
Schists	L	0.7
Gneiss	S or LS or L	0.3
Tertiary deposits	SL-L	0.15

* S: Sandy, L: Loam, Si: Silty, C: Clay

LS-factor calculation

The *LS*-factor map was derived from the DTM using the "Terrain Analysis" extension of "Arcview 3.2", which was developed by Schmidt in 2002, based on the work of Moore et al. (15) for calculation of the *S* (slope steepness) and *L* (slope length) factors as follows:

$$L = 1.4\left(\frac{A_S}{22.13}\right)^{0.4} \tag{7}$$

$$S = \left(\frac{\sin\beta}{0.0896}\right)^{1.3} \tag{8}$$

where A_S: specific catchments area (m^2/m), β: slope angle in degrees.

Table 2: The k-values as they were calibrated according to specific soil parameters.

Textural Class	O.M. average	O.M. less than 2%	O.M. more than 2%
Clay	0.22	0.24	0.21
Clay Loam	0.30	0.33	0.28
Coarse Sandy Loam	0.07	--	0.07
Fine Sand	0.08	0.09	0.06
Fine Sandy Loam	0.18	0.22	0.17
Heavy Clay	0.17	0.19	0.15
Loam	0.30	0.34	0.26
Loamy Fine Sand	0.11	0.15	0.09
Loamy Sand	0.04	0.05	0.04
Loamy Very Fine Sand	0.39	0.44	0.25
Sand	0.02	0.03	0.01
Sandy Clay Loam	0.20	--	0.20
Sandy Loam	0.13	0.14	0.12
Silt Loam	0.38	0.41	0.37
Silty Clay	0.26	0.27	0.26
Silty Clay Loam	0.32	0.35	0.30
Very Fine Sand	0.43	0.46	0.37
Very Fine Sandy Loam	0.35	0.41	0.33

C-factor calculation

The *C*-factor represents how management affects soil loss. It is mainly related to the vegetation's cover percentage and it is defined as the ratio of soil loss from specific crops to the equivalent loss from tilled, bare test-plots. The value of *C* depends on vegetation type, stage of growth and cover percentage. For applications on national scale the *C*-factor can be estimated from mid-resolution satellite images (e.g., Landsat TM) by applying the Normalised Difference Vegetation Index (*NDVI*). It should be noted that for the scale of 1:100 000 or coarser scales, a link with the CORINE land cover database by means of a lookup-table is suggested when homogenous climatic conditions could be ensured (16). However, an alternative approach was followed here by replacing the *C*-factor with the *NDVI* as a response to the need for seasonal land cover information. The *NDVI* was generated from satellite images (Landsat-7 ETM+) and the cell size was set at 100 $\times$ 100 m^2 (scale 1:100000). The *NDVI* value was estimated by the following equation:

$$NDVI = \frac{NIR - IR}{NIR + IR} \tag{9}$$

where *NIR*: the reflection of the near infrared portion of the electromagnetic spectrum and *IR*: the reflection in the upper visible spectrum. The values lie in the range [-1,+1], but vegetation traces are detected in values bigger than +0.18.

Since the original *C*-factor of USLE ranges from 0 (full cover) to 1 (bare land) and the *NDVI* values range from 1 (full cover) to 0 (bare land), the calculated *NDVI* values were inversed using "Raster Calculator" tool of the "Spatial Analyst" extension of "ArcGIS 9.0" software package. More specifically, the *C*-factor map for each month was produced using the following exponential equation (Figure 5):

$$C = \exp\left(-a\frac{NDVI}{\beta - NDVI}\right) \tag{10}$$

where α, β: parameters determining the shape of the *NDVI-C* curve. An α-value of 2 and a β-value of 1 seem to give reasonable results.

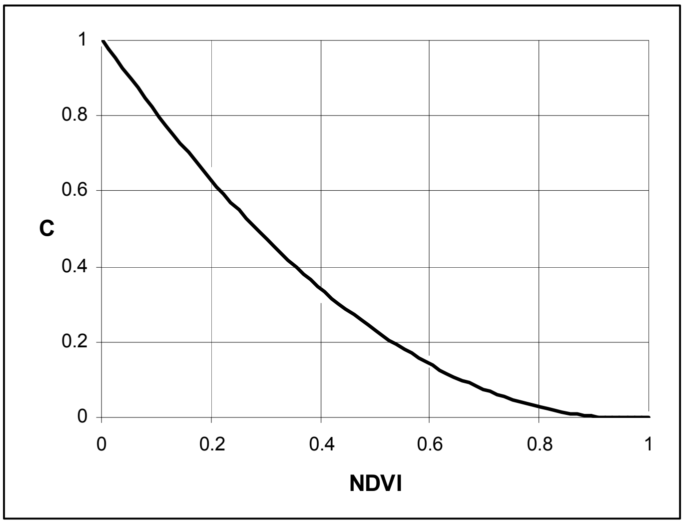

Figure 5: The exponential line used for C calculation from NDVI.

P-factor calculation

The support practice factor *P* represents the effects of those practices that help prevent soil from eroding by reducing the rate of water runoff. The values of *P* are calculated as rates of soil loss caused by a specific support practice divided by the soil loss caused by row farming up and down the slope (Table 3). In this work, however, the *P*-factor was not taken into account, because it was not possible to obtain data regarding the support farming practices on a scale of 1:100000.

Table 3: P values for different support practices (11).

Support Practice	*P*-Factor
Up & Down Slope	1.00
Cross Slope	0.75
Contour farming	0.50
Strip cropping, cross slope	0.37
Strip cropping, contour	0.25

RESULTS

The results of USLE implementation in the raster (grid) geographic domain (i.e. raster GIS) after the revision of the basic methodology for the estimation of C and k factors comprised the following:

- Three maps of soil erosion risk (in tonnes/ha/year) in N. Chalkidiki, one per month of examination (April, August, and November, respectively).
- A table, where the areas (in ha) covered by every class of risk severity in the different seasonal maps are presented comparatively.

Initially, the erosion maps gave each individual cell's original value of soil erosion risk as it was derived from the implementation of eq. (1). However, in order to obtain a better view and understanding and at the same time be able to compare areas, these original values were classified in 9 classes of severity and were finally presented in a colour scheme of green (low risk) to red (high risk) in all the maps (Figures 6, 7, 8). Reclassification is consistent with the USLE model's role as a conservation management tool, where relative comparisons among areas are more significant than any assessment of the absolute soil loss in a particular location. Moreover, in a raster GIS environment, the resulting maps can be overlaid, thus making a comparison of risks between the different seasons possible for each individual cell or group of cells.

Using the attribute tables of the mapping results, information about the area (in ha) that is covered by every risk class for each season was extracted and presented in a tabular format (Table 4). This made a comparison of results between the different seasons easier, though in such an approach a geographical reference is missing and results can be evaluated only on an overall study area scale. For an assessment in the spatial domain one should use the produced mapping results.

Table 4: Seasonal changes in Erosion Risk classes (in ha) in the study area.

Erosion classes	April	August	November
0 - 0.5 tn/(ha year)	78,670	68,532	79,137
0.5 - 1 tn/(ha year)	12,552	11,338	15,135
1 -2 tn/(ha year)	15,510	17,501	19,114
2 - 5 tn/(ha year)	20,273	25,294	22,496
5 -10 tn/(ha year)	12,927	15,630	12,142
10- 20 tn/(ha year)	10,276	12,007	7,524
20 -30 tn/(ha year)	4,261	4,368	1,951
30 - 50 tn/(ha year)	2,998	3,027	986
> 50 tn/(ha year)	1,334	1,104	316

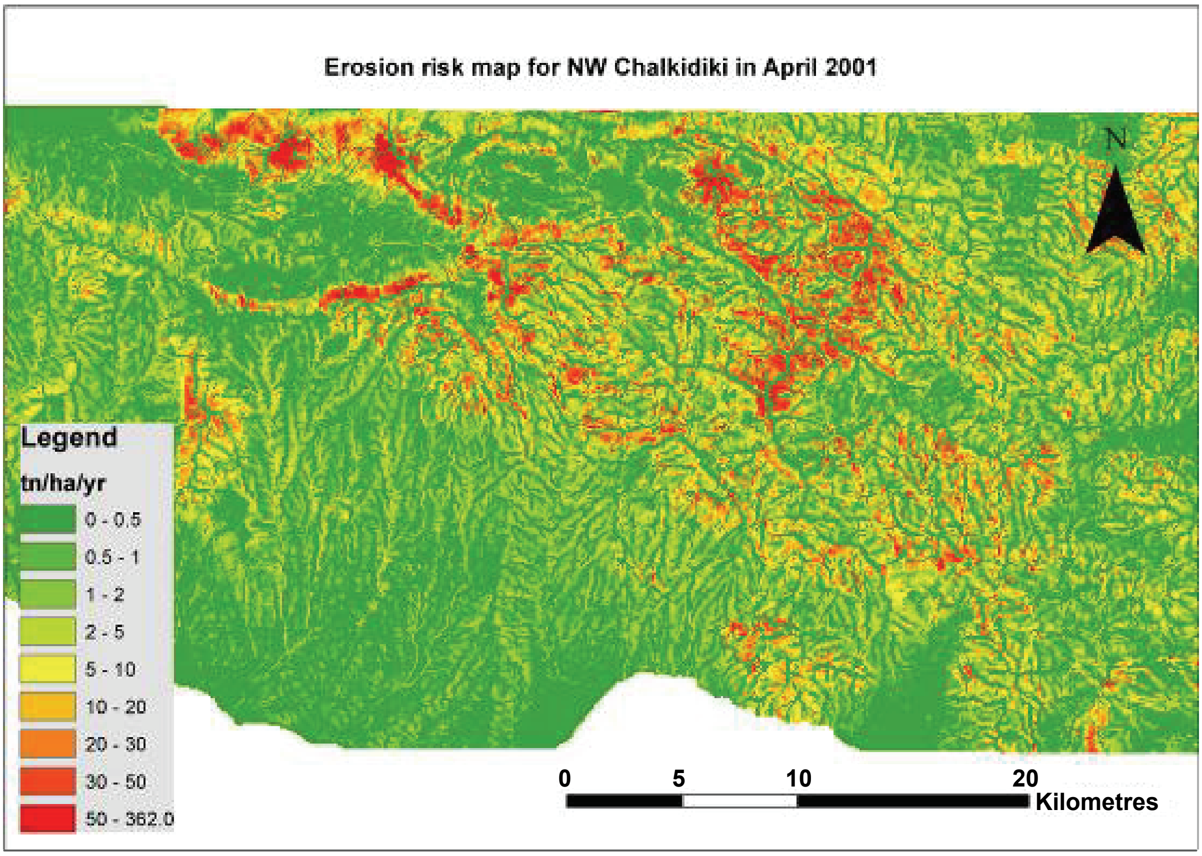

Figure 6: The soil erosion risk map for April 2001.

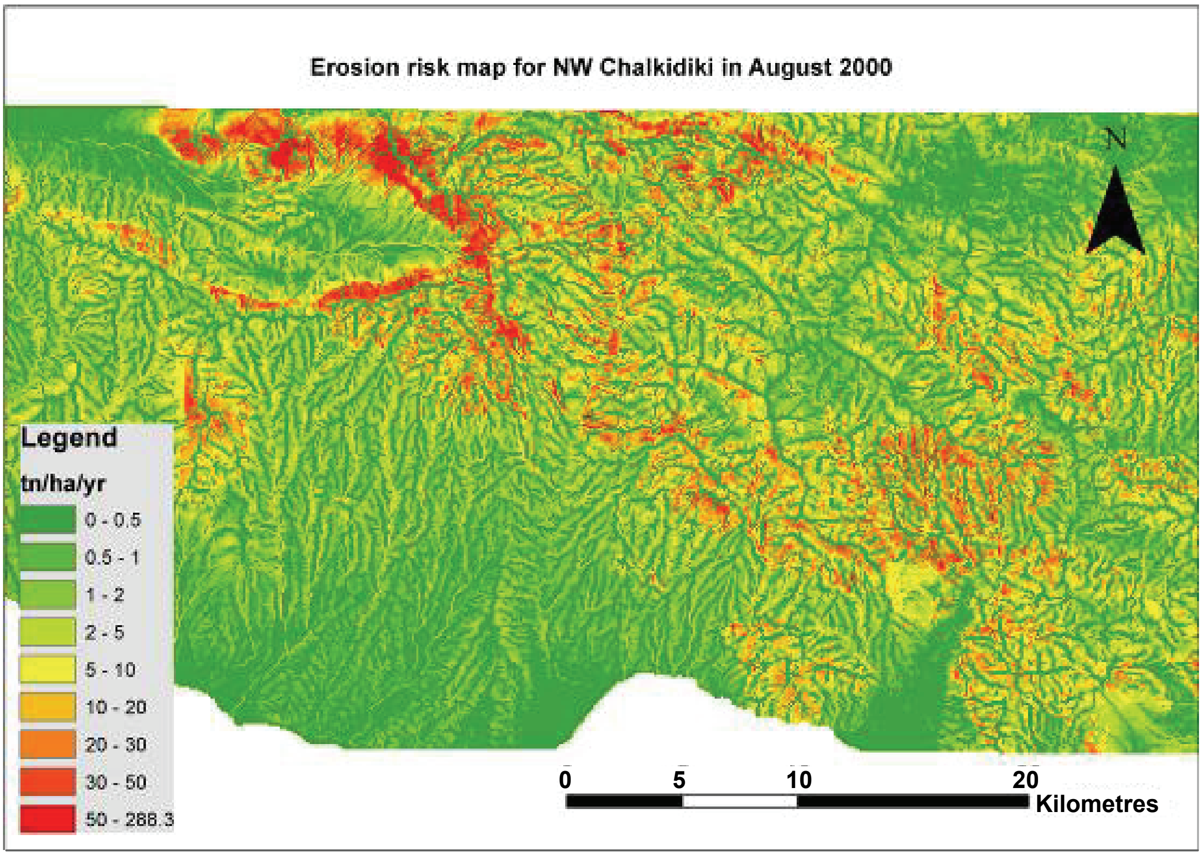

Figure 7: The soil erosion risk map for August 2000.

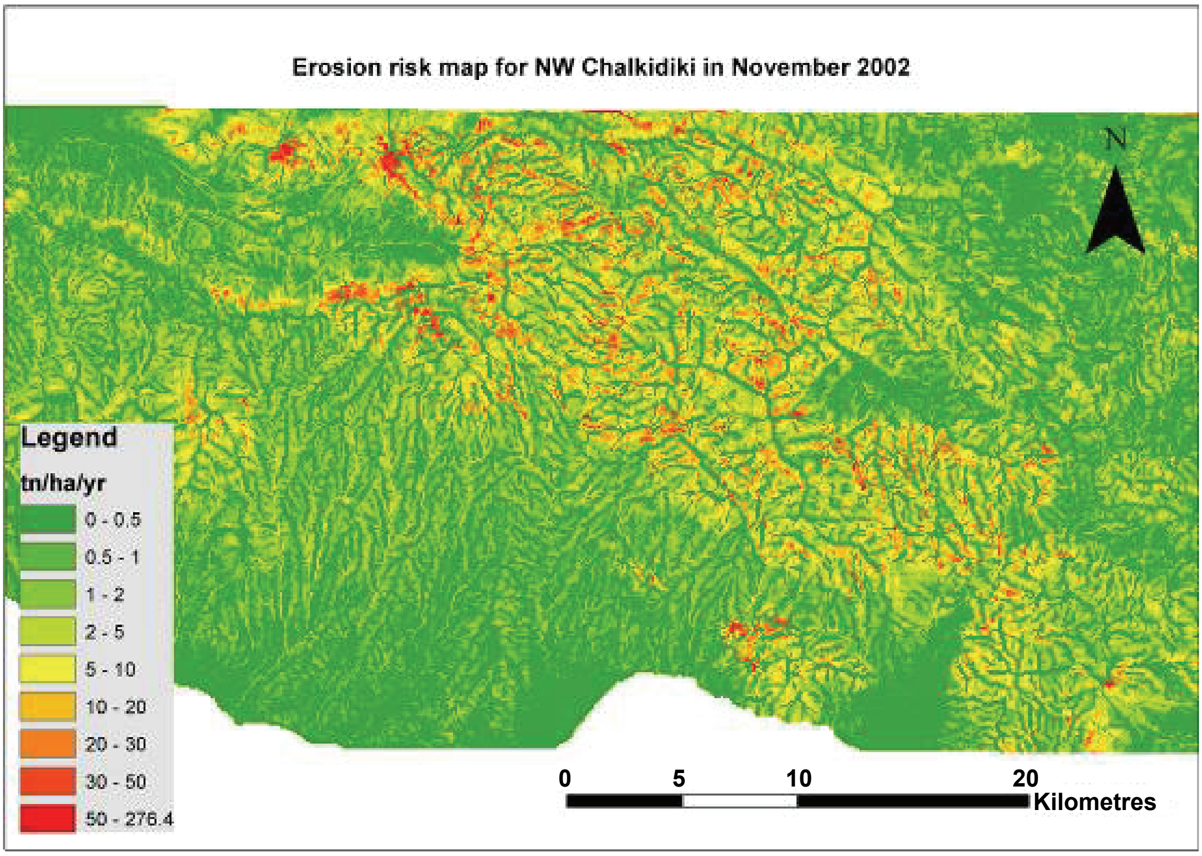

Figure 8: The soil erosion risk map for November 2002.

CONCLUSIONS

Generally, on the specific scale of application (1:100000) one should implement error assessment and quantitative validation. However, given the fact that no data for detailed assessment was available, assessment of the results was conducted only by field experts in a qualitative way; this assessment indicated:

- good accuracy, given the poor availability and precision of the specific data;
- a rational distribution of the soil erosion risk values throughout the study area;
- a rational variance of the soil erosion risk values through the seasonal sequences.

Summarising the experience gained from this work and taking into account the generic constraints and benefits of USLE, one can conclude the following:

- The model was not data-demanding because it was fed only by data usually available in institutional databases, such as medium-high resolution satellite images, limited rainfall data (interpolated over the study area), geologic maps, etc; in the same sense, the implementation was not expensive as well.
- The modified calculations of *C* and *k*-factors proved necessary and efficient, preparing the floor for further revisions and adaptations if appropriate.
- The model behaved better in agricultural areas confirming its original design to estimate long-term annual erosion rates in agricultural fields.
- The model must be further calibrated in order to fit to the local conditions of N. Chalkidiki (for future implementation), given the fact that it was originally developed and designed to operate in the USA (17).

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