Erosion Risk Map of a Foupana River Watershed in Algarve, Portugal

THOMAS PANAGOPOULOS and VERA FERREIRA
Research Centre for Spatial and Organizational Dynamics (CIEO), University of Algarve,
Campus de Gambelas, 8000 Faro, Portugal
email: tpanago@ualg.pt

Abstract: - Soil erosion is a major global environmental problem. In south Portugal typical ecosystems locally named “montados” are subject to extensive dry periods followed by erosive rains on fragile soils subject to intensive soil management and improper practices, such as deforestation and agricultural intensification. To assess soil erosion in these areas are important to protect water resources and to prevent loss of sustainable crop production. There has been important research in the last few years, about appropriate erosion models to predict the soil loss and sediment delivery. The Revised Universal Soil Loss Equation (RUSLE) model has been the most widely used for estimating annual soil loss from agricultural watersheds, because it is simple and easy to use. These models are becoming progressively more suitable in combination with geographic information systems (GIS) and geostatistical tools, as a solid base for decision making in soil conservation planning. The objectives of the study were to develop and validate a soil erosion-predicting model based on the revised RUSLE in a geographic information systems (GIS) environment. The maps resulting from the interpolation techniques were introduced in a GIS and their values reclassified. After that, spatial modeling was used do develop the final overlay map from all the information of the analyzed soil properties and RUSLE parameters simulating a “potential soil erosion map”. The study showed that the serious eroded area (when sediment is higher than 50 t/ha) was 20%, but contributed for 60% sediments of the watershed. This system will be used to provide site specific land use and management methods that could decrease risk of erosion in the higher risk locations of the study watershed.

Key-Words: - Desertification, RUSLE, Geostatistics, Vegetation management, Decision support system, Erosion risk Portugal.

1 Introduction

Soil erosion is a complex land degradation process, in many parts of the world, which leads to decline in soil quality and productivity, because resulting in a decrease in effective root depth, nutrient and water imbalance in the root zone, reduction in infiltration and increase in runoff [1, 2, 3]. This is a serious environmental and economic problem and it is sensitive mainly to land-use, through deforestation, agricultural intensification and improper practices, and due to climatic change [2, 4]. The Mediterranean regions are particularly exposed to erosion, because are subject to extensive dry periods followed by heavy erosive rains falling on steep slopes characterized by fragile soils [1, 5]. Soil erosion is a serious problem in Portugal, where about thirty percent of the area has high risk erosion [6].

The Iberian Peninsula montados (or Dehesa, in Spain) are 'man-made' ecosystems (Fig. 1), characterized by savannah-type low density woodlands dominated by Mediterranean evergreen oak species [7]. Those ecosystems are subjected to numerous attempts to reassess by linking them with livestock systems. Following intensive soil management techniques, soil is harrowed annually or before cork harvesting, in order to establish fodder species, increase aeration and destroy shrubs and other weeds, leaving bare soil exposed to erosion.

Figure 1- Montado type landscape with low density forest of Quercus suber in Algarve, Portugal (Used by permission of Thomas Panagopoulos ©2007, all rights reserved).

Therefore, assessment and mapping of soil erosion in south Portugal are extremely important, for adopt measures to protecting water and soil resources (figure 2 and 3) and to prevent decrease of crop productivity in agriculture, to decide on to sustainability of the montados [8, 9]. Modeling can provide a quantitative and consistent approach to estimate soil erosion and sediment yield under a wide range of conditions [10].

Figure 2- Minimum soil mobilization to decrease risk of erosion. (Used by permission of Thomas Panagopoulos ©2008, all rights reserved).

There has been important research and development, in the last few years, about appropriate erosion models to predict the soil loss and sediment delivery. Available models in the literature for sediment yield estimation can be grouped in three categories: physically-oriented models, empirical models [10, 11, 12] and conceptual models [13, 14, 15, 16]. The difference between these models is based in terms of complexity, processes considered, and the data required. Nevertheless, in general, no model is considered the “best” for all applications, because depend on the intended use and the characteristics of the catchment considered [16].

To describe the essential mechanisms controlling the erosion process, in a high level of detail, through the solution of the fundamentals physical equations, physically-based models are employed. Although these have several disadvantages, because they include large computational demands, almost always requires calibration against observed data of more parameters, this creates additionally uncertainty and lack of identifiably [11, 12]. Only considered by some authors, the conceptual models, pay some attention to the physics process and represent a catchment as a series of internal storages, including a general and aggregated description of catchment processes, though without including the specific details of process interactions [13]. Generally, the simplest of all three model types are empirical models because are based on analyses of observations data using stochastic techniques [13,16]. These models often employ unrealistic assumptions about the physics of the catchment system, ignoring the heterogeneity of catchment inputs and characteristics. However, are used instead of more complex models as they can be employed in situations with limited data and parameters inputs, and are particular useful as a first step in identifying sources of sediment generation, the erosion “hot spots” [13].

Figure 3- Severe erosion due to luck of soil cover after heavy rain in Serpa, Alentejo. (Used by permission of Thomas Panagopoulos ©2008, all rights reserved).

The Revised Universal Soil Loss Equation (RUSLE), revised from the Universal Soil Loss Equation (USLE), is the most widely used empirical equation for estimating annual soil loss from agricultural watersheds [7, 17]. It is simple and easy to use, but it lacks insights on the soil erosion process and mechanism.

RUSLE is defined as $A=R\ K\ L\ S\ C\ P$ (1)

where A= potential erosion (computed annual average soil loss in t ha^{-1} $year^{-1}$), R= rainfall and runoff factor, K= soil erodibility factor, LS= slope length and gradient factor, C= vegetation cover factor and P= vegetation control practice factor.

Modelling soil erosion is very complicated because soil loss is spatially varied, due to the spatial variation in rainfall and field heterogeneity. Therefore, erosion models often deal with great amounts of spatial data like topography, soil and land use, which can be easily treat with Geographic Information System (GIS) instruments [11]. GIS is an integrated suite of computer-based technology and methodology, is a powerful set of tools for collecting, storing, retrieving at will, transforming, analyzing and presenting spatial data from the real world, [18, 19] which has developed rapidly in recent years. The GIS can be used for the separation of the watershed into small grid cells, computation of such physical characteristics of these cells, as land-use and soil type, and to extract slope angles from Digital Elevation Models (DEM) [11, 20].

Regionalized variables are distributed in space and time, and are usually known only at number finite experimental points. Geostatistic is a tool that has been progressively more used, which can be used in combination with GIS, to generate a map of erosion risk, to account local uncertainly [21]. The methods of geostatistic use stochastical theory of spatial correlation both to predict values at unsampled locations, based on the sampled data, and to assess the uncertainty attached to these predictions [22, 23]. Geostatistics provide a set of statistical tools for incorporating the spatial coordinates of soil observations in data processing, allowing for description and modelling of spatial patterns, taking to account the spatial dependence between observations in the prediction of attribute values [24, 25].

The main tool in the geostatistic is the semivariogram, which express this dependence [26]. In general, kriging is one of the most widely used interpolation geostatistical methods that assumes that variables close in space tend to be more similar than those further away, minimizing the error variance with unbiased estimates [27]. Geostatistics, spatial modeling and geographic information systems (GIS) are tools that are becoming progressively more suitable in fields of research like forestry, agriculture, hydrogeology and soil science [28, 29, 30 and 31].

Aside from geostatistical works, the conjugation of geostatistics and GIS has proved to be a solid base in development of precision agriculture which is based on the exact knowledge of soil's actual conditions, yields and erosion risk, and this information is useful for decision-makers and planners to take appropriate land-management measures [32, 33, 34, 35, 36 and 37]. Soil erosion assessment is a capital-intensive and time-consuming exercise. Until recently the variability present in agrosilvopastoral fields has not been taken into consideration. The lack of tools for spatial analysis has been one of the reasons for it.

Objective of the present work was to use geostatistical techniques and GIS to identify the site specific risk of erosion on a watershed of south Portugal and help decision makers to take the appropriate management measures and land use planning.

2 Materials and Methods

The study area is located in South Portugal in a low altitude hilly formation between Alentejo and Algarve (Figure 4). The area has mostly poor soils with low agricultural potential and moderate slopes. Most of the soils are classified as bedrock or very thin soils derived from clay schist. Quercus suber L., Quercus ilex L., Cistus spp., Olea europaea L., cereals and fodder plants are the main vegetative species that can be found in the area.

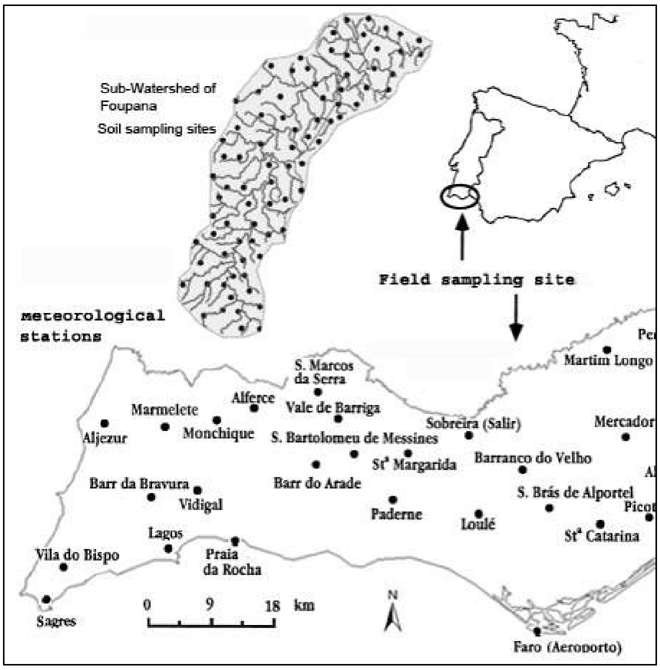

Fig. 4- Location of the study site

Soil erosion and forest fires are the main environmental problems of the region. The climate of the area is continental Mediterranean with very hot and dry summers and mild winters. Average annual precipitation is between 300 and 800 mm.

The revised universal soil loss equation (RUSLE) was used to estimate potential erosion [9].

The rainfall-runoff erosivity factor (R) is generally known as one of the most important indicators of the erosive potential of raindrops impact [25]. This factor R is the sum of erosive storm values EI30 occurring during a mean year, which result for the product of total storm energy (E) times the maximum 30 minute intensity (I30), where E is in MJ/ha and I30 is in mm/h [9]. In this study, this factor was estimated from Modified Fournier Index to account the existing combined effect of rainfall amount and within-year distribution. According to Silva [39] to determine the monthly and annual values of the rain erosivity:

$$R=42.307*(M2/P)+69.763 \quad (2)$$

R factor (MJ mm ha^{-1} h^{-1} $year^{-1}$) for month *x*, M_x is average monthly precipitation depth (mm), and *P* is average annual precipitation (mm).

According to Goovarets [25], using the monthly erosive storm values EI30 which is calculated by the regression equation (3) where rain10 is monthly rainfall for days where precipitation exceeds 10 mm and days10 is the monthly number of days where precipitation exceeds 10mm. Annual rain erosivity was computed for these stations, as the sum of monthly erosivities. It was used data from 32 meteorological stations of South Portugal for 30 years of measurements and a prediction map was created by ordinary kriging.

$$EI30month = 6.56rain10 - 75.09\ days10 \quad (3)$$

Soil data, vegetation cover and type of management were collected from a small watershed of the "ribeira da Foupana" located close to the village Mestras, Portugal. A total of 81 soil samples were collected. Sampling points were localized on a georeferenciated aerial photograph of the area and in the field using a Global Positioning System (GPS).

Soil erodibility factor (K) represent the soil-loss rate per erosion index unit for a specified soil as measured on a standard plot, which is defined as a 22.1m length of uniform 9% slope in continuous clean-tilled fallow. This factor is a quantitative value experimentally determined and was estimated using soil properties, such as soil texture, content of organic matter, soil structure and permeability [9]. This factor was estimated using the equation 4 [17].

$$K=[2.1\times10^{-4}(12-OM)M^{1.14}+3.25(s-2)+2.5(p-3)]/100 \quad (4)$$

where OM is organic matter, s is soil structure, and p is permeability class. M is the product of the primary particle size fractions (% Silt) × (%Silt + %Sand), where % Silt is percent modified silt (0.002-0.1 mm) and % Sand is percent modified sand (0.1-2 mm).
Individual soil samples of about 1 kg were collected from each sampling position at a depth of 20cm and were analyzed for soil properties using standard procedure described by Carter [38]. Infiltration was measured in situ using the field-saturated hydraulic conductivity (Kfs) "Guelph permeameter" (fig. 5).

Figure 5- Measuring field saturated hydraulic conductivity to predict soil erodibility K factor (Used by permission of Thomas Panagopoulos ©2008, all rights reserved).

Slope length is the horizontal distance from the origin of overland flow to the point where the slope gradient decreases enough that deposition begins or runoff becomes concentrated in a defined channel. The slope steepness shows the influence of slope gradient [9]. To calculate these values for each of these 81 locations, was used a Digital Elevation Model (DEM) in GIS To create a DEM of the study area, contour segment map and spot-height point map were prepared by digitizing contour lines and spot-heights from the topographic map Nº 581 (1975, 1:25,000 scale). . The slope length factor (L) was estimated according Wischeimer and Smith equation [17].

$$L= (\lambda/22.13)^{m} \quad (5)$$

where λ is the field slope length in meters, 22.13 is the RUSLE unit plot length in meters and m is a designated slope-length exponent.

The slope steepness factor (S) was calculated using the equation (6) proposed by Nearing [40], where θ is the slope angle in degrees:

$$S = -1.5 +17 /[1+ \exp(2.3- 6.1\sin\theta)] \quad (6)$$

Multiplying the L and S values, a map of the LS factors is performed.

The cover-management factor (C) reflects the effect of cropping and management practices on soil erosion rates [9].To estimate this factor was recorded the canopy cover, prior land-use, surface cover, surface roughness, soil moisture and vegetation management practices for each sampling point. Yaolin and Zhijun [41] established a relationship between soil-loss ratios and canopy-cover and surface-cover subfactors. The cover and management factor (C) of the RUSLE expressed as a function of canopy/surface-cover (c) in % as follow:

For $0 < c < 78.3\%$ $C = 0.6508 - 0.3436 \lg c$ (7)

The support practice factor (P) reflects the effect on rangeland erosion of mechanical practices, which affect surface cover, runoff amount, runoff rate, flow direction of runoff and hydraulic forces exerted by runoff on the soil. In the present study area, three types of vegetation management techniques were considered: a) undisturbed b) plough and seeded with cereals, c) use of rotary cutter mowers to clear vegetation cover at 10 cm height leaving the soil covered with leftovers.

In order to understand the variation of the erodibility factors, graphical interpretation of these properties was performed using geostatistics. Those graphical interpretations were digital maps of the factors needed according to the RUSLE relationship to estimate susceptibility to soil erosion (figure 6).

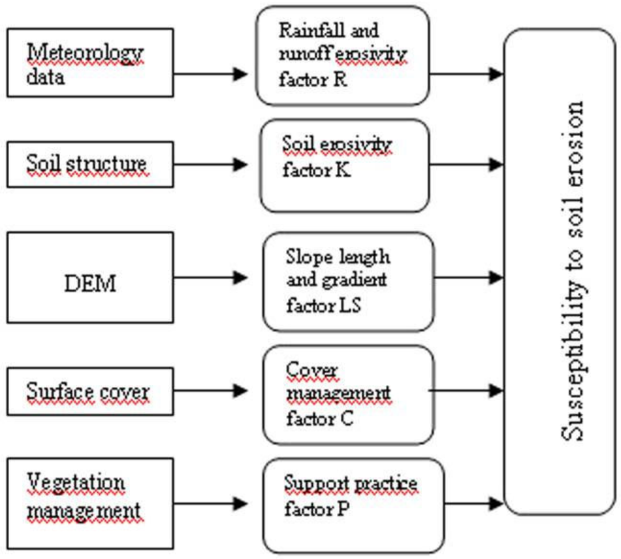

Figure 6- Digital maps of the factors needed according to the RUSLE relationship to estimate susceptibility to soil erosion.

A dataset of soil properties and vegetation cover was created with their geo-referenced position in the field by using the Arcview 9.3 (ESRI). Before creating surface diagrams, the distribution of data was analysed to get a better understanding of trends, directional influences and obvious errors. Transformation and trend removal was performed when necessary. Ordinary kriging was used and semi-variograms were produced for each soil factor. Cross validation was used to compare the prediction performances of the semi-variograms.

3 Results

Initially it was created the map of the rainfall erosivity of South Portugal. From the prediction map produced after ordinary kriging and trend removal, it was found that the rainfall and runoff factor R for the experimental area was estimated to be 2500MJ mm ha^{-1} h^{-1} yr^{-1} in more than 78% of the watershed, while for the rest 22% was about 2564MJ. According to Silva [39] the study area watershed was classified by medium annual rain erosivity values.

Kriging after trend removal was carried out on the residual data of electric conductivity, texture (clay, modified silt, silt, sand), and organic matter. The prediction map of each factor was calculated and trend was added back to the output surface.

All maps of soil properties were reclassified, weighted and overlaid in Arcview model builder. The soil erodibility map was created following the Wischmeier nomograph after arithmetic overlay. From the map derived it could be seen that the areas with heavy textured soil and low permeability had the highest values of soil erodibility.

In figure 7 it can be seen the three-dimensional surface created as triangulated irregular network (TIN) in Arcview 9.3, which was the digital terrain model (DTM) for the area of interest. Darker zones indicate higher altitude.

The DTM was used to calculate the inclination at the experimental area and to estimate the slope length for each of the 81 locations. The basic idea consisted in dividing the entire watershed into a number of smaller sub-watersheds ending in each of the 81 locations. Next, the boundaries of the sub-watersheds were detected by the computer program. The slope steepness and the top-end of that particular segment of the slope were measured. The slope length and gradient factor (LS) were then computed for each of the 81 sampling locations. The map derived from ordinary kriging was overlaid in ArcGIS for arithmetic overlay in model builder.

The cover-management factor and the support practice factor for rangelands were computed for each of the 81 sampling locations at the moment of sampling and after consulting the shepherds using the area. For soil moisture and surface cover it was used the mean of summer and winder measurements. The maps of C and P factors were also superimposed in model builder.

Table 1 presents summarily the indicators which helped to choose the most appropriate model of semivariogram for the creation of the prediction map for electric conductivity. The closer to 0 was the mean cross-validation error (ME) and the closer to 1 was the root-mean-square standardized error (RMSE) signified that the prediction values were closer to measured values. When models presented similar values for ME and RMSE it was taken in consideration the lowest values of RMSE and average standard error (ASE). Table 2 was repeated for every parameter studied following the rules mentioned above and it was selected a semivariogram model for each one, in order to have an indication on how the samples were related to each other. Table 2 presents the final semivariogram model chosen for the prediction map of each parameter analysed.

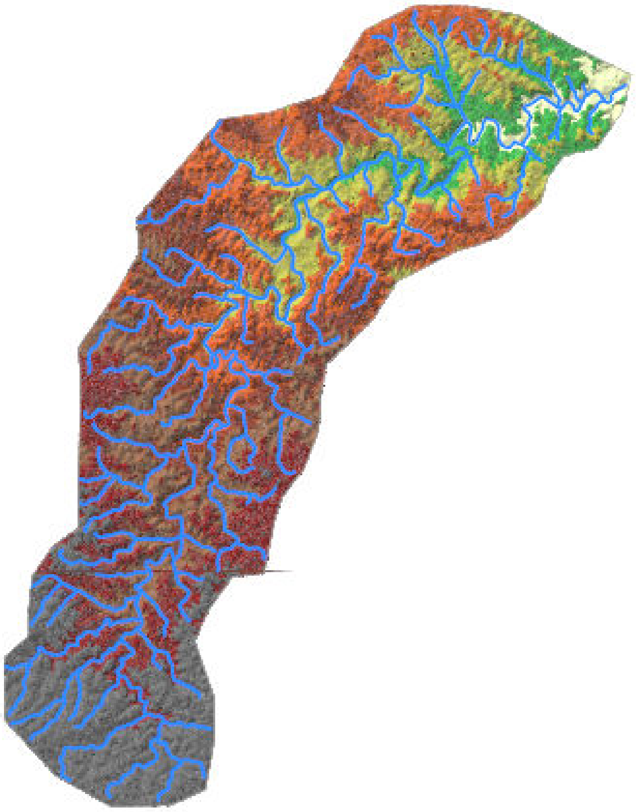

Figure 7- Three-dimensional surface of the study watershed, created as triangulated irregular network (TIN) in Arcview 9.3.

The final soil loss prediction map (figure 8) resulted according to the RUSLE relationship following map algebra in Arcview 9.3. In this final map one large areas of high soil erosion risk are identified in the northern part of the experimental area. At those locations the potential erosion was estimated between 76 to 99tn/ha. The rest of the area has a low to moderate risk of erosion (14 to 60tn/ha). Calculating the total area with serious risk on erosion (when sediment is higher than 50 t/ha) it was found that even if it was only 20% contributed for 60% sediments of the watershed.

4 Discussion

According to Renard [9] RUSLE enables planners to predict average rate of soil erosion for each alternative cropping system, management technique and control practice on any particular site. This study showed that simple sampling and the calculation of an average, usually used as normal procedure for soil erosion, is not always the best technique for identifying soil erosion risk and analysing spatial problems [42].

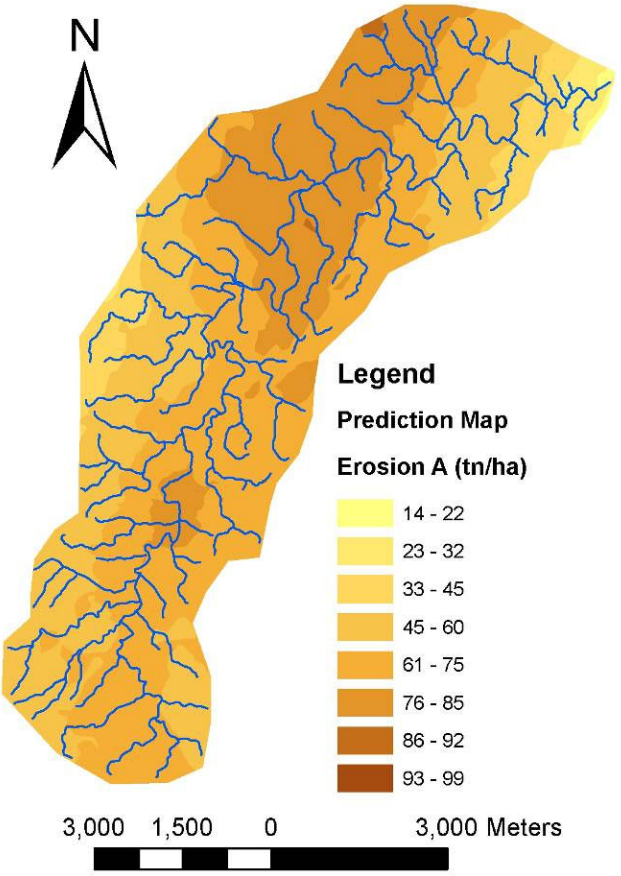

Figure 8- Risk for soil loss prediction map of the study area watershed according to RUSLE.

The spatial variability of the erosion factors of the study area makes soil reclamation an ideal practice to apply site specific management. Geostatistical methods described the spatial variability of a site, showing the confidence levels for samples taken [43].

Decision-makers need local and regional estimates of soil loss as well as their corresponding uncertainties. According to Wang et al. [44], neglecting the local and detailed information may lead to improper decision-making.

Table 1 Model parameters used to find the best semivariogram to predict hydraulic conductivity (ds/m).

Model	Nugget	Partial Sill	Major Range	Minor Range	Direction	ME	RMSE	ASE	RMSSE
Circular	9.42	5.71	1964.9	306.9	357	0.02	4.09	4.57	0.97
Spherical	7.87	7.19	1975.1	306.5	355	0.01	3.65	3.12	0.98
Tetraspherical	10.10	6.49	1966.6	306.5	358	0.02	4.69	4.08	0.98
Pentaspherical	9.65	8.42	1991.1	302.3	354	0.02	4.71	4.09	0.78
Exponential	10.43	6.24	1993.1	306.5	357	0.05	4.75	4.24	0.99
Gaussian	10.51	3.51	1997.0	306.1	351	0.01	5.68	4.91	1.11
Rational Quadr.	9.14	4.07	1996.1	306.5	356	0.06	4.83	4.69	1.01
Hole effect	9.53	4.99	1454.5	1131.8	318	0.01	5.73	5.91	0.86
K-Bessel	8.35	8.05	1991.7	306.5	355	0.01	5.74	5.04	0.87
J-Bessel	8.71	6.21	1575.6	1238.2	8	0.04	5.72	5.84	0.95
Stable	9.44	3.90	1910.8	306.5	359	0.04	5.75	5.25	1.06

Using the cross-validation of the models the mean error (ME), root-mean-square error (RMSE), average standard error (ASE) and root-mean-square standardized error (RMSSE) were used.

Table 2 Results of the semivariogram used to create the prediction maps of the soil erosion factors studied.

Soil erosion factor	Model	Nugget	Sill	Range	ME	RMSE	ASE	RMSSE	Nugget/ Sill
Rain erosivity EI_{30}	Exponential	4.6	14.6	1945.4	0.25	2.64	3.27	0.91	0.31
Soil stucture	Exponential	0.01	0.03	1994.5	0.01	0.79	0.14	1.00	0.33
Organic matter (%)	Exponential	0.45	1.49	1943.4	0.01	2.28	2.73	0.88	0.31
Hydr.cond. (cm/h)	Spherical	7.87	14.99	1975.1	0.01	3.65	3.12	0.98	0.52
Electr.cond. (dS/m)	Gaussian	0.49	2.11	1987.7	0.01	0.21	0.32	0.88	0.25
Clay (%)	Gaussian	4.87	10.9	1994.5	0.78	1.54	3.56	0.93	0.46
Modified silt (%)	Gaussian	6.38	14.9	1974.3	0.65	1.11	5.77	0.97	0.41
K factor (t*ha/h*N)	Exponential	0.01	0.02	1985.1	0.01	0.12	0.12	1.33	0.50
Soil moisture	Gaussian	0.27	0.49	1988.8	0.02	0.66	0.56	0.82	0.41
Soil cover (%)	Exponential	40	80	1932.7	0.74	4.62	4.33	0.91	0.40
Support practice	Exponential	1	3	1955.8	0.01	0.95	0.91	0.88	0.33

Using the cross-validation of the models the mean error (ME), root-mean-square error (RMSE), average standard error (ASE) and root-mean-square standardized error (RMSSE) were used.

The maps created demonstrate the existence of a heavy textured area in a large area of the site which could affect erosion and vegetation management techniques. Also it was located areas of low water infiltration and low organic matter content. Having located the areas of highest risk to erosion, this could be decreased by suggesting simple changes in the vegetation management, keeping tillage only in the lowest risk of erosion areas. The most adequate area for annual fodder cultivation was the Northwestern part of the experimental plot, because it had average permeability, high nutrient content and vegetation cover and low to moderate risk of erosion. The most degraded and less suitable area was the north-east part of the study watershed. Geostatistics and GIS can therefore be used to identify the risk of degradation as well as being used to help apply precision management in extensive agrosilvopastoral areas [45].

5 Conclusions

Capability to predict the pattern of erosion and to identify the location of high risk areas for various land use alternatives is critical for effective management. Spatial analysis can also provide supporting information for allocation of resources to those areas and those types of practices which will provide the most effective protection. Geostatistics and GIS linked with simple erosion models provide tools for evaluation of vegetation management alternatives at both local and watershed levels and planning of prevention practices. The classification techniques used in the present work to estimate potential erosion determine which areas with high erosion risk should be reclaimed and conserved. Localized problems with impermeable soil could be solved with simple geographically restricted amendment treatments. Steep slopes should be revegetated and protected. This approach could help the regional authorities to spend less money in agroenvironmental subsidies and stop damaging the environment with unnecessary and expensive management practices that some times destroy local biodiversity.

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References

[1] Grimm, M., Jones, J., and Montanarella, L. *Soil Erosion Risk in Europe. European Soil Bureau Research Report*, EUR 19939 EN, Office for Official Publications of the European Communities, Luxembourg. 2002.

[2] Yang, D., Kanae, S., Oki, T., Koikel, T. and Musiake, T. Global potential soil erosion with reference to land use and climate change. *Hydrological Processes,* Vol. 17, 2003, pp. 2913–2928.

[3] Zhang, Y., De Groote, J., Wolter, C., Sugumaran, R. Integration of Modified Universal Soil Loss Equation (MUSLE) into a GIS Framework to assess Soil Erosion Risk. *Land Degradation & Development,* Vol. 20, 2009, pp. 84-91.

[4] Lal, R. Soil Erosion impact on Agronomic Productivity and Environment Quality. *Critical Reviews in Plant Sciences*, Vol. 17, 1998, pp. 319-464.

[5] Lal, R. Soil degradation by erosion. *Land Degradation & Development,* Vol. 12 (6), 2001, pp. 519–539.

[6] Panagopoulos, T., Ferreira, V. Decision support system for erosion risk assessment, In “Latest Trends on Systems”, Mastorakis, N, Mladenov, V, Bojkovic, Z, Eds. 14th WSEAS Int. Conf. on Systems, Corfu, Greece July 22-25, 2010, pp: 76-80.

[7] Panagopoulos, T., Antunes M.D.C. Integrating geostatistics and GIS for assessment of erosion risk on low density Quercus suber woodlands of South Portugal. *Arid Land Research and Management*, Vol. 22(2), 2008, pp. 159-177.

[8] Yang Q., Zhao *Z.,* Chow T.L., Rees H.W., Bourque C.P.A and Meng F. Using GIS and a digital elevation model to assess the effectiveness of variable grade flow diversion terraces in reducing soil erosion in northwestern New Brunswick, Canada. *Hydrological Processes*, Vol. 23, 2009, pp. 3271–3280.

[9] Renard, K.G., G.R. Foster, G.A. Weesies, D.K. McCool, and D.C. Yoder. Predicting Soil Erosion by Water: A Guide to Conservation Planning With the Revised Universal Soil Loss Equation (RUSLE). USDA, Agric. Handbook No 703. 1996.

[10] Bhattarai, R. and Dutta, D. Estimation of Soil Erosion and Sediment Yield Using GIS at Catchment Scale. *Water Resources Management* Vol. 2, 2007, pp. 1635-1647.

[11] Bhattarai, R. and Dutta D. A comparative analysis of sediment yield simulation by empirical and process-oriented models in Thailand. *Hydrology Sciences Journal,* Vol. 53(6), 2008, pp. 1253-1269.

[12] Fu B., Newham L.T., Ramos-Sharrón C.E. A review of surface erosion and sediment delivery models for unsealed roads. *Environmental Modelling & Software*, Vol. 25, 2010, pp. 1-14.

[13] Merritt W.S., Latcher R.A., Jakeman A.J. A review of erosion and sediment transport models. *Environmental Modelling & Software*, Vol. 18, 2003, pp. 761– 799.

[14] De Vente J., Poesen J. Predicting soil erosion and sediment yield at the basin scale: scale issues and semi-quantitative models. *Earth-Sci Review,* Vol. 71, 2005, pp. 95–125.

[15] Mulligan M. Modelling catchment hydrology. In: Wainwright J. and Mulligan M (eds.) Environmental Modelling: finding the simplicity in complexity. Wiley, 2004, pp. 107-121**.**

[16] Volk M., Möller M.and Wurbs D. A pragmatic approach for soil erosion risk assessment within policy hierarchies. *Land Use Policy*, Vol. 27 (4), 2010, pp. 997-1009.

[17] Wischmeier W.H. and Smith D.D. *Predicting*

rainfall erosion losses. USDA Agricu. Handbook 537. Agricultural Research Service, Washington, DC, USA. 1978

[18] Burrough P.A. and McDonnell R.A. *Principles of Geographical Information Systems.* Oxford University Press, New York, 2000.

[19] Panagopoulos, T, Blumberg, D. Orlovsky, L. Monitoring the Aral Sea landscape change. Proceedings of the 4th WSEAS Int. Conf. on Energy, Environment, Ecosystems & Sustainable Development, June 11-13, 2008 Faro, Portugal, pp: 254-258.

[20] Dunn M. and Hickey R. The Effect of Slope Algorithms on Slope Estimates within a GIS. *Cartography*, Vol. 27 (1), 1998, pp. 9 – 15.

[21] Diodato N. and Ceccarelli M. Multivariate indicator Kriging approach using a GIS to classify soil degradation for Mediterranean agricultural lands. *Ecological Indicators*, Vol. 4, 2004, pp. 177–187.

[22] Burrough, P.A. GIS and geostatistics: Essential partners for spatial analysis. *Environmental and Ecological Statistics,* Vol. 8, 2001, pp. 361–377.

[23] Goovaerts P. Geostatistical tools for characterizing the spatial variability of microbiological and physico-chemical soil properties. *Biology and Fertility of Soils,* Vol. 27, 1998, pp. 315-334.

[24] Goovaerts, P. Geostatistics in soil science: state-of-the-art and perspectives. *Geoderma*, Vol. 89, 1999, pp. 1–46.

[25] Goovaerts P. Using elevation to aid the geostatistical mapping of rainfall erosivity. *Catena*, Vol. 34, 1999, pp. 227-242.

[26] Chilès, J.-P., Delfiner, P. Geostatistics. Modeling Spatial Uncertainty, Wiley, New York, 1999.

[27] Wackernagel, H. Multivariate geostatistics: An introduction with applications. Springer, Berlin, 1995.

[28] Kohl, M. and G. Gertner. Geostatistics in evaluating forest damage surveys: considerations on methods for describing spatial distributions. *Forest Ecology and Management,* Vol. 95, 1997, pp. 131-140.

[29] Castrignanò, A. Cherubini, C. Giasi Consetta, I. Musci, F. Pastore, N. Multivariate geostatistical and natural attenuation model approach for remediation of chlorinated compounds, *WSEAS Transaction on Environment and Development*, Vol. 3, No. 5, 2007, pp. 90-98.

[30] Boroujerdy, P. K. The analysis of precipitation variation and quantiles in Iran, Proceedings of the *3rd WSEAS International Conference on Energy & Environment*, University of Cambridge, UK, February 23-25, 2008, pp. 248- 253.

[31] Costa, A.C., Soares, A., Pereira, M.J., Durao, R. Evaluation of space-time dynamics in extreme precipitation frequency using geostatistical cosimulation with elevation. *WSEAS Transactions on Environment and Development,* Vol. 6, 2010, pp: 33-42.

[32] Jesus, J., Panagopoulos, T., Blumberg, D., Orlovsky, L. and BenAsher, J. Monitoring Dust Storms in Central Asia with Open-Source WebGIS Assistance. *WSEAS Transactions on Environment and Development*, Vol. 2(6), 2006, pp. 895-898.

[33] Yalouris, K.P., V. Kollias, N.A. Lorentzos, D. Kalivas, and A.B. Sideridis. An integrated expert geographical information system for soil suitability and soil evaluation. Journal of *Geographic Information Decision Analysis,* Vol. 1, 1997, pp. 90-100.

[34] Kaffka, S.R., S.M. Lesch, K.M. Bali, and D.L. Corwin. Site-specific management in salt-affected sugar beet fields using electromagnetic induction. *Computers and Electronics in Agriculture,* Vol. 46, 2005, pp. 329-350.

[35] Jesus, J., Panagopoulos, T, Neves, A. Fuzzy logic and geographic information systems for pest control in olive culture. Proceedings of the *4th WSEAS Int. Conf. on Energy, Environment, Ecosystems & Sustainable Development,* June 11-13, 2008 Faro, Portugal, pp: 497-501.

[36] Panagopoulos, T.The use of geostatistical techniques applied to soil conservation of low density woodlands. In *Eco- and Ground Bio-Engineering: The Use of Vegetation to Improve Slope Stability*. Stokes A., Spanos I., Norris J.,Cammeraat, L.H. (Eds). Springer, Kluwer Academic Publishers, Dordrecht, 2007, pp.239-246.

[37] Pandey, A., Chowdary, V.M., Mal, B.C. Identification of critical erosion prone areas in the small agricultural watershed using USLE, GIS and remote sensing. *Water Resources Management*, Vol, 21, 2007, pp. 729–746.

[38] Carter, M. R. Soil sampling and methods of analysis. Canadian society of soil science, Lewis Publishers, Charlottetown, Canada, 1993.

[39] Silva, A.M. Rainfall erosivity map for Brazil. Catena, Volume 57, 2004, pp. 251-259.

[40] Nearing, M. A. A single, continuous function for slope steepness influence on soil erosion. *Soil Science Society of America Journal*, Vol. 61, 1997, pp. 917–919.

[41] Yaolin, L. and Zhijun, L. A study on estimation of the amount of soil erosion in small watershed based on GIS: a case study in the Three Gorge Area of China. Geoscience and Remote Sensing

Symposium,. IEEE International, 2005, pp. 1859-1862.

[42] Goovaerts, P. Geostatistics for natural resources evaluation. Oxford University Press, New York, 1997.

[43] Panagopoulos T, Rodrigues S, Neves N, Cruz S, Antunes D. Decision support tools for optimising kiwifruit production and quality. Acta horticulturae, Vol. 753 (1), 2007, pp. 407-414.

[44] Wang, G., G. Gertner, V. Singh, S. Shinkareva, P. Parysow, and A. Anderson. Spatial and temporal prediction and uncertainty of soil loss using the revised universal soil loss equation: a case study of the rainfall–runoff erosivity R factor. *Ecological Modelling*, Vol. 153, 2002, pp. 143–155.

[45] Panagopoulos, T., Neves, M.A. Vegetation cover for sustainable olive grove management, Proceedings of the *3rd WSEAS International Conference on Energy, Environment, Ecosystems and Sustainable Development,* Agios Nikolaos, Greece, July 24- 26, 2007, pp. 71-74.