ABSTRACT

Soil erosion is serious economic and environmental concern. Assessing soil erosion risk in the Alqueva dam watershed is urgently needed to conserve soil and water resources and prevent the accelerated dam siltation, taking into account the possible land-use changes, due to tourism development, intensification of irrigated farming and biomass production, as well as climate change. A comprehensive methodology that integrates Revised Universal Soil Loss Equation (RUSLE) model and Geographic Information Systems (GIS) with geostatistical techniques was adopted to study different land-use and management scenarios. The main objective of this study stage is to determine the soil erosion vulnerability of an agro-silvo pastoral system. The resultant soil erosion map shows an average of 14.1 t/ha/year, with serious erosion risk (higher than 50 t/ha/year) in 4.3% of area. The highest values are associated mainly to high slopes and low vegetation. The final prediction maps for soil erosion and for each factor considered, can be used as a solid base to create a Decision Support System so as to provide specific procedures for decision-makers, promoting for sustainability of the ecosystems, reducing the risk of erosion and consequently increase lifetime of dam, under various land use and management scenarios.

Keywords: Soil Erosion; Land-use; Geostatistic; RUSLE; Geographic Information System.
Predicting Soil Erosion Risk at the Alqueva Dam Watershed

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 (Yang et al., 2003; Lal, 2001). This sediment yield can result in the acceleration of natural sedimentation in rivers and reservoirs reducing their storage capacity as well as life span (Pandey et al., 2007). Consequently, soil erosion 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 (Zhang et al., 2009; Yang et al., 2003; Nearing et al., 2004).

Land-use change in Europe over the past century has been largely driven by the technology development and in future the land-use depends of social, political and economic development (Bakker et al., 2008). The relationship between land-use and soil erosion has attracted the interest of a wide variety of researchers (Kosmas et al., 1997; Wang et al., 2003; Long et al., 2006; Cantón et al., 2011). These investigations found that these changes in land-use greatly affected runoff and soil erosion. Mediterranean environment may be particularly vulnerable because of specific poor soil characteristics, low vegetation cover and contrasted climate, with extensive dry periods followed by heavy erosive rains falling on steep slopes characterized by fragile soils (Grimm et al., 2002). According to the CORINE program, mediterranean countries, such as Portugal and Spain, face the greatest risks of erosion (Desir and Marín, 2007). In Portugal, areas at high risk of erosion cover almost one third of the country (Grimm et al., 2002).

Management of reservoirs is of major importance regarding the water supply in Portugal. The Alqueva reservoir constitutes the largest artificial lake in Europe, however the capacity cannot be maintained due to a yearly deposition of sediment resulting in a silting up. Alqueva surrounding region now has new challenges as traditional land-uses and human activities are changing and new risks are arising. The possible land-use changes in this region will be due to tourism development, intensification of irrigated farming and biomass production.

Therefore, the objective of this research is to use a soil loss prediction model (in that case RUSLE) in combination with Geographic Information Systems (GIS) and geostatistical techniques to model the potential soil erosion risk in this region under different land-use-scenarios. In this fist study stage, erosion risk maps were produced on smaller sub-watersheds of Alqueva, an agro-silvo pastoral system, to consider the vulnerability of this lans-use. These results are essential to increase the knowledge about local conditions, to create a solid base for a Decision Support System (DSS), to provide site specific measures to site specific methods and measures for decision-makers. These methods and measures could decrease the risk of soil erosion, helping spend less money, increasing the dam’s life span, promoting for sustainability of the ecosystems.
2. LITERATURE REVIEW

2.1 Soil Erosion Models

Research on erosion issues and the essential basics of erosion processes have been studied over the past few years. But research is still continuing and progressively focuses on these fundamentals as well as its modeling. Parallel to the detailed modeling of physical processes, many efforts are undertaken to develop universally appropriate erosion models to predict the soil loss and sediment delivery. Models available in the literature for sediment yield estimation can be grouped in following categories: physically-oriented models and empirical models (Bhattarai and Dutta, 2008; Fu et al., 2010) and conceptual models (Merrit et al., 2003; De Vente and Poesen, 2005; Mulligan, 2004; Volk et al., 2010). These models differ in terms of complexity, processes considered, and the data required. However, according to Volk et al. (2010) in general there is no “best” model for all applications, because depend on the intended use and the characteristics of the catchment considered.

Physically based models characterize the essential mechanisms controlling the erosion process, in a high level of detail, through the solution of the fundamentals physical equations, namely equation of mass conservation (Bhattarai and Dutta, 2008; Merrit et al., 2003). Examples for physically-based models include the Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS, Beasley et al., 1982), the European Soil Erosion Model (EUROSEM, Morgan et al., 1999) and Water Erosion Prediction Project (WEPP, Nearing et al., 2000). 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 (Merrit et al., 2010; Fu et al., 2010; Bhattarai and Dutta, 2007).

Conceptual models only considered by some authors, 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 (Merrit et al., 2003; Mulligan, 2004). Agricultural Non-Point Source model (AGNPS, Young, 1989) and Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) are some of the examples of conceptual models, according to De Vente and Poesen (2005) and Volk et al. (2010).

Empirical models are generally the simplest of all three model types, and are based on analyses of observations data using stochastic techniques (Merritt et al., 2003; Volk et al., 2010). Empirical models are frequently used for the estimation of surface erosion and sediment yield from catchment areas (Bhattarai and Dutta, 2008), are useful for annual loads and for identifying erosion “hot spots” (Fu et al., 2010). Among the commonly used empirical erosion models include the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) and Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997). Empirical models are often censured for employing unrealistic assumptions about the physics of the catchment system, for not considered temporal variation of rainfall, runoff and erosion processes, for ignoring the heterogeneity characteristics of the system (Merit et al., 2003) and because are limited to conditions for which they have been developed (Aksoy and Kavas, 2005), hindered the application in different scale (Fu et al., 2010). However, these models are frequently used in preference to more complex models as they can be implemented in situations with limited data and parameters inputs, and are particular useful as a first step in identifying sources of sediment generation (Merrit et al., 2003).

2.1.1 RUSLE

The Universal Soil Loss Equation, an empirical model, is one of the most widely used models for estimating annual soil loss (USLE, Wischemeier and Smith, 1978). The USLE
was originally applied to the prediction of soil losses from agriculture in the USA in order to preserve soil resources, but has been extended for use in numerous countries. The USLE has been modified in the last few decades and its modifications include the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997). RUSLE was developed to take advantage of knowledge and data obtained initially and to be applied in different crops and management systems not present in the original experiments used to develop the model (Kinnell, 2010). USLE and its modifications are defined as:

\[ A = R \cdot K \cdot L \cdot S \cdot C \cdot P \]  

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

Although developed for application to small hill slopes, the RUSLE and its derivatives have been incorporated into many catchment scale erosion and sediment transport modeling applications. The typical output from the USLE is an annual estimate of soil erosion from hill slopes (Merit et al., 2003). It is simple and easy to use, because of the simplicity of structure, less input data requirements and the availability of parameter values, compared with most other models. However it lacks insights on the soil erosion process and mechanism (Bhattarai, 2007, Volk et al., 2010, Merrit, et al., 2003). One of the main criticisms of USLE (Universal Soil Loss Equation) (Wischmeier and Smith, 1978; Renard et al., 1997) based models is that they fail to consider the interdependence of soil erosion factors.

### 2.2 Geographic Information Systems (GIS)

GIS is an integrated suite of computer-based technology and methodology, is a powerful set of tools for collecting, storing, retrieving, transforming, analyzing and presenting spatial data from the real world for a particular set of purposes (Burrough and McDonnell, 2000). In essence, GIS are spatial databases of digital maps which accumulate information on various characteristics and their locations (Davis, 2001).

GIS have been used in various environmental applications, for representing and simulating different scenarios (Lang, 2003). A GIS provides an important spatial/analytical function performing the time-consuming georeferencing and spatial overlays to develop the model input data at various spatial scales (Sharma et al., 1996). The ability to represent elevation in terms of topographic surfaces is central to geomorphological analyses and thus to the importance of representing topography using Digital Elevation Maps (Schmidt et al. 2000).

Due to the spatial variation in rainfall and field heterogeneity, soil erosion is spatially varied, and erosion models often require moderate to high amounts of spatial data like topography, soil properties and land use, which can be effectively handled through GIS (Bhattarai and Dutta, 2007; Mulligan, 2004). The GIS can be used for the discretization of the watershed into small grid cells, to determine the factor values for predicting erosion (Bhattarai and Dutta, 2007).

The combination use of GIS and erosion models, such as RUSLE, has been vastly adopted in many studies and showed to be an effective approach for estimating the magnitude and spatial distribution of erosion (Millward, 1999; Shi et al., 2004; Fu et al., 2006; Bhattarai and Dutta, 2007; Terranova et al., 2009, Kouli et al., 2009). GIS have emerged as a powerful tool useful for effective decision-making (Renschler and Harbor 2002).
2.3 Geostatistics

Spatial variability is a well-known phenomenon of soil systems and this variation in soil has been recognized for many years (Burrough, 1993). Spatial variability means that soil variables are correlated as a function of distance, i.e. the sample values are not independent of each other and one sample value gives some information about its neighbouring data point (Wackernagel, 1995).

Geostatistics is a branch of applied statistics that focusses on the characterization of spatial dependence structure of the underlying random field (Wackernagel, 1995; Webster and Oliver, 2001; Atkinson and Lloyd, 2010). Geostatistics (Goovaerts, 1997; Webster and Oliver, 2001) has been extensively used for quantifying the spatial pattern of environmental variables. It has been used in combination with GIS, to identify the risk of erosion areas, to account local uncertainly (Diodato and Ceccarelli, 2004). This approach allows various measurements and soil properties at a specific location to be combined into a single integrative indicator of soil erosion.

2.3.1 Semi-Variogram

Regionalized variables are distributed in space and time, and are usually known only at number finite experimental points. The methods of geostatistics use the stochastical theory of spatial correlation (Burrough, 2001) for incorporating the spatial coordinates of soil observations in data processing, allowing for modeling of spatial patterns, predicting at unsampled locations, and assessing the uncertainty attached to these predictions (Gooverts, 1999).

Semi-Variogram is the main tool in the geostatistic, which express the spatial dependence among samples (Chilés and Delfiner, 1999). The semivariogram is a plot between the distances of ordered data and their value of semivariance (Isaaks and Srivastava 1989). This plot explains the spatial relation between the samples, and is given by the following Equation 2 (Clark, 1979):

\[
\hat{\sigma}(h) = \frac{1}{2} N(h) \sum (Z_i - Z_{i+h})^2
\]

The most related samples have lower values of semi-variance (\(\gamma(h)\)), where \(N(h)\) is the number of samples that can be grouped using vector \(h\); \(Z_i\) represents the value of the sample; \(Z_{i+h}\) is the value of another sample located at a distance \(||h||\) from the initial sample \(Z_i\).

For a quantitative description of these features, it is useful to fit standard models to the semivariance functions. Typical standard semivariograms include linear, spherical, and exponential models (Wackernagel, 1995). The model fitted provided two important parameters which are the Nugget and Sill. Those parameters help to determine if the samples are spatially correlated or not. If the ratio between Nugget and Sill is low (<0.25) then the samples are spatially correlated, if the ratio is high (>0.75) then the samples have a very low spatial correlation (Cambardella et al., 1994).

2.3.2 Ordinary Kriging (OK)

Geostatistics provide great flexibility for interpolation, providing ways to interpolate to areas or volumes larger than support, methods for interpolating binary data, and methods for incorporation soft information about trends or stratification. All these methods of interpolation yield smoothly varying surfaces accompanied by an estimation variance surface. Combining soft information and conditional simulation is useful for computing data for raster-based environment models (Burrough and McDonnell, 2000).
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 (Gooverts, 1999).

Kriging tries to have a mean residual error equal to zero with the lowest possible value of the standard-deviation of the error, at the same time that estimates the weighted linear combinations \( \{w_i\} \) of the available data \( \{z(x_i)\} \) for the interpolation result \( z(x_0) \) as it is shown in Equation 3 (Wackernagel 1995).

\[
z(x_0) = \sum_{i=1}^{n} w_i \cdot z(x_i) \quad \wedge \quad \sum_{i=1}^{n} w_i = 1
\]  

(3)

The linear weight necessary for the interpolation is obtained by the ordinary kriging Equation 4 (Wackernagel 1995).

\[
C \cdot w = D
\]
\[
\begin{bmatrix}
C_1 & \cdots & C_k & 1 \\
\vdots & \ddots & \vdots & \vdots \\
C_d & \cdots & C_n & 1 \\
1 & \cdots & 1 & 0
\end{bmatrix} \cdot \begin{bmatrix} w_1 \\ \vdots \\ w_n \\ i \end{bmatrix} = \begin{bmatrix} C_0 \\ \vdots \\ C_n \\ 1 \end{bmatrix}
\]  

(4)

In the above equation the matrix \( C \) contains the co-variances from all samples surrounding the sample to be interpolated. The matrix \( w \) contains the weights as well as a parameter called Lagrange Parameter. The matrix \( D \) contains the co-variance from the sample to be determined and the surrounding ones. The final objective of the ordinary kriging interpolation is to determine the matrix \( w \).

2.3.3 Inverse Distance Weighted

In some cases that ordinary kriging could not be used due to low spatial correlation of the samples and a nugget effect Semi-Variogram the Inverse Distance Weight method is used. The samples had a very weak spatially correlation (nugget/sill > 0.75) and the nugget model was the best fitting model, the Inverse Distance Weighted was used instead (Eq. 5). This interpolation method is very simple and considers the importance of the samples to be used in the interpolation to be inversely proportional to the Euclidean distance (Isaaks and Srivastava 1989).

\[
z(x_0) = \frac{\sum_{i=1}^{n} \frac{1}{d_i^p} \cdot z(x_i)}{\sum_{i=1}^{n} \frac{1}{d_i^p}}
\]  

(5)

In this equation, \( z(x_0) \) is the interpolated point, \( z(x_i) \) is a known value, \( d_i \) is the distance from the know value to the interpolated value. The importance of the weight is mainly dictated by the value of \( p \). According to Isaaks and Srivastava (1989), when \( p \) tends to infinite then a bigger weight is given to the nearest sample, and if \( p \) tends to 0 then the
different weights become similar and the final interpolated value will be the simple average of the closest points.

3. STUDY AREA

3.1 Alqueva Dam

The Alqueva reservoir is located on the river Guadiana in Alentejo, a semiarid region in the south of Portugal (8°30’ W, 38°30’ N) (Figure 1). It covers an area of 250 km² (from which 35 km² are in Spain) and the total capacity of the reservoir is 4150 hm³. The lake total shoreline is approximately 1100 km, it extends for 83 km and is considered one of the biggest in Europe (Lindim et al., 2011). The complex project was constructed during 1998-2002 (Figure 2), and the main objective was to create a strategic water reserve, for supply water to the populations, irrigation for farms in the surrounding area (about 110000 ha), produce hydroelectric power, as well as a large reservoir where several tourist projects are also being built. Alqueva dam has direct influence in the regions surrounding it (namely 18 counties).

This region of Alentejo, Southern Portugal, is characterized by a highly heterogeneous and complex landscape structure. A typical landscape is named “Montado”, is an agro-forestry system in which agricultural and forest activities complement each other (Borges et al. 2010), comprising an open formation of cork oak (Quercus suber) and holm oak (Quercus ilex) in varying densities, combined with a rotation of crops/fallow/pastures (Figure 2). In some montado areas, oaks are mixed with olive trees. In this region, during the 20th century, the intensification of agriculture led to numerous environmental impacts and namely increased soil erosion. In the past few years increased the abandonment of agricultural activities in Alentejo, however Bakker et al. (2008) believes there are already, a problem associated with soil erosion in some sites, because exist an environmental imbalance. Thus, it is necessary to decide on to sustainability of the montados, important for protection and restoration of soils.

The climate is Mediterranean, with very hot and dry summers and mild winters. The annual average temperature ranges from 24 to 28 °C in hot months (July/August), and from 8 to 11 °C in cold months (December/January). The average annual precipitation ranges between 450 and 550 mm (Sanches and Pedro, 2007).

Figure 1. Location of the Alqueva Dam
3.2 Experimental study area
An experimental research site (Figure 3) was primarily chosen to study the potential risk of the soil erosion and to help making the first conclusions for the total area. The study area lies in Herdade do Roncão (Roncao D’el Rey) beside the dam, near the Regengos de Monsaraz city. A tourism project will be implemented in this site (included in “Parque do Alqueva” project). It has about 739 ha and the future land-uses are: a marina, a hotel and several golf areas. Currently, the typical local landscape is the “Montado” (Figure 4). As we can see in the Figure 5 the project is being employed.

4. METHODOLOGY

This study was an initial phase of soil erosion risk assessment in this region. RUSLE was used to predict the average annual soil loss.

4.1 RUSLE data collecting and processing

The value of RUSLE factors are computed on the methods described by Renard et al., 1997. Soil data, land use inventory, digital elevation data, and climate data are used as resource data sets to generate RUSLE factor values (outlined in Figure 6).

![Figure 6. RUSLE factors and data collected](image)

4.1.1 Rainfall-runoff Erosivity Factor (R)

The rainfall-runoff erosivity factor is generally known as one of the most important indicators of the erosive potential of raindrops impact (Goovaerts, 1999b). According to Renard et al. (1997), the rainfall-runoff factor is determined through 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. Coutinho et al. (1994) obtained an exponential relationship between rainfall and erosivity index. The equation was defined as:

\[ EI30 = 0.33P - 52.9 \]  

where \( P \) is precipitation. In the study we used this relation with precipitation data from 137 meteorological stations, between 1990 and 2011, to estimate erosivity. The R-factor is
usually calculated according to the values measured over 20 years to accommodate apparent cyclical rainfall patterns. Annual erosivity was computed for these stations, as the sum of monthly erosivities. An erosivity map for south of Portugal was created with geostatistical techniques (ordinary kriging).

### 4.1.2 Soil Erodibility Factor \( (K) \)

Soil erodibility factor \( (K) \) represents the susceptibility of a soil to erode and the amount and rate of runoff, as measured under the standard unit plot condition. The unit plot condition is a continuously cultivated fallow plot, 72.6 ft (22.1 m) long with a slope of 9% (Renard et al., 1997). The soil erodibility factor is a quantitative value experimentally determined. The \( K \) values is estimated using information about soil properties, such as soil texture, content of organic matter, soil structure and permeability (Renard et al., 1997).

An algebraic approximation (Wischmeier and Smith, 1978) of the nomograph was used to estimate soil erodibility factor \( (K) \):

\[
K = \left[ 2.1 \times 10^{-4} (12 - OM) M^{1.14} + 3.25 (S - 2) + 2.5 (P - 3) \right]/100
\]  

(7)

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) \( \times \) (%Silt + %Sand), where % Silt is percent modified silt (0.002-0.1 mm) and % Sand is percent modified sand (0.1-2 mm). \( K \) is expressed with U.S. units and division with the factor 7.59 will yield \( K \) values expressed in SI units of t. ha. h.ha\(^{-1}\) MJ\(^{-1}\)mm\(^{-1}\).

To evaluate this factor, a total of eighty-two (82) soil samples of about 1 kg and with 0 to 20 cm depth were collected (Figure 7). The sample localizations, in field, were determined using a Global Positioning System (GPS). In laboratory the individual samples were dried, weighed and carefully sieved through a 2 mm screen and later analysed their properties. Soil texture was analysed using standard hydrometer procedure. Organic matter was estimated after it goes to muffle during 24 hours at 375\(^{\circ}\)C. To estimate the permeability the field-saturated hydraulic conductivity was measured in field using an infiltrometer (Figure 8). Permeability class and soil structure class was defined in accordance with Renard et al. (1997). Computed \( K \) factor values for each soil sample unit were added into GIS environment and a continuous surface representing the spatial distribution was created using geostatistics.
4.1.3 Slope Length and slope steepness factors (LS)

Slope Length (L) is defined as the horizontal distance from the origin of overland flow to the point where either the slope gradient decreases enough that deposition begins or runoff becomes concentrated in a defined channel. The slope steepness (S) factors show the influence of slope gradient on erosion (Wischemier and Smith, 1978). Ever since the first applications of USLE, estimating the slope length factor has given rise to many calculation difficulties. Direct measurements of slope and slope length were initially proposed to evaluate these factors (Renard et al., 1997). However this method is only suitable for small plots and parcels, because intensive field measurements are obviously not feasible on a regional scale. In watershed scale, the use of a Digital Elevation Model (DEM) in GIS, for data input is a better approach (Nekhay et al., 2009).

In this study, to estimate this factor we created a Digital Elevation Model (DEM) in ArcGIS software (ESRI, 2008) by digitizing contour lines from topographic maps. GIS analyses allow users to generate slope steepness (S) and slope length (L) raster covers by a number of different methods. In that case, the combined LS factor was computed for the watershed by means of ArcGIS spatial analyst extension using DEM, following the equation (4), as proposed by Moore and Burch (1986).

\[ LS = (\text{flow accumulation} \times \text{cell size}/22.13)^p (\sin \alpha/0.0896)^q \]  

where \( p \) and \( q \) are empirical exponents (\( p = 0.4 \) and \( q = 1.3 \)) (Moore and Wilson, 1992), flow accumulation signifies the accumulated upslope contributing area for a given cell, cell size is the size of DEM grid cell (for this study is 14.98) and \( \alpha \) is the slope degree value.

4.1.4 Vegetation Cover and Management Factor (C)

C Factor reflects the effect of cropping and management practices on soil erosion rates, considering that vegetation reduces the erosive impact of precipitation. This factor ranges between 0 and 1, and is 1 for bare soil (Renard et al., 1997). The C factor has a close linkage to land use types. According to the Land Cover Corine 2006 (Caetano et al., 2008) there are three types of soil cover in the study area: 77% of agro-forestry areas, 20% of broad-leaved forest and 3% of wetlands. Vegetation cover can be estimated using vegetation indices derived from satellite images. The most widely used remote-sensing derived indicator of vegetation growth is the Normalized Difference Vegetation Index (NDVI), that ranges from -1 to 1 (Van der Knijff et al., 2002; Kouli et al., 2009). In this study Landsat TM data was used and the NDVI was therefore computed utilizing band 3 (red) and band 4 (near-infrared) as follows:

\[ \text{NDVI} = \frac{(\text{Band}4 - \text{Band}3)}{(\text{Band}4 - \text{Band}3)} \]  

Satellite images with a spatial resolution of 30 m were used from February of 2007. To estimate C factor, the most common procedure using NDVI involves the use of regression equation model derived from the correlation analysis between the C factor values measured in the field and a satellite-derived NDVI (Van der Knijff et al., 2002; De Asis and Omasa, 2007; Karaburum et al., 2010). Landsat TM images were processed using the IDRISI software (Eastman, 2006) and the following formula was used to generate a C factor surface from NDVI values (Van der Knijff et al., 2002):

\[ C = e^{-\alpha(\text{NDVI})/\beta-\text{NDVI}} \]
where $\alpha$ and $\beta$ are unitless parameters that determine the shape of the curve relating to NDVI and the C factor. Van der Knijff et al. (2002) found that this scaling approach gave better results than assuming a linear relationship and the values of 2 and 1 were selected for the parameters $\alpha$ and $\beta$, respectively. The C factor map was produced with ArcGIS software.

4.1.5 Vegetation Control Practice Factor (P)

The P factor is an expression of the effects of specific conservation practices in soil loss, such as contouring, stripcropping, terracing, and subsurface drainage. These practices affect erosion by modifying the flow pattern, grade, or direction of surface runoff and by reducing the amount and rate of runoff (Renard et al., 1997). In this case P factor was assigned the value of 1 (no support practice factor), because the support practices in this area are mainly nonexistent (before the implementation of the tourism project) and the objective of this first study was to analyze the erosion risk according to the actual conditions.

4.2 Statistical and spatial analysis

All spatial data were processed within a GIS (ArcGIS 9.3). A dataset of soil factors was created with their geo-referenced position in the field. Different digital maps of RUSLE factors are created and integrated in algebra map to understand the variation of the erosion.

Graphical interpretation of each factor is performed. To obtain some factors, namely erosivity (R) and erodibility (K) it was necessary use geostatistical techniques. The techniques were used for each soil property considered in the nomograph K Factor, and helped to obtain spatial distribution. The interpolation method used for raster creation was Ordinary Kriging (OK) which is a common method for data interpolation, which gives the most accurate results after validation (See section 2.3.2).

The first step for making use of ordinary kriging method was to investigate the presence of spatial structure among available data in order to get a better understanding of trends, directional influences and obvious errors. Before the creation of the maps, semi-variograms were produced for each property. Transformation and trend removal was performed when necessary.

Cross-validation was used to compare the prediction performances of the semi-variograms, and the best fitted, i.e. the one that gives the most accurate predictions, was chosen. From the cross-validation of the models the mean error (ME), root-mean-square (RMSE), average standard error (ASE) and root-mean-square standardised error (RMSSE) were used. The closer the ME was to zero, and the closer the RMSE was to 1, signified that the prediction values were close to measured values (Wackernagel, 1995). Where models presented similar values for ME and RMSE, the lowest values of root-mean-square error and average standard error were taken into consideration. After cross-validation, all maps of properties were reclassified, weighted and overlaid to obtain final prediction map.

5. RESULTS AND DISCUSSION

The first step was to generate a map of rainfall erosivity in the South Portugal. R-factor values were calculated from over 20 years of rainfall intensity data from all the meteorological stations of this region. The prediction map of the rainfall erosivity was created using ordinary kriging (Figure 9).
Erosivity values were found to range in the South Portugal region between 477-3603 MJ mm ha⁻¹ h⁻¹ yr⁻¹, for a mean annual rainfall of 515.3 mm. The mean value of the R factor in the experimental area (Herdade do Roncão) was found to be 1156 MJ mm ha⁻¹ h⁻¹ yr⁻¹.

Soil erodibility (K) was analysed according to laboratory results. Descriptive statistics of soil proprieties are given in Table 1. The statistical results of soil properties reflect mostly sandy loam soils that are formed mainly with sand (62.711%), followed by silt (22.013%) and clay (15.276%) with relativity low average of organic matter and moderate to fast hydraulic conductivity (15.1 cm/h). Skewness results indicated that almost all properties were normally distributed (skewness between -1 and 1), whereas silt and especially hydraulic conductivity was not normally distributed (skewness more than +1). Normal distribution is essential in order not to cause large prediction errors, however in this case the possibility of errors is low (see Table 2).

Cross-validation was applied and many indicators, shown in Table 2, were studied in order to facilitate the choice of the most appropriate model of semivariogram, for the creation of prediction maps. The cross-validation results of the mean values of the estimation of error (ME) were very low, i.e. close to zero, and the root mean square standardized of error (RMSSE) is close to 1 which shows that the estimation had an acceptable accuracy and the prediction values are close to the measured values. The root mean square (RMSE) and average standardized error (ASE) are low which means good quality of prediction. The nugget-to-sill ratio presented in Table 2 indicted weak spatial dependence for almost all soil properties, which reflects high variance at short distances (high heterogeneity). Moderate and high spatial dependence was obtained for clay and hydraulic conductivity, respectively. Cambardella et al. (1994) suggested that there is weakly spatially dependent if the ratio was

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**Table 1. Descriptive statistics of soil proprieties and RUSLE-K values**

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Sand (%)</th>
<th>Clay (%)</th>
<th>Silt (%)</th>
<th>Msilt (%)</th>
<th>OM (%)</th>
<th>H.C. (cm/h)</th>
<th>K factor (t ha⁻¹ h⁻¹ MJ⁻¹ mm⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>62.711</td>
<td>15.276</td>
<td>22.013</td>
<td>33.533</td>
<td>3.631</td>
<td>15.116</td>
<td>0.023</td>
</tr>
<tr>
<td>Min</td>
<td>36.470</td>
<td>8.560</td>
<td>5.640</td>
<td>13.710</td>
<td>0.800</td>
<td>1.500</td>
<td>0.003</td>
</tr>
<tr>
<td>Max</td>
<td>80.800</td>
<td>27.280</td>
<td>44.980</td>
<td>64.830</td>
<td>7.280</td>
<td>62.400</td>
<td>0.047</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>8.402</td>
<td>3.511</td>
<td>4.480</td>
<td>9.788</td>
<td>1.395</td>
<td>17.552</td>
<td>0.009</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.796</td>
<td>0.623</td>
<td>1.077</td>
<td>0.468</td>
<td>0.630</td>
<td>1.515</td>
<td>0.550</td>
</tr>
</tbody>
</table>
>0.75. According to the same author, weak spatial dependence is controlled by non-intrinsic changes such as inappropriate management. In the other hand, these results could show that, for these properties, the number of samples isn’t enough or the distribution isn’t the best.

### Table 2. Cross-validation results of the fitted semi-variogram models used to create the prediction maps of soil properties and K factor values

<table>
<thead>
<tr>
<th>Soil property</th>
<th>Sand (%)</th>
<th>Clay (%)</th>
<th>Silt (%)</th>
<th>MSilt (%)</th>
<th>OM (%)</th>
<th>Hydr C. (cm/hr)</th>
<th>K factor</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model</strong></td>
<td>Pentaspherical</td>
<td>Pentaspherical</td>
<td>Exponencial</td>
<td>Exponencial</td>
<td>Exponencial</td>
<td>Exponencial</td>
<td>Exponencial</td>
</tr>
<tr>
<td>Nugget</td>
<td>44.567</td>
<td>4.7433</td>
<td>42.606</td>
<td>68.544</td>
<td>0.89201</td>
<td>0</td>
<td>0.00005551</td>
</tr>
<tr>
<td>Sill</td>
<td>17.534</td>
<td>8.9499</td>
<td>15.558</td>
<td>50.649</td>
<td>1.1115</td>
<td>10.381</td>
<td>0.000035367</td>
</tr>
<tr>
<td>Range</td>
<td>921.785</td>
<td>640.178</td>
<td>3323.6</td>
<td>5104.63</td>
<td>277.8</td>
<td>372.49</td>
<td>5104.63</td>
</tr>
<tr>
<td>ME</td>
<td>0.07544</td>
<td>-0.01481</td>
<td>-0.03616</td>
<td>-0.04387</td>
<td>-0.00072</td>
<td>-0.00283</td>
<td>-0.000032</td>
</tr>
<tr>
<td>RMSE</td>
<td>8.162</td>
<td>3.352</td>
<td>7.687</td>
<td>9.012</td>
<td>1.384</td>
<td>3.161</td>
<td>0.00799</td>
</tr>
<tr>
<td>ASE</td>
<td>7.458</td>
<td>3.358</td>
<td>6.978</td>
<td>9.093</td>
<td>1.402</td>
<td>3.205</td>
<td>0.00812</td>
</tr>
<tr>
<td>RMSSE</td>
<td>1.093</td>
<td>0.9883</td>
<td>1.099</td>
<td>0.9949</td>
<td>0.9891</td>
<td>0.9829</td>
<td>0.9893</td>
</tr>
<tr>
<td>Nugget/ Sill</td>
<td>2.54174</td>
<td>0.529984</td>
<td>2.738527</td>
<td>1.353314</td>
<td>0.802528</td>
<td>0</td>
<td>1.569542229</td>
</tr>
</tbody>
</table>

Figure 10 shows the soil texture prediction maps in study area.

From the maps derived it could be seen some trends. Soils with low sand contents are located mainly in the north and south part. Clay percentages show a high spatial variation, with highest values in some zones in the north and centre. Silt percentage has a strong negative correlation with sand percentage because the areas with higher sand are associated with areas with lower silt contents. Modified silt prediction map (silt and very fine sand) shown in Figure 11 reveal identical trends to silt prediction map.

Soil hydraulic conductivity is a fundamental parameter to understand flow process in soils. Figure 11 shows the geostatistical results. The highest hydraulic conductivity, i.e.
permeability occurs at the central and east part, near dam (more than 4 mm/min), where soils generally have highest values of sand and lowest values of clay.

The prediction map of soil erodibility (K), obtained through nomograph previously presented, is presented also in Figure 11. The K factor values were predicted to vary from 0.0026 to 0.047 t ha h ha⁻¹ MJ⁻¹ mm⁻¹, with a mean value of 0.023 t ha h ha⁻¹ MJ⁻¹ mm⁻¹. From the map derived it could be seen that the highest soil erodibility K values are mainly located in the south and north sections, where the highest amount of susceptible particles (silt and very fine sand) are found. Soils with high permeability are more resistant to erodibility, and this was confirmed with the results.

Figure 11. Soil erodibility (K factor) prediction map

Figure 12 shows the typical NDVI values in this area and the corresponding estimated C factor. NDVI values in this agro-silvo pastoral system, before the implementation of the tourism project, were found to have a maximum of about 0.714 and an average of 0.434. By analysing the maps it can be concluded that C Factor has a negative correlation with NDVI values and that the highest values of NDVI caused the lowest values of C factor, resulting in lowest erosion values.
Regarding LS factor, in Figure 13 can be seen the Triangulated Irregular Network (TIN), a map of slopes and LS factor created in ArcGIS 9.3 after the production of a DEM. It was found that the elevation in this area ranges between 145-215 meters. Slope values in this study area vary from 0 to 36% with an average of 5.4%, whereas only 2.5% of total area exceeds a slope of 15%. The highest slopes result in an increased overland flow, rilling and concentrated flow depth. LS factor in the study area, which depends on slopes and flow accumulation, varies from 0 to 28.96, with mean and standard deviation of 1.62 and 1.81, respectively. The results demonstrate that LS factor has a clear correlation with slope, because areas with highest slope values have the highest LS factor values. The highest values of LS occur in the centre of the area, in the southwest part and the east side close to the dam.
The RUSLE factors were integrated within the raster calculator option of the ArcGIS spatial analyst to obtain and quantify soil erosion rates using RUSLE equation. The spatial distribution of soil erosion is shown in Figure 14. The annual soil loss in this agro-silvo pastoral system was estimated to have a mean 14.1 t/ha/year. The terrain with serious erosion risk (higher than 50t/ha) cover about 4.3% of area. In this map, it can be seen that these high soil-erosion risk values lie mostly in the southwest part of the experimental area. Comparing with previously results, this area has the highest slope values and lowest vegetation cover (highest values of C Factor). In addition, soils in this zone have moderate soil erodibility. These results demonstrated that the soil erosion is highly dependent on the local terrain, soil properties and land-use. The estimated values are according to the predicted values for the entire Guadiana River Watershed (INAG, 2000), that were found to vary from 0 to more than 25 t/ha and values greater than 50 t/ha occur exceptionally.

6. CONCLUSION

Modelling soil erosion is complicated because soil loss varies spatially and temporally depending on many factors and their interactions. The study proves that soil erosion model in combination with GIS is an efficient tool for determining the spatial distribution of sediment yield under a variety of simulation scenarios. The RUSLE is a good method to estimate soil erosion risk for different scenarios because it is simple, fast and economic to use. This study demonstrates that geostatistic techniques are advantageous to estimate soil erosion and their factors at unsampled locations, based on the sampled data, showing the confidence level for samples. Remote Sensing also reveals to be very useful to analyze land-use the total area of watershed.

The evaluation of soil erosion risk vulnerability is essential for sustainable land-use planning and comprehensive local and regional development. Those maps can be important to plan the future land-use alternatives and to apply specific soil conservation practices at the
identified high-risk areas. Some land-use changes in vegetation management of those areas could be positive, because some soils are degraded since they were subjected to intensive agriculture in the past, some without any conservation practice. However it is important to be aware of that these future uses without adequate soil management and conservation solutions can also result in negative impacts.

In the future research we intend to analyze different land-use scenarios, which will be implemented in the region. The prediction maps produced can be used as a solid base to create a Decision Support System (DSS) so as to provide site specific methods and mitigation measures for decision-makers (Figure 15). These methods and measures could decrease the risk of soil erosion, reducing costs, increasing the dam’s life span and promoting sustainability of these ecosystems. In the other hand, one DSS could increase the quality and justification of decisions.

Figure 15. Chart illustrating the potential service of a new modelling approach based on the RUSLE model

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REFERENCES


