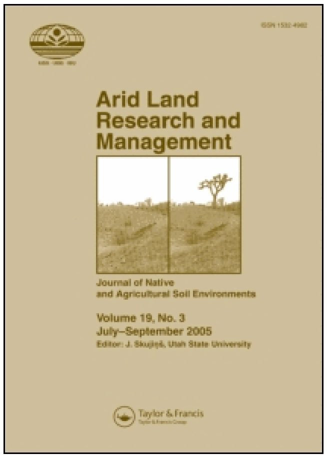



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# Comparison of Traditional and Geostatistical Methods to Estimate Soil Erodibility Factor

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*Soil erosion is a major environmental problem that threatens the sustainability and productivity of agricultural areas. Assessment and mapping of soil erosion are extremely important in the management and conservation of natural resources. This study was carried out to evaluate and compare the relationship between soil erodibility (K) maps prepared by traditional and geostatistical methods of the Sogulca Basin soils south of Ankara, Turkey. Ninety-three soil samples (0–20 cm) were collected from the study area to determine the soil erodibility (K). A kriged contour map was drawn based on the spatial variance structure of the data and was combined with the detailed soil map. A soil erodibility map formed using traditional methods underestimated the soil erodibility. A kriged K map displayed significantly better results than K map formed using traditional methods. The spatial variability of the K data changed with the land use and land form. The low erodibility class (K2) that was found 30.6% using a traditional approach decreased to 10.8% using a geostatistic method and the high erodibility class (K4) increased from 31.7% to 50.9%.*

**Keywords** geostatistics, K factor, kriging, semi-variogram, soil erodibility, universal soil loss equation (USLE)

## Introduction

Soil erosion is the process of detachment and transport of soil particles caused by water and wind (Morgan, 1995). Opening new agricultural lands, conversion of rangelands, overgrazing, deforestation, and mismanagement causes inevitable soil erosion. The prevention of soil erosion is of paramount importance in management and conservation of natural resources (Hudson, 1995; Morgan, 1995; Agassi, 1996).

Soil loss in the U.S. is currently predicted using either the universal soil loss equation (USLE) (Wischmeier and Smith, 1978) or the revised universal soil loss equation (RUSLE) (Renard et al., 1994, 1997) for the purpose of agricultural, rangeland, and environmental management. Both USLE and RUSLE are related to rainfall erosivity factor (R), soil erodibility factor (K), slope length factor (L), slope steepness factor (S), cover management factor (C), and support practice factor (P). In these models, soil erodibility is called K-factor, which in turn is a function of particle size distribution, organic matter content, structure, and permeability (Parysow et al., 2001).

Determining the soil erodibility factor (K) directly from soil loss data collected from repeated measurement plots over the long term (over 20 years) is the most

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reliable method for assessing soil erodibility (Wischmeier and Mannering, 1969; Soil and Water Conservation Society, 1995; Renard et al., 1997). This method, however, is costly and can take a long time to obtain results, which can be impractical for many situations (Renard et al., 1997).

Soil surveys generate maps of soil classes, where the average values of soil properties are estimated within a defined region or mapping unit (Webster, 1985). Values for soil properties are predicted for the majority of locations in the region where the values are not actually measured. The variability of soil properties within fields is often described by classical statistical methods, which assume that variation is randomly distributed within map units. Soil variability is the outcome of many processes acting and interacting across a continuum of spatial and temporal scales and is inherently scale-dependent (Parkin, 1993). In addition, soil properties frequently exhibit spatial dependency. Generally, samples collected close to one another are more similar than samples collected at greater distances. Therefore, parametric statistics are inadequate for analysis of spatially dependent variables because they assume that measured observations are independent in spite of their distribution in space (Hamlett et al., 1986).

Due to the fact that traditional approach does not account for spatial variability of soil erodibility, information contained in soil surveys implies that soil erodibility values are free of estimation errors and constant within a soil series, and remain unchanged over time (Parysow et al., 2001). However, the soil properties vary also in space because of the variation of soil formation factors. A soil erodibility value for a specific soil may vary dynamically and spatially (Wang et al., 2001), and for this reason the traditional approach does not account for the spatial variability of the soil erodibilty. Several studies for assessment of soil erodibility factor showed that the reliable determination of variability and uncertainty is associated with soil survey information. For example, Arnold (1996) states that soil unit homogeneity is rare, and that impurities may occupy from 20 to 70% of the soil units. Mays (1996) reveals that reliability and precision of soil survey data is largely unknown and usefulness of soil surveys depend on the accuracy of mapped properties.

Prediction methods to reliably estimate soil erodibility in space and time should be based on spatial variability of soil properties. Geostatistical methods that are based on the theory of regionalized variables (Journel and Huijbregts, 1978; Isaaks and Srivastava, 1989; Goovaerts, 1997a,) can provide reliable estimates at the unsampled locations provided that the sampling interval resolves the variation at the level of interest (Kerry and Oliver, 2004). Recently, the kriging interpolation method has been used increasingly in USLE and RUSLE soil erosion models. For example, runoff erosivity R factor (Wang et al., 2002a), mapping vegetation cover C factor (Wang et al., 2002b), assessment of topographic factor (Wang et al., 2001), soil erodibility factor (Parysow et al., 2001; Parysow et al., 2003), assessment of topographic factor for the revised universal soil loss equation (Wang et al., 2000), are estimated by geostatistical methods. Wang et al. (2003) used a sample ground dataset, thematic mapper (TM) images, and digital elevation model (DEM) through geostatistical methods. They showed that such methods provided significantly better results than using traditional methods in which a soil map is used to generate a K factor distribution map.

The objectives of this study are:(i) to describe spatial variability of soil erodibility factor (K) in a small catchment, and (ii) to evaluate and compare the relationship between the kriged K map and the traditional K map.

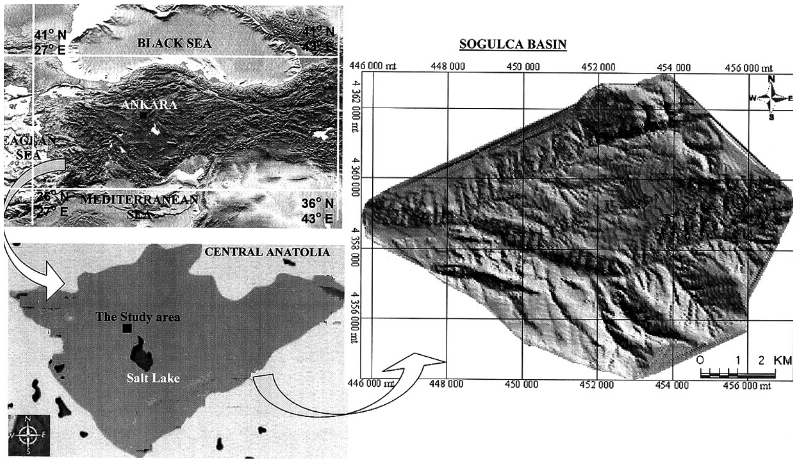


**Figure 1.** Location of the study area.

## Materials and Methods

### *Field Description*

Sogulca Basin is located at the southern part of Ankara, 23 km from Haymana district and lies between 4352734–4364382m N and 444495–458350m E (UTM). The area of the basin is approximately 5740 ha. (Figure 1). About 46.2 % and 52.7 % of this total is being used as rainfed agriculture and rangeland, respectively. Only 1.1 % of the study area is water surface. Average altitude above sea level ranges from 948 m to 1382 m. Mean annual temperature is 11.1 degrees centigrade, total annual precipitation is 457 mm. The study area has "*Mesic*" soil temperature and "-*Xeric*" soil moisture regime according to the Soil Taxonomy (Soil Survey Staff, 1999). Quaternary new alluvium deposits formed on both sides of Sogutcesme stream and Palaeocene formations generally distributed over north and south parts and composed of limestone and sandstone in Sogulca Basin (MTA, 1994).

A digital satellite image (Landsat TM5, 10 May 2000, 177/32) and a DEM, aerial photographs, geological and topographical map were used to determine different land use and land cover types, landforms, slope, and aspect. After all these data were produced and an extensive field checking/sampling and corrections of the preliminary soil map, a final soil map was produced and published in 1:25.000 scale (Figure 2). Eight different soil series were classified and placed in Entisols and Inceptisols according to the Soil taxonomy (Soil Survey Staff, 1999). Basic mapping units were the phases of slope, texture, stoniness, depth, and erosion.

The total study area is composed of eight soil series and the soil characteristics of these series are given in Table 1. The dominant soil series in this area are Km (27.6%), G (19.5%), and Ka (14.2%). These are hilly and upland soils and formed on sandstone and limestone, limestone, sandstone and marl, respectively.

The soil-sampling scheme for the soil erodibility factor (K value) was evaluated using a 1:25.000 scale soil map in the study area. The stratified random sampling (stratification was based on soil series and their phases) scheme consisted of a total 93 locations (Figure 3).

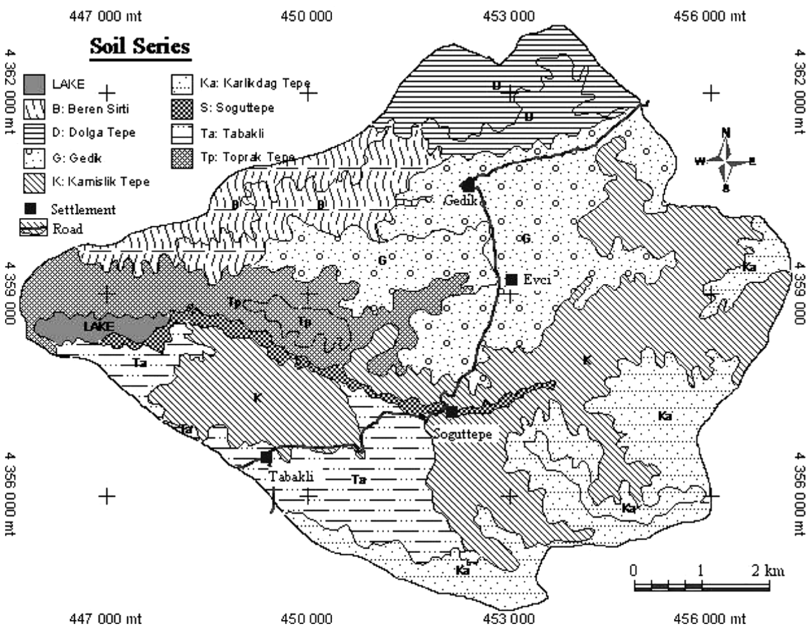


**Figure 2.** Soil map of the study area.

## Methods

A detailed soil map scaled 1:25.000 was used to determine distribution of the K values in the study area. Ninety-three soil samples were collected from topsoil (0–20 cm) taking into consideration the soil series. Soil samples were analyzed, and particle size distribution (Gee and Bauder, 1986), hydraulic conductivity (Klute and Dirksen, 1986), aggregate stability (Kemper and Rosenau, 1986), and organic matter content (Jackson, 1958) were determined in the laboratory.

### *Soil Erodibility Factor (K)*

After generating a detailed digital soil map, soil samples were collected from each soil series to determine K values of them and to create a traditional K map of the study area. Soil samples were analyzed to determine soil properties including sand %, silt %, clay %, organic matter %, and classes for structure and permeability. The values of the soil erodibility factor (K) were computed from these soil properties according to the following equation (Wischmeier and Smith, 1978):

$$K = \frac{1}{100}\Big\{2.1 \times 10^{-4} \times (12 - OM) \times [SI \times (SA + SI)]^{1.14}. \\ +2.5 \times (PE - 3) + 3.25 \times (ST - 2)\Big\} \quad (1)$$

where K is expressed in units of t ha h $ha^{-1}$ MJ $mm^{-1}$. OM, SI, SA, PE, and ST are percentages of soil organic matter content, silt content, sand content, permeability class, and structure code, respectively. If soil organic matter content was equal or greater than 4%, OM was constant at 4% in this equation. Extrapolation of the K factor nomograph beyond an organic matter of 4% is not recommended or allowed in USLE and RUSLE (Renard et al., 1997).

**Table 1.** Soil properties and classification based on *Soil Taxonomy* (1999) of eight soil series and covering ratio of the study area

| Soil series | Soil and classification | Area (%) | Sampling points | Organic matter (%) | Depth | Land position | Land use | Parent material |
|---|---|---|---|---|---|---|---|---|
| B | Beren silty clay (Lithic Haploxerept) | 8.8 | 11 | 3–4 | moderate | upland | Dry farming and range land | sandstone |
| G | Gedik fine clay (Typic Calcixerept) | 19.5 | 20 | 1–2 | deep | upland | Dry farming | limestone |
| Ka | Karlik Dagi gravelly clay (Typic Xerorthent) | 14.2 | 12 | 3–4 | very shallow | hilly | Dry farming | sandstone + marl |
| Tb | Tabakli fine clay (Petrocalcic Calcixerept) | 9.7 | 9 | 2–3 | moderate | upland | Dry farming | limestone + marl |
| D | Dolga Tepe clay loam (Typic Xerorthent) | 8.1 | 6 | 3–4 | shallow | | Range land and barren land | limestone |
| Km | Kamisli Tepe very stony fine clay loam (Lithic Xerorthent) | 27.6 | 22 | 3–4 | very shallow | hilly | Range land and barren land | sandstone + limestone |
| S | Sogut Tepe gravelly clay (Typic Xerfluvent) | 1.8 | 3 | 2–3 | moderate | floodplain | Dry and irrigated farming | alluvium |
| Tp | Toprak Tepe very stony clay (Lithic Xerorthent) | 9.3 | 10 | <1 | shallow | hilly | Range land | limestone + marl |

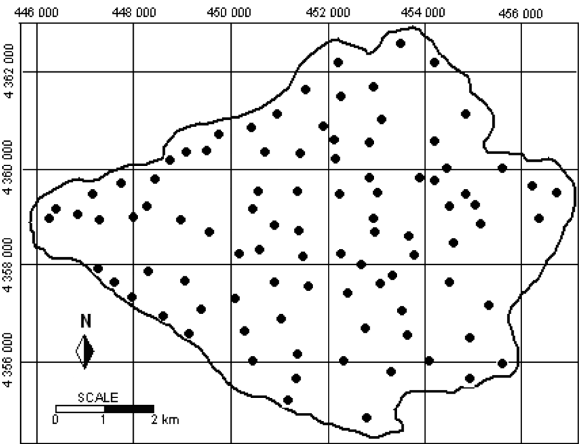


**Figure 3.** The study area and sampling points (UTM).

### *Descriptive Statistics*

Descriptive statistics of soil properties and K values including sample mean, variance, standard deviation, coefficient of variation, skewness, kurtosis, minimum, and maximum were calculated. The hypothesis that the samples were taken from a random function with a normal or lognormal distribution was tested using the Kolmogorov-Smirnov (KS) test.

### *Geostatistical Analysis*

The theoretical basis of geostatistics has been described by several authors (Matheron, 1963, Campbell, 1978; Isaaks and Srivastava, 1989; Kitanidis, 1997). The main tool in geostatistics is the semi-variogram, which expresses the spatial dependence between neighboring observations.

Geostatistics provides a tool for the optimum sampling design and interpolation on unsampled locations, taking into account the spatial correlation of adjacent pixels based on the semi-variance. This procedure is optimal in the sense that estimates are unbiased and the estimation variance is minimum (Di et al., 1989; Burgess and Webster, 1980a, 1980b). The block kriging interpolation method is more suitable for delineation of soil patterns than punctual kriging, since we are more interested in average values across larger areas than at a point. Besides, this method has the advantages of reducing estimation variance and creating a smoother map.

On the other hand, kriging performance can be significantly affected by variability and spatial structure of the data (Leenaers et al., 1990). Kriging is also affected by the anisotropy of data, aside from all the variogram models, search ratio, etc. By calculating semi-variograms in different directions and evaluating the associated ranges, the anisotropy can be determined. In practice, two types of anisotropy exist: (i) geometric and (ii) zonal anisotropy. The range of the semi-variogram changes according to the direction while the value of the sill remains constant, geometric anisotropy will occur. Zonal anisotropy differs from geometric anisotropy in that the ranges of the semi-variograms remain constant while the sill changes with direction.

The choice of a variogram model, search radius, and the number of closest neighbors used for the estimation led to a significantly better estimation precision (Kravchenko and Bullock, 1999).

Experimental semi-variograms were developed to determine the spatial dependence of soil properties using the following equation given by Journel and Huijbregts (1978):

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \tag{2}$$

where $\gamma^*(h)$ is the semi-variance; $N(h)$ the number of experimental pairs separated by a distance $h$; $z(x_i)$ the measured sample value at point $i$; and $z(x_i + h)$ measured sample value at point $i + h$.

The spherical model that is most commonly used in the soil science (Burgess and Webster, 1980a) is described with the following equation:

$$\gamma(h) = \begin{Bmatrix} C_0 + C_1 \left[ \frac{3}{2}\left(\frac{h}{a}\right) - \frac{1}{2}\left(\frac{h}{a}\right)^3 \right] \ldots\ldots 0 < h \le a \\ C = C_0 + C_1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots h > a \end{Bmatrix} \tag{3}$$

where $C_0$, $C_1$, $C$, $a$, and $h$ are nugget variance, structural variance, sill value, range of influence, and lagged distance for spherical model, respectively. The parameter $C_0$ is the inherent random variability, or background noise, of the sample values at zero distance, referred to as the nugget value. The distance at which samples become independent of one another is presented by the parameter $a$, referred to as the range of influence. The constant variability that the expression levels off to at distances greater than a is represented by $C_0 + C_1$, where the parameter is referred to as the sill of the semi-variogram model, and is generally of the same order as the statistical semi-variance of the sample population. The experimental semi-variogram and the fitted model were obtained using the GS+ software (Gamma Design, 1995).

### *Kriging Procedure*

The parameters of the semi-variogram model provide the essential information for kriging, which is a method for optimal local estimation embodied in the regionalized variable theory. The estimates are linear sums of weighted observations within a given neighborhood (Oliver, 1987):

$$z(x_0) = \sum_{i=1}^{n} \lambda_i z(x_i) \tag{4}$$

where $z(x_0)$ is the estimate of $z$ at $x_o$, $\lambda_i$ is the weight associated with the ith observation, and $n$ the number of observations within the neighborhood, usually no more than 16 (Oliver, 1987).

Cross validation was used to compare the results obtained with a different number of the closest samples (Goovaerts, 1997b). In this procedure, every known value is omitted, respectively, and estimated by using a neighborhood around it. Having made such calculations, the mean reduced error defined by

$$\bar{R}_{\in} = \frac{1}{n} \sum_{i=1}^{n} [z(x_i) - z^*(x_i)]/\sigma_k(x_i) \tag{5}$$

should be close to zero, and reduced variance,

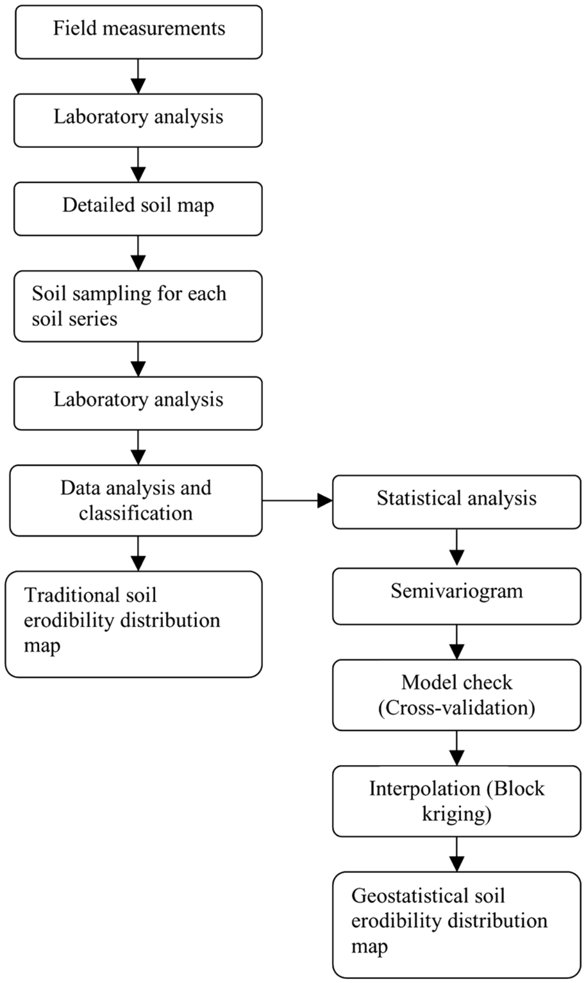


**Figure 4.** Overall methodology of the traditional and geostatistical method used for soil erodibility mapping.

$$S_{R\in}^2 = \frac{1}{n}\sum_{i=1}^{n} \{[z(x_i) - z^*(x_i)]/\sigma_k(x_i)\}^2 \tag{6}$$

should be close to the unity, where $n$ is total number of samples; $z(x_i)$ measured points, $z^*(x_i)$ estimated points, and $\sigma_k^2(x_i)$ estimation variances, $i = 1$ to $n$. Both parameters are important measures of estimation accuracy (Yates and Warrick, 1987)

Block kriging was used to draw a contour map of K values at the unsampled locations using GS+ software (Gamma Design, 1995). The map was exported to TNT Mips (1999) to be overlaid on the detailed soil map and this provided the basis for the validation of the soil maps for their use as erodibility map. The overall methodology, both traditional and geostatistical, is outlined in Figure 4.

## Results and Discussion

### *Characterization of Soil Properties and K Values*

The descriptive statistics of soil properties and soil erodibility values (K) are given in Table 2. The coefficients of variation of soil properties varied between 0.28 and 0.85 with spatial heterogeneity being particularly large for the permeability, clay, and organic matter. High negative correlation was found between clay content and permeability. A medium coefficient of variation of clay contents may have probably affected permeability. Similarly, when the relationship between organic matter and soil erodibility values was considered, varying organic matter contents in the area, which had no management practices to prevent soil erosion, may have affected the soil erodibility. Silt fractions showing the lowest variability and high relationships with a soil erodibility factor affected the variation of the soil erodibility. The coefficient of variation of soil erodibility factor was 0.366, due to variability of landscape position and land use. Due to soil properties used to calculate a soil erodibility factor showing differences, the soil erodibility factor was affected and took different values. Statistical values obtained from a Kolmogorov-Simirnov test ($KS_t$) were compared with the values from a critical table ($KS_c$). When KS test results were considered, the results indicated that for a probability level of $p < 0.05$, K data were normally distributed.

### *Spatial Variability and Kriging*

The spatial variability of this area was analyzed with semi-variograms computed in four different directions (0, 45, 90, and 135°) to check geometric anisotropy in this area. There were no great differences in semi-variograms for the different directions in the area. Therefore, the isotropic approach was used for fitting the results of semi-variances. Five models were tested to fit the semi-variogram models in this study. The isotropic spherical model showed the best fitting value for the computed semi-variance points (Figure 5). This model was selected on the basis of the results of a cross-validation test and determination coefficients of the different models (Table 3). The range of influence relating to distance for soil erodibility values was 1910 m. At distances shorter than the range, variability was nonrandom and a pairwise sample variation depended upon the distance of separation. The geostatistical range of values obtained for soil erodibility K values were greater than the distance between any two nearby test sites and thus could provide useful information about the spatial structure of K. If the geostatistical range of values is greater than any nearby test sites, the spatial structure information is useful (Vieira et al., 1981; Ersahin, 2003).

The nugget parameter of the semi-variogram is a measure of unexplained variability. The percent unexplained variability can be estimated from the ratio of the nugget to the sill. Approximately 12% of the variation in measured soil erodibility values at the study area was unexplained. Because the ratio was found less than or equal to 25%, the variable was considered strongly spatially dependent (Cambardella et al., 1994).

A cross-validation procedure was carried out to check if a theoretical semi-variogram model fitted to the data. Table 4 summarizes cross-validation results. The $\bar{R}_{\in}$ and $S^2_{R\in}$ were calculated using Eqs. (5) and (6), respectively. The cross

**Table 2.** Descriptive statistics of the soil properties and K values

| Statistics | Sand (%) | Silt (%) | Clay (%) | Permeability (cm $h^{-1}$) | OM (%) | K (t ha h $ha^{-1}$ MJ $mm^{-1}$) |
|---|---|---|---|---|---|---|
| Mean | 48.218 | 26.536 | 25.659 | 7.647 | 1.176 | 0.172 |
| Variance | 354.872 | 54.096 | 149.704 | 41.874 | 0.301 | 0.004 |
| Standard deviation (SD) | 18.245 | 7.355 | 12.235 | 6.471 | 0.549 | 0.063 |
| Coefficient of variation (CV) | 0.378 | 0.277 | 0.476 | 0.846 | 0.466 | 0.366 |
| Skewness ($C_s$) | 0.588 | −0.718 | −0.004 | 0.949 | 0.597 | −0.578 |
| Kurtosis ($C_k$) | −0.611 | −0.443 | −0.717 | −0.613 | 0.144 | −0.505 |
| Minimum | 17.400 | 9.810 | 4.380 | 1.430 | 0.200 | 0.030 |
| Maximum | 84.860 | 39.880 | 51.260 | 21.720 | 2.590 | 0.270 |
| $KS_t^*$ | | | | | | 0.134 |
| $KS_c^{**}$ | | | | | | 0.141 |
| N used | | | | | | 93 |

*$KS_t$ is the Kolmogorov-Smirnov statistic calculated from data set.
**$KS_c$ is the critical value at $P < 0.05$.

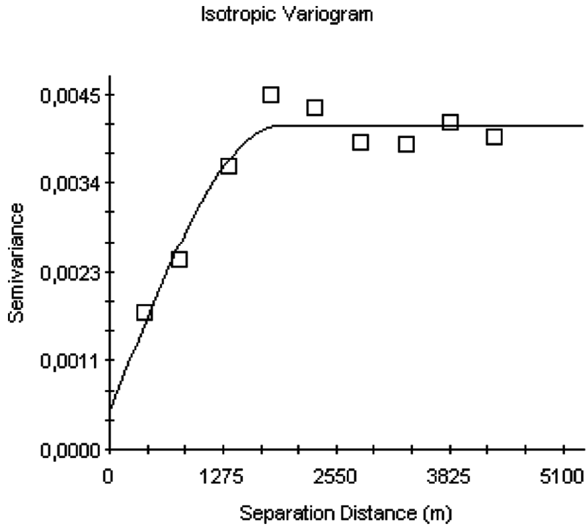


**Figure 5.** Experimental semi-variogram model for K. Solid line represent the spherical model fitted to experimental values.

validation indicated that mean reduced error and reduced variance for the 93 measured K values were 0.005 and 1.008, respectively. The results of the normality test (Kolmogorov-Smirnov) indicated that the residuals from the cross-validation test were normally distributed. The results showed that the selected semi-variogram model described spatial behavior of K data very well.

Using Eq. (4) and a selected semivariogram model, kriged estimates were calculated for spatial structure and studied soil properties were determined with selected semi-variogram parameters at $113 \times 113$ m interval ($82 \times 71$ data points) at 5822 grid points in order to map spatial changes of K and overlaid on the basin boundary (Figure 6). Eight neighboring data points were used for kriging estimations. Block kriged K data were useful for the study area that had experienced low, moderate, or high rates of soil erodibility status. An important change in the spatial variability of K data was recognized as a function of land use and landform.

K values were high especially on hilly and sloppy areas where agriculture was practiced. Physical detachments and variation or insufficient organic matter contents at the soil surface caused an increase in erosion rates by agricultural practices and tillage operations. Similar results were reported by Fraizer and Cheng (1989).

In the study area a total of eight soil series were classified and placed in Entisols and Inceptisols according to the Soil taxonomy (Soil Survey Staff, 1999). A traditional K map which was formed from the soil series map, was overlaid on the kriged K

**Table 3.** Parameters for isotropic spherical semi-variogram model at K

| Variable | Model | $C_0$ | $C_0 + C$ | $C_1$ | a (m) | $C_0/C_0 + C$ |
|---|---|---|---|---|---|---|
| K | I. Spherical | 0.00048 | 0.00410 | 0.00362 | 1910 | 0.117 |

$C_0$- nugget variance; $C_1$- structural variance; $C_0 + C$- sill variance; a- range of influence in meters

**Table 4.** Cross validation results of chosen semi-variogram model for K data

| | | | Reduced Error | |
|---|---|---|---|---|
| Statistics, N = 93 | Observed K | Estimated K | Mean | Variance |
| Mean | 0.172 | 0.173 | 0.005 | 1.008 |

map to compare an estimation of erodibility status in the basin. A traditional K map was inadequate in describing the spatial structure of the basin due to the fact that all soil properties are assumed to stay constant in soil series when compared with kriged K map. Predictions of specific soil properties are commonly performed by using detailed soil maps. Nevertheless, soil properties change from place to place and even more within the same soil type (Warrick and Nielsen, 1980). Roose and Sarrailh (1990) summarized that estimation of K factors from soil types, in general, can be problematic because soil classifications are often not based on those parameters reflecting erodibility. Several studies have been unable to find a correlation between predicted and observed K factors, and generally found that the USLE K factor was being underestimated (Vaneslande et al., 1987; Jaiyeoba and Ologe, 1990; Igwe et al., 1995; Torri et al., 1997).

Distribution maps of soil parameters used to estimate that K values were produced by using the geostatistic method. Distributions of these soil parameters that most influence soil erodibility values were given in Figure 7. After at, the relationship between soil erodibility parameters and soil erodibility maps prepared by traditional and geostatistical methods in the study area were compared. In the east and west part of the study area in which there was the highest sand content and permeability values, the lowest values of clay, silt, and organic matter content

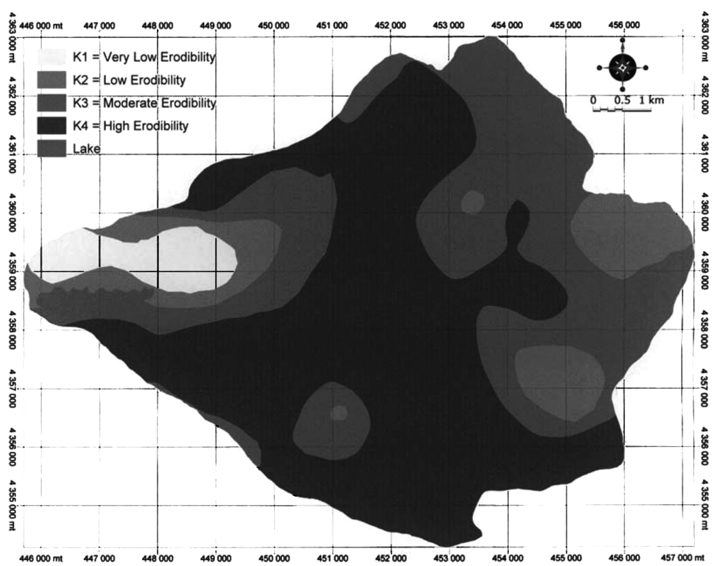


**Figure 6.** Map of distribution K values (t ha h $ha^{-1}$ MJ $mm^{-1}$) of the study area. Categories of K are shown in Table 5.

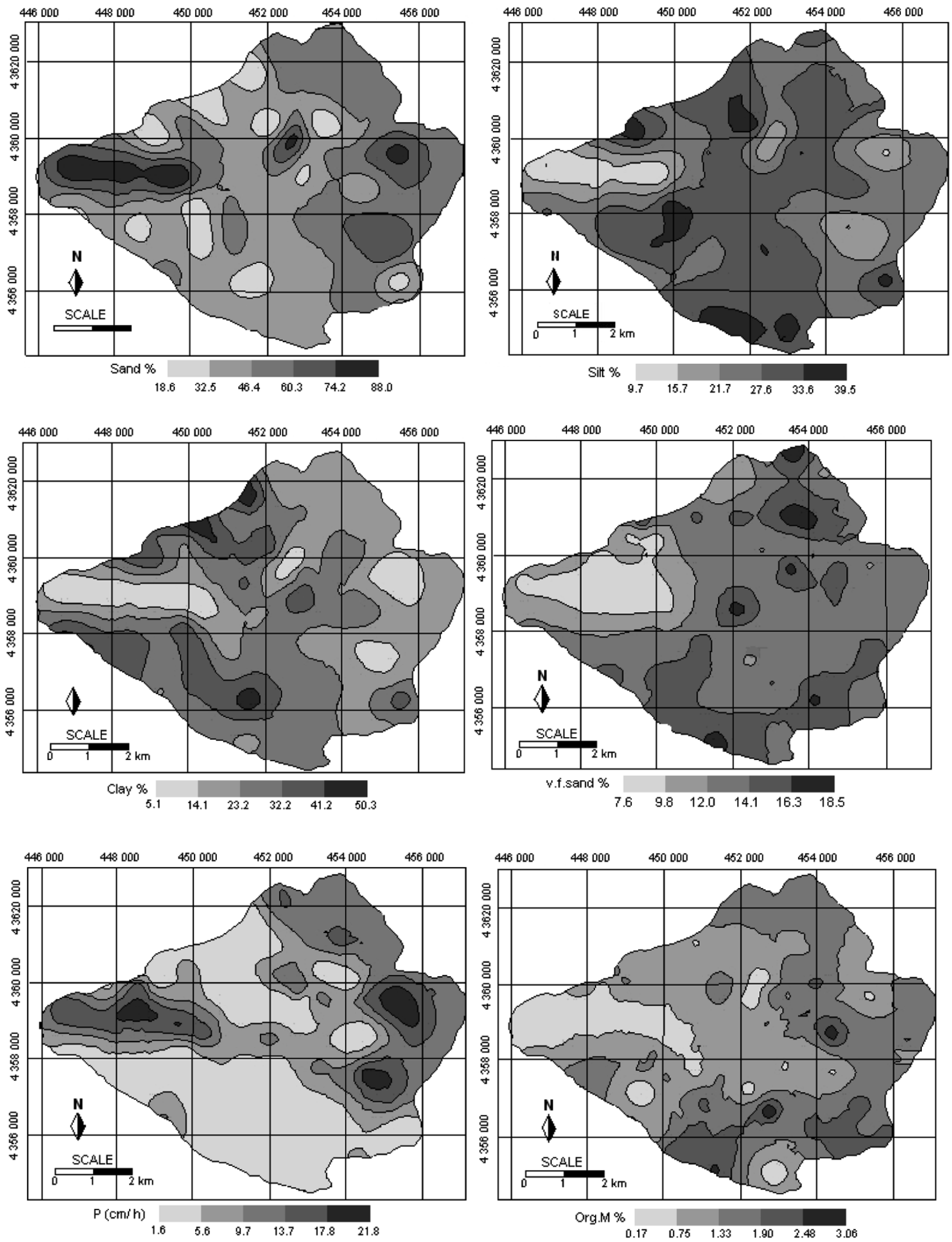


**Figure 7.** Distribution maps of soil erodibility parameters.

were measured. These areas were classified as having a very low (K1) and a low (K2) erodible level in K map prepared with the geostatistical method while the same places were classified as low (K2) and high (K4) erodible level in K map produced with the traditional method. Although southern parts of the study area have high silt, partially high clay values, low organic matter, and sand content, these areas were classified as low (K2) erodible in K map produced with the traditional method.

**Table 5.** Distribution of K values using traditional and geostatistical method

| Class* ($t\,ha\,h\,ha^{-1}\,MJ\,mm^{-1}$) | Description | Traditional Area (ha) | Traditional Ratio (%) | Geostatistical Area (ha) | Geostatistical Ratio (%) |
|---|---|---|---|---|---|
| 0–0.05 (K1) | very low erodible | 316.8 | 5.5 | 269.0 | 4.7 |
| 0.05–0.1 (K2) | low erodible | 1754.5 | 30.6 | 622.2 | 10.8 |
| 0.10–0.20 (K3) | moderate erodible | 1785.9 | 31.1 | 1859.8 | 32.5 |
| 0.20–0.30 (K4) | high erodible | 1817.4 | 31.7 | 2923.6 | 50.9 |
| Lake | | 65.2 | 1.1 | 65.2 | 1.1 |
| Total | | 5739.8 | 100 | 5739.8 | 100 |

*Wischmeier and Smith, 1978

On the other hand, these areas were classified as high (K4) erodible in the soil erodibility map generated by the geostatistical method.

While low erodibility class (K2) covered 30.6% of the basin in the K map formed by the traditional method, this rate reduced to 10.8% in the kriged K map (Table 5). Moreover, the area covered by high erodibility class increased from 31.7% to 50.9% in the kriged K map. Approximately more than half of the study area (51%) had high soil erodibility value (K4) commonly at the center and southern parts of the Sogulca Basin.

Because of the spatial and temporal variability of the landscape, high labor costs, and the time needed to collect sufficient data, there are difficulties in measuring soil erosion over large areas with traditional methods. Therefore, the soil erodibility factor (K) is a very important indicator of erosion for lands under the soil erosion risk, because soil properties, slope, and land cover are the major factors that affect soil erosion. After overlapping with K values map, land use, and soil map using the GIS technique, it was also found that there are significant differences, especially K2 and K4 class among them, which are presented in Table 5 and Figure 8.

## Conclusion

The present study shows the heterogeneous nature of erodibility. In this study, not only is erodibility determined by a wide range of interconnected parameters, but it was also shown that some erodibility parameters can be related to the soil types on the soil map of the study area.

Kriged estimates were adequate to explain distribution of the soil erodibility factor in this basin. This technique is more reliable than traditional methods due to the fact that reliable estimation of soil erodibility in space should be based on spatial variability of soil properties. In addition, distribution maps of soil parameters and a soil erodibility map created by geostatistical method were found compatible with each other. But K distribution determined by the traditional method showed disharmony with soil parameters, because spatial structures of soil parameters were not accurately reflected in the K map formed by the traditional method.

A K map formed using the traditional method by taking into consideration the soil series map caused an underestimation of soil erodibility values. The area covered by a low erodibility class (K2) decreased from 30.6% to 10.8% when a traditional approach was compared with a geostatistical technique. On the other hand, the area

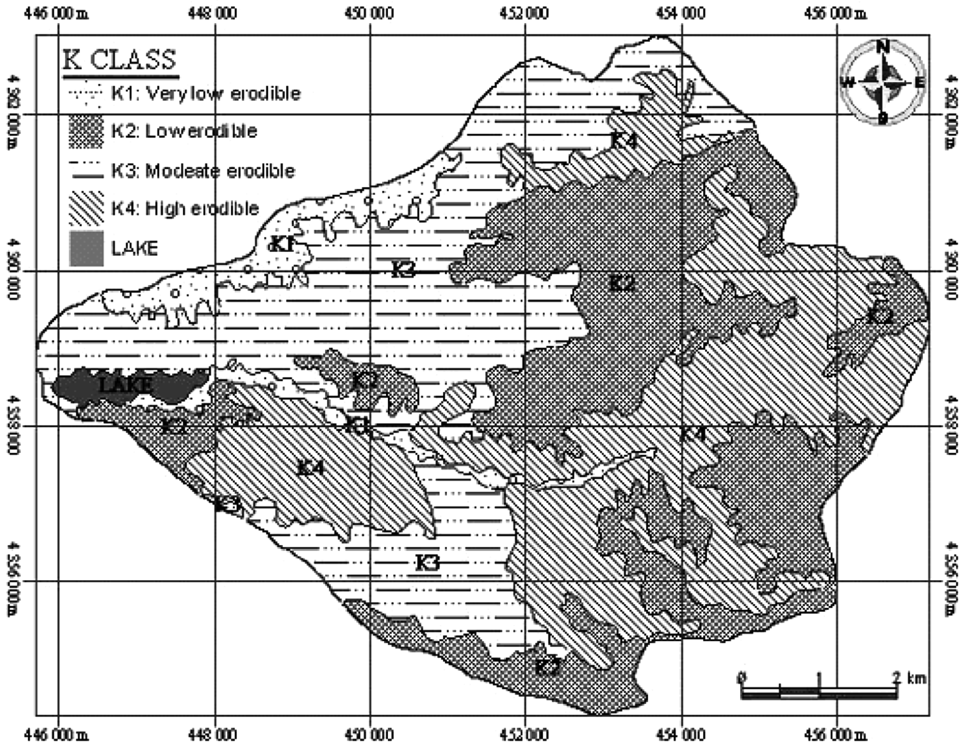


**Figure 8.** Distribution of K values on soil series map.

covered by high erodibility class (K4) increased from 31.7% to 50.9%. The traditional method does not account for soil properties changing over space. In fact, the soil erodibility K values within a soil series varied within a certain range and using average value may cause error. Therefore, the traditional K map values should be used with care.

Similar conclusions were also supported by Parysow et al. (2001). They also indicated that K values had considerable and smooth spatial variation, and the application of geostatistical methods might prove to be a valuable modeling tool for obtaining estimates and reducing uncertainty in soil erodibility, as well as erosion prediction in their study. However, assessment of soil erodibility should be periodically renewed and spatial data of the Sogulca Basin updated to provide a quick evaluation of its fragility and sustainable land management, due to dynamical behavior of soil erodibility in time.

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