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EVALUATION OF DESERTIFICATION POTENTIAL IN A SLOPING CATCHMENT

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Abstract: Variability of soil resources in space and time can be a useful indicator in evaluating desertification risk in arid and semi-arid regions. We have compared the coefficient of variation (CV) and the fractal dimension of spatial variation (D) for some selected properties of soils with a slope of <3°, designated as mild-to-moderate sloping (MMS) and soils with the slope of >3°, designated as moderate-to-steep sloping (MSS) soils, in a 1,041.2 ha catchment located in North-Central Anatolia, Turkey. The study area was sampled based on a random sampling scheme, taking a total of 142 geo-referenced samples from 0-0.30 m soil depth. All soil samples were analyzed for soil properties of electrical conductivity (EC), pH, soil organic matter (SOM), sand, silt, clay, and coarse material, cation exchange capacity (CEC), crusting index (CI), penetration resistance (PR), and soil erodibility factor (K). The spatial variation of soil variables was characterized in MHS and SMS soils by CV, semivariogram analysis, and D. In general, higher CV values occurred in SMS soils, and the nugget effect values calculated for these variables was lower in SMS soils, revealing a greater spatial dependency of these variables in these soils, and a greater potential for desertification in these areas. Variables with a stronger spatial structure had a higher CV and a lower D. In general, higher CV values and lower D values occurred in SMS soils, indicating a greater desertification potential of these soils. Strong spatial distribution of soil properties in both slope classes suggested that D should be preferred over CV in evaluating the desertification risk in these areas.

Key words: Desertification risk, probabilistic fractals, coefficient of variation, self-similarity, slope steepness

1. INTRODUCTION

Desertification operates principally in arid, semi-arid, and sub-humid environments. It involves excessive human pressure, changes in land use, as well as in the natural processes (Mouat et al., 1997). Desertification reduces productivity, biodiversity, and economic viability of land, and is associated to long-term changes in ecosystem function (Dregne, 1977), involving both the spatial and temporal components of the ecosystem function (Mouat et al., 1997).

Desertification results from a number of diagnostic processes, which are different in different ecosystems (Mouat et al., 1997). Physical, chemical, and biological properties of soils are often used as desertification indices (Schlesinger et al., 1990). Among these properties, soil erosion, salinization, and soil chemistry are generally included in desertification studies. Mouat et al. (1997) listed potential indicators that can be used in evaluating desertification. The list included soil variables such as organic matter content, albedo, erosion index, ratio of soil carbon-to-nitrogen, and soil salinization. Schleinger et al. (1990) suggested that soil heterogeneity at local levels may be used as inputs to desertification models operating at global scales. Selecting a set of potential indicators of desertification may differ in terms of the models used. Miller and Donahue (1995) suggested carbon to nitrogen ratios as indicator of the nutrient status of soils. Others (Su et al., 2004) related fractal coefficient of soil particles (D_s) to soil desertification degree, showing that the higher the sand content, the lower the D_s one, indicating a greater desertification degree of farmlands. Su et al. (2004) also detected a significant relationship between D_s and each of the total N and organic C content of the soils they studied.

Soil heterogeneity was suggested to be a potential indicator of desertification. Schlesinger at al. (1990) suggested that the changes in ecosystem function at the transition between arid and semi-arid regions can well be understood in the context of the spatial and temporal distribution of soil resources, hypothesizing that when net long-term desertification of productive grasslands occurs, the relatively uniform distribution of water, nitrogen, and other soil resources is replaced by an increase in their spatial and temporal heterogeneity. Schlesinger et al. (1990) used the coefficient of variation for pH, saturation percentage, soil moisture, and total nitrogen as indicators of desertification, higher CV showing a greater potential for desertification in their studies.

In classical statistics, parameters such as standard deviation, coefficient of variation, and standard error from the mean are frequently used to characterize spatial variability of a given property (Webster, 2001). Eghball et al. (1999) pointed out that the use of classical statistics in evaluating data on spatial or temporal dependency may result in misleading conclusions. They further suggested that semivariogram and fractal analyses can be useful in determining and comparing the domination of short- or long- range variation between treatments or management systems.

Fractal analysis has proved useful in characterizing plant and soil parameters. Burrough (1983) first suggested that the fractal theory of Mandelbrot (1982) would be appropriate to describe scale-dependent variability of soil properties. In fractal analysis, the fractal dimension, D, is a scale independent indicator of the shape (geometry) of the fractal object being studied (Eghball et al., 1999). The slope of the regression line of log semivariogram versus log lag (h, distance) is used to estimate D. Contrary to a small D, which indicates the importance of long-range variations, a large D indicates the importance of short-range variations (Burrough, 1983).

Topography greatly influences the soil genesis due to its controlling effects on water-related processes (Kachanoski et al., 1985). The processes leading to soil heterogeneity in space and time would act at different magnitudes depending on slope steepness. This should result in desertification processes to act in different magnitudes in different topographies. This motivated the hypothesis that slope steepness should be an important factor in desertification studies of sloping soils and that spatial variation of soil properties with different slope steepness may be compared to verify this hypothesis. Therefore, the objective of this study has been to compare the desertification potential of soils stratified in two slope complexes within a small catchment. With this regard, probabilistic fractals and classical statistics have been applied in evaluating the desertification potential and results are discussed.

2. MATERIALS AND METHODS

2.1. Materials

This study has been conducted in the small Çelikli catchment, located in the Tokat region, North Central Anatolia (Fig. 1). The catchment is 1,041.2 ha, and lies at an average altitude of 1,300 m. It is situated in the area of transition from Central Anatolia to the Middle Black Sea region.

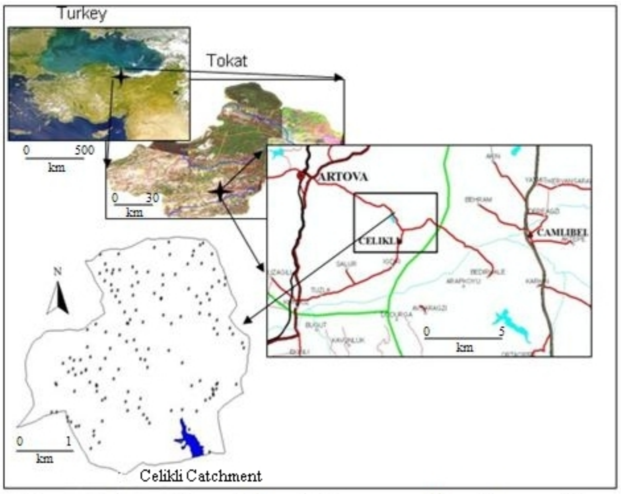

Figure1. Location of the study area with soil sampling sites shown by dots

The soils, Entisols, Mollisols, and Alfisols, which are moderate-to-well drained soils with slope of 1.3° to 6.3° in most of the area. The catchment contains mild-to- moderate steep areas with low vegetation densities and/or under cultivation. The areas with <6.3° slopes are mainly cultivated. The major vegetation type in fallow areas is grassland, with *Graminea* and *Fabaceae* as dominant species, other types being shrubs and meadows. The cultivated areas are relatively large, covering 67.8% of the catchment. Wheat, sugar beet, and cover crops constitute most of the agricultural production; wheat is the main agricultural crop in the study area. Some woodland, mostly shrubs with a few trees, covering approximately 5% of the catchment, are scattered about. The natural grassland mostly degraded due to heavy grazing, cover 24.8% of the area. The mean annual temperature is 8.1^{o}C, and the annual precipitation mean is 535.9 mm, 84.7% of which fall between October and May.

2.2. Methods

2.2.1. Soil Sampling and Analysis

Geo-referenced soil samples were taken in July 2002 from 142 sites at 0-0.30 m soil depths, based on the same type of slope, management, soil, and visual properties of the landscape in the catchment. The sampling points, GPS localized with an error of ± 3 m Euclidean (x, y) relative positions within the study area, have been used in spatial analysis. The locations of soil sampling sites are shown in figure 1. After removing stones and large plant roots or debris by air drying, each sample was thoroughly mixed and pulverized to pass through a 2-mm sieve and then stored in a plastic container prior to analysis. The soil samples then have been analyzed for soil organic matter (SOM) by the Walkley-Black procedure (Nelson & Sommers, 1982), soil pH in 1:2 soil:water suspension (McLean, 1982), soil textural elements separated with a Bouyoucos hydrometer (Gee & Bauder, 1986), and for cation exchange capacity (CEC) by saturating the soil samples with sodium acetate (Rhoades, 1982). Particles, greater than 2-mm in diameter, were separated and reported as coarse material (CM) (Gee & Bouder, 1986). Soil penetration resistance was measured with a cone penetrometer (Bradford, 1986). The soil erodibility factor (*K*) was calculated by the regression equation (Wischmeier et al., 1971):

$$K=2.8x10^{-7}M^{1.14}(12-a)+4.3x10^{-3}(b-2)+3.3x10^{-3}(c-3) \quad (1)$$

where, *M* is the particle-size parameter (% silt + % very fine sand) x (100-% clay), *a* is percent organic matter, *b* is soil structure code (very fine granular: 1, fine granular: 2, medium or coarse granular: 3, and blockish, platy, or massive: 4), which was determined in the field, *c* is soil profile permeability class (rapid: 1, moderate-to-rapid: 2, moderate: 3, slow-to-moderate: 4, slow: 5, and very slow: 6). The crusting index (*CI*) was calculated from soil organic matter ratio index by the following equation (Lal et al., 1997):

$$CI = Soil\ Organic\ Matter\ Content(\%)/Clay(\%)x100 \quad (2)$$

2.2.2. Exploratory Data Analysis

Statistical parameters of mean, maximum, minimum, standard deviation, coefficient of variation, skewness, and kurtosis have been calculated for EC, pH, SOM, CEC, sand, silt, and clay contents, coarse fragments, soil penetration resistance, erodibility (*K*), and crusting potential in order to characterize their distributions in MMS (mild-to-moderate sloping) and MSS (moderate-to-steep sloping) soils.

2.2.3. Spatial and Fractal Analysis

Semivariograms have been used to describe the spatial distribution of soil variables in MMS and MSS soils. A semivariogram is a graphical representation of spatial self-correlation by plotting the semivariance for several distance intervals (Diekmann et al., 2007). Semivariograms have been calculated by the equation (Diekmann et al., 2007):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{N(h)} \left[z(s_i) - z(x_i + h) \right]^2 \quad (3)$$

where, γ *(h)* is the estimated semivariogram, $z(x_i)$ and $z(x_{j+h})$ are the values of a variable separated by the lag *h*, and *N(h)* is the number of data pairs in the corresponding lag.

Fractal analysis has been performed by using spatial data of soil variables to evaluate their pattern and extent of spatial variability in MMS and MSS soils according to the method of Burrough (1983) and Eghball et al. (1999).

The data which deviated from normal, have been transformed. The type of transformation was based on the coefficient of skewness, as suggested by Webster (2001). The variables with a coefficient of skewness greater than the absolute value of 1.0 were transformed to logarithms, while those between 0.5-0.99 were transformed to square root (Webster, 2001). No transformation has been made to the data with a coefficient of skewness<0.5. Anisotropy data have also been checked in order to calculate the directional semivariograms, whenever necessary. We have used the most adequate lag intervals yielding the best representative semivariograms. Minimum 20 data pairs have been used in a lag for a safe calculation of semivariance. The semivariograms have been extended to 1,800 m, which is less than the shortest axis of the study area, as suggested by Rossi et al. (1992). We have applied the least square analysis for goodness of fit for semivariograms. Although the spherical models are generally preferred since they are a good fit to semivariograms of soil properties (Webster, 1985), exponential and Gaussian models have been applied in some cases since they better described our experimental semivarograms. The semivariogram analysis has been made by GS+ (version 7, Gamma Design Software, Plainwell, MI).

The spatial structure of a fractal function for variables has been described as:

$$\gamma(h) \propto kh^{H} \quad (4)$$

where, $\gamma(h)$ is the semivariogram, h is the lag, H is the codimension, and k is a constant related to the extent of variation.

The fractal dimension D is calculated based on the following relationship (Burrough, 1983; Eghball et al., 1999):

$$D = d - 0.5H \quad (5)$$

where, d is the Euclidean dimension, which is 2 for a plain (Mandelbrott, 1982). Regression of log-lag (distance) vs. log-semivariogram of a variable yielded an estimated fractal dimension (D = 2-0.5H), where H is the slope (codimension) of resulting regression line (Eghball et al., 1999). To improve the fit of least square analysis, the data points lying within the clearly defined range of the semivariogram were used as suggested by Burrough (1983).

3. RESULTS AND DISCUSSION

The exploratory statistics for soil variables in MMS and MSS soils is presented in Table 1. Slope steepness had a slight influence on soil chemical properties compared to soil physical properties. Studies have shown that soil electrical conductivity (EC) is an integrated measure of many soil physical and chemical properties that it can be used as a surrogate of soil properties affecting soil productivity (Bekele et al., 2005). Mean EC values in both SMS and MHS areas were not high enough to constrain crop growth, and they exhibited a slight difference between the two slope classes. The soils in the study area are poor in OM as indicated by the mean value in both slope classes. Dexter (2004) established a very close relation between soil physical quality and SOM content.

Table 1. Descriptive Statistics of Soil Variables in MMS (mild- to-moderate sloping) and MSS (moderate- to-steep sloping) soils.

Variable	Mean	#SD	Min	Max	#CV	Skewness	Kurtosis
MMS							
#EC, mmhoscm^{-1}	0.636	0.145	0.35	0.91	22.80	0.16	0.73
pH	7.339	0.512	6.40	8.63	6.98	0.09	0.83
#SOM, %	0.393	0.407	0.89	1.47	103.56	0.48	1.37
#CEC, meq100g^{-1}	5.909	0.763	4.42	8.19	12.91	0.18	0.23
Sand, %	44.851	9.136	28.27	64.95	20.36	0.20	0.80
Silt, %	23.646	3.747	12.91	32.36	15.85	0.16	0.27
Clay, %	31.503	9.117	12.17	47.88	28.94	0.10	0.83
#CM, %	17.109	9.001	4.14	38.40	52.61	0.48	0.81
#PR, KPa	1553.4	1047.0	170.7	3882.3	67.4	0.38	1.13
#K, Dimensionless	0.3102	0.096	0.10	0.55	31.04	0.11	0.13
#CI, Dimensionless	1.002	0.452	0.25	2.24	45.11	0.20	0.94
MSS							
#EC, mmhoscm^{-1}	0.631	0.144	0.32	0.92	22.82	0.05	0.42
pH	7.616	0.367	6.65	8.30	4.85	0.78	0.05
#SOM, %	0.410	0.404	0.89	1.28	98.54	0.27	0.75
#CEC, me100g^{-1}	5.807	0.851	4.20	8.07	14.65	0.44	0.12
Sand, %	6.919	0.691	5.63	8.65	9.99	0.56	0.39
Silt, %	23.233	4.174	14.25	33.20	17.97	0.09	0.21
Clay, %	28.426	8.873	4.08	46.31	31.21	0.22	0.06
#CM, %	2.949	0.579	1.61	4.22	19.63	0.17	0.52
#PR, KPa	1795.8	1109.4	200.5	3568.4	61.78	0.17	1.56
#K, Dimensionless	0.116	0.053	0.01	0.24	45.69	0.28	0.36
#CI, Dimensionless	1.092	0.474	0.20	2.24	43.41	0.27	0.31

#SD: Standart deviation, CV: Coefficient of variation, EC, Electrical conductivity, SOM: Soil organic matter, CEC: Cation exchange capacity, CM: Coarse material, PR: Penetration resistance, CI: Crusting index, K: Soil erodibility factor.

That higher SOM found in MHS soils has been attributed to the majority of soils being cultivated. Comparably lower cation exchange capacity (CEC) in MMS areas may be assigned to the lower organic matter and higher coarse material (CM) content in these soils. The K-factor was comparably high in MSS soils while PR and crusting index (CI) remained relatively similar. Higher CM content in MSS soils has been attached to the transportation by gravity of coarse material from steeper areas and its accumulation in gently sloping localities.

Schlesinger et al. (1990) designated CV as an indicator of potential desertification, suggesting that greater CV is an indicator of a greater potential for desertification. This is caused by the fact that in time, the islands of fertility become favored sites for shrub generation and yield self-augmented levels of local fertility. Such changes alter not only the local distribution of soil resources but also the extent and location of other ecosystem sites in the landscape. Table 1 reveals that, in general, higher CV of variables occurred in MMS soils than in MSS soils. Mulla and McBratney (2002) grouped CV-values nominally. According to their grouping, SOM exhibits a considerably high variation in both MMS and MSS areas (Table 1). The K-factor shows a comparable difference in CV between MMS and MSS soils, while PR and CI reveal greater, but similar, variations in both MMS and MSS soils. That the variation of CM is considerably different has been attributed to the fact that the gravity-induced translocation of CM would be highly heterogeneous in the landscape.

When the soil is cropped, it has additional sources of heterogeneity, exclusively caused by the effects of management in agriculture (Veronese Júnior et al., 2006). Therefore, the somewhat greater variation of soil properties in MMS areas would be related to the way agriculture is being managed. According to the basic principles of experimentation, established by classical statistical methods, soil variability occurs entirely at random, requiring the validation of basic hypotheses such as the independence between observations due to randomness of variations from one place to another (Veronese Júnior et al., 2006).

Table 2. Geostatistical parameters and corresponding goodness of fit parameters for soil variables in MMS (mild- to-moderate sloping) and MSS (moderate-to-steep sloping) soils.

Soil property	Nugget (C_0)	Sill (C_s)	Range, m	Model	#R^2	#RSS	NE, %
			MMS				
#EC, mmhoscm^{-1}	0.0058	0.0226	460.7	Gausian	0.63	$1.57x10^{-4}$	20.55
pH	0.0923	0.2946	801.9	Gausian	0.80	0.0154	23.86
#SOM, %	0.0492	0.2404	1742.0	Spherical	0.88	$6.94x10^{-3}$	16.99
#CEC, cmolkg^{-1}	0.1090	0.6350	804.0	Exponential	0.73	0.0638	14.65
Sand, %	13.8000	86.9400	276.0	Spherical	0.63	829.0	13.70
Silt, %	0.0100	12.8400	139.0	Spherical	0.13	38.4	0.08
Clay, %	1.3000	81.8100	222.0	Spherical	0.60	894	1.56
#CM, %	2.7000	81.6400	323.0	Spherical	0.79	632.0	3.20
#PR, KPa	$1.19x10^5$	$1.06x10^6$	93.0	Exponential	0.01	$3.40x10^{11}$	10.07
#K, Dimensionless	$4.0 x 10^{-5}$	$8.4 x 10^{-3}$	153.0	Spherical	0.23	$1.32x10^{-5}$	0.47
#CI, Dimensionless	0.0948	0.2596	1497.0	Spherical	0.82	$8.65 x 10^{-3}$	26.75
			MSS				
EC, mmhoscm^{-1}	0.0108	0.0218	672.0	Gaussian	0.81	$3.49x10^{-5}$	33.23
pH	$2.8x10^{-3}$	$5.7x10^{-3}$	972.0	Exponential	0.38	$7.76x10^{-6}$	33.29
SOM, %	0.0246	0.1782	111.0	Spherical	0.04	$4.40x10^{-3}$	12.13
CEC, cmolkg^{-1}	0.1590	0.7560	700.0	Spherical	0.93	0.0245	17.38
Sand, %	0.2408	0.4846	1353.0	Exponential	0.40	0.0761	33.20
Silt, %	6.6900	17.7100	819.0	Exponential	0.52	71.5000	27.42
Clay, %	38.4000	76.8100	1257.0	Exponential	0.50	1084	33.33
CM,%	0.0020	0.3120	81.0	Spherical	0.00	0.0159	0.64
PR, KPa	$4.08x10^5$	$1.32x10^5$	747.0	Exponential	0.74	$1.79x10^{11}$	23.56
K, Dimensionless	0.000159	0.0027	183.0	Exponential	0.13	$2.42x10^{-6}$	5.60
CI, Dimensionless	0.01900	0.2320	141.0	Spherical	0.14	0.0136	7.57

#RSS: Residual sum of squares, EC: Electrical conductivity, SOM: Soil organic matter, CEC: Cation exchange capacity, CM: Coarse material, NE: nugget effect calculated as $(C_o/C_o+C_s)x100$, PR: penetration resistance, CI: Crusting index, K: Erodibility factor

However, many studies have shown that soil attributes exhibit some degree of spatial dependence (Journel & Huijregts, 1991; Mulla & McBratney, 2002; Veronese Júnior et al., 2006). This necessitates the use of geostatistical methods (Veronese Júnior et al., 2006). Geostatistics is based on the theory of regionalized variables, which considers the structure of spatial variability within the sample site (Trangmar et al., 1985; Isaaks & Srivastava, 1989; Mulla & McBratney, 2002; Veronese Júnior et al., 2006). The structure of spatial variation can be analyzed either by the correlation function (correlogram), the covariance function, or the semivariogram (Isaaks & Srivastava, 1989).

The semivariogram is widely used in analyzing spatial dependence of variables in a sample site. The nugget variance, sill, and range parameters together with the type of semivariogram (spherical, Gaussian, exponential, etc.) are interpreted in order to understand the nature of spatial dependence (Trangamar et al., 1985; Isaaks & Srivastava, 1989). Cambardella et al. (1994) designated spatial continuity according to the nugget effect calculated as C_o/C_s+C_o, where, C_o is the nugget variance and C_s is the structural component (the variance due to distance). According to these authors, a soil property with a nugget ratio<25% was highly space-dependent, between 25% and 50% moderately space-dependent, and above 75% weakly space-dependent. Except for CI, all the variables studied were highly space-dependent in MMS areas, being moderate space-dependent in MSS areas (Table 2). The soil textural components were more spatially dependent in MMS soils, and contrary to PR, CI and the K-factor were more space-dependent in MSS soils. The geostatistical range values differed from 139 m for silt content to 1,742 m for OM content in MMS soils, while it ranged from 81 m for CM to 1,353 m for clay content in MSS soils. Considerably different values in the geostatistical range were found for the variables SOM, sand, clay, and silt contents, CM, CI, and PR (Table 2). As suggested by Eghball et al. (1999) and Veronese Júnior et al. (2006), for those space-dependent variables, the use of their CV-values would lead to erroneous conclusions on their spatial variations since they have a spatial structure. Therefore we have used probabilistic fractals to compare the variation of the variables in MMS and MSS areas.

3.1. Fractal Analysis

Fractal analysis has been conducted separately in MMS and MSS soils over data for each variable. The linear portion of log semivarince versus log distance of SOM-data has been used in linear regression analysis and the fractal dimension D (known technically as Hausdorff-Besicovitch dimesion, Burrough 1983) has been calculated by the slope of the resultant regression line as described under Methods 2.2. Table 3 shows the calculated fractal coefficients and the corresponding parameters of goodness of fit for the variables studied in MMS and MSS soils.

Table 3. Fractal coefficients (D), calculated for variables studied, and parameters of goodness of fit for the corresponding regression analysis MMS (mild-to-moderate sloping) and MSS (moderate-to-steep sloping) soils.

Soil variable	n	R^2	D
	MMS		
#EC, mmhoscm^{-1}	9	0.8040	1.83
pH	14	0.8090	1.81
#SOM, %	11	0.8693	1.81
Sand, %	9	0.9100	1.90
Clay, %	10	0.9474	1.89
#CM, %	11	0.8349	1.85
#CEC, cmolkg^{-1}	15	0.9389	1.84
#K, Dimensionless	15	0.9143	1.91
#CP, Dimensionless	15	0.9418	1.85
#PR, KPa	15	0.8544	1.92
	MSS		
#EC, mmhoscm^{-1}	13	0.8100	1.90
pH	15	0.9191	1.90
#SOM, %	15	0.8451	1.93
Sand, %	15	0.8046	1.87
Clay, %	15	0.8612	1.91
Silt, %	10	0.8045	1.90
#CM, %	10	0.9339	1.95
#CEC, cmolkg^{-1}	15	0.8435	1.82
#K, Dimensionless	9	0.7609	1.93
#CP, Dimensionless	10	0.7525	1.92
#PR, KPa	14	0.8069	1.89

#EC: Electrical conductivity, SOM: Soil organic matter, CEC: Cation exchange capacity, CM: Coarse material, K: Erodibility factor, CP: Crusting potential, PR: penetration resistance, n: number of data points included in the calculations.

The values of D reported in Table 3 are higher than 1.50 in all the cases. In spatial analysis, a large D indicates the dominance of the short-range effect and closeness of scales of variation (Burrough, 1983; Eghball et al., 1999). For spatial variability, D can take any value between 1 and 2. A D, close to 2, indicates that a two dimensional surface is approximately covered by the extent of variation, while D close to 1 signifies that values in the spatial range lie approximately on a line (Eghball et al., 1999). For soil variables, high D values have often been reported (Burrough, 1983; Eghball et al. 1999; Bekele et al., 2005). These high D-values are expected to be the short-range variation in these soil variables caused by many interacting processes such as rock weathering, biological action, micro-relief, cryoturbation, erosion, deposition, and so on. Table 3 also indicates that while spatial variation of soil properties such as silt, CEC, and CI strongly fractal, others are poorly fractal as revealed by the values of the corresponding D-values. Table 3 further shows that the fractal quality of variables in MMS and MSS soils is dissimilar.

In general, higher D-values have occurred in MSS soils than in MMS soils, showing more self-similarity in spatial variation of the variables studied in MSS areas. D-values obtained for SOM in MMS and MSS soils are highly different, while those for K-factor and PR are very similar (Table 3). With the exception of CEC, self-similarity in the spatial heterogeneity of soil chemical properties has differed more between MSS and MMS soils than those of soil physical properties (Table 3). However, values of CV calculated for the same soil variables in the same areas indicate a greater difference in the spatial variation of soil physical parameters between two contrasting soils.

We found that soil variables with a stronger spatial structure also had greater CV-values (Tables 1,2), while self-similarity in their spatial variation is lower as their lower D-values indicate (Table 3). Therefore, our calculations have shown that, in terms of a higher CV, lower D values indicate a greater potential for desertification.

One of the advantages using fractal analysis in characterizing variability parameters is that the fractal dimension is scale-independent (Eghball et al., 1999). Once the properties of fractal are known at one scale, they can be deduced for another scale (Burrough, 1983). Thus, once we have determined the variance of a particular soil variable at one scale, we can determine it at another scale if that particular property is self-similar as implied by a high fractal dimension. Our analysis resulted in higher CV-values for MMS soils, indicating a greater desertification potential in these soils. The lower D-values calculated for MMS areas may be interpreted as lesser self similarity (heterogeneity) of soil properties in these areas. Therefore, as already stated above, a high value for probabilistic fractals may be indicative of a lower degree of desertification potential.

In spite of large D-values that point to the importance of short-range variation, the low nugget effect (Table 2) indicates the importance of long-range variation. In a likely sampling campaign in the study area, to resolve confusing long-range variation for short-range variation, the sampling spacing yielding the lowest D values should be sought as suggested by Burrough (1983).

4. CONCLUSIONS

Heterogeneity of electrical conductivity (EC), pH, soil organic matter (SOM) content, cation exchange capacity (CEC), sand, silt, and clay content, and soil erodibility factor (*K*), crusting index (*CI*), and penetration resistance (*PR*) were compared by means of the coefficient of variation of classical statistics, semivariogram analysis, and probabilistic fractals in order to evaluate the effect of slope steepness on desertification in a 1,021-ha catchment with sloping landscapes. The variables were evaluated separately in the soils of mild- to-moderate sloping areas (MMS) and in moderate-to-steep sloping areas (MSS). Unexpectedly, in general, higher CV values in MMS areas, indicate a greater potential for the desertification of these soils. The semivariogram analysis has revealed that soil variables are generally stronger space-depended in both slope classes, suggesting the use of D values calculated from semivariograms of soil variables. Contrary to CV, higher D values occurred for variables in MMS areas, indicating a greater self-similarity or homogeneity of the spatial variation of these variables and suggesting a lower desertification potential in these areas. Compared to higher D-values for soil chemical properties, lower D-values have been found for soil physical variables; the *K*-facor, PR, and *CI* in MMS soils. That the spatial variation of the soil variables studied is more self-similar in MMS areas is attributed to a lower desertification potential in these areas than in MSS areas, because MMS soils are mostly cultivated and differences in agricultural practices would be an additional source of dissimilarity in the spatial structure of these variables.

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