African Journal of Agricultural Research Vol. 6(5), pp. 1109-1113, 4 March, 2011
Available online at http://www.academicjournals.org/AJAR
DOI: 10.5897/AJAR10.657
ISSN 1991-637X ©2011 Academic Journals

Full Length Research Paper

Spatial patterns of soil degradation in Mexico

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Accepted 31 January, 2011

The spatial pattern of soil degradation in México was evaluated to test the hypothesis of non-random correlation. For this purpose, data on the degree of soil degradation in the 16,040 ecological systems in which the country is divided was used to calculate the Moran coefficient. A graphical analysis, based on the dispersion diagram and the local indicator of spatial association, was also applied. Soil degradation showed a positive and statistically robust pattern of spatial auto-correlation, since the Moran coefficient was able to synthesize 42.8% of the global structure of linear correlation among the degrees of degradation. The underlying variables that explain the relationship remain to be identified.

Key words: Spatial autocorrelation, geostatistics, Geoda.

INTRODUCTION

Soil is a natural resource that is considered non renewable because of the cost and difficulty involved in recovering it once it has been degraded. As soil loss endangers ecological balance, investigation of soil degradation processes is essential in order to develop scientifically based plans for soil conservation. Recent studies show that 64% of the soils in Mexico are degraded to a greater or lesser extent (CONAFOR, 2006). Soil degradation is one of the major threats to ecosystem conservation worldwide, because it reduces the soil potential for food production and leads to desertification and soil erosion.

Although, there are numerous technical reports concerning soil degradation (Evelyn et al., 2008; Christopher et al., 2009), spatial distribution aspects are often ignored, thus reducing the ecological and practical importance of this information with regard to future trends, constraint factors and environmental policies (Pompa, 2008).

Spatial information about the phenomenon enables identification of spatial correlation patterns among data, and revelation of whether the spatial distribution is random or auto-correlated (clustered or dispersed). In order to design suitable strategies and actions for soil management, robust information regarding the nature of soil degradation is required, especially with regard to the causal agents and conditions that induce erosion. Research on causal agents is of prime importance because the design and operation of prevention programs, based on awareness of risk and danger factors, requires strong background knowledge and represents economic advantages for large areas of land.

Autocorrelation can be defined as the influence of the coincidence of similar values of a variable on nearby geographical spaces (Anselin, 2004). To test for autocorrelation in the spatial distribution of soil degradation in Mexico, we chose the statistical method developed by Moran (Moran, 1950), since several of the indexes used to obtain a global estimation of this pattern are based on this method (Greig, 1964; Pielou, 1969; Diggle, 1983; Upton and Fingleton, 1985; Krahulec et al., 1990; Condés and Martínez, 1998; Dale, 1999; Liu, 2001). In addition, authors such as Acevedo and Velásquez (2008) have stated that Moran's index is still the most commonly used. It had been applied in several different types of study, such as the study of demographic trends (Martori and Hoberg, 2008),

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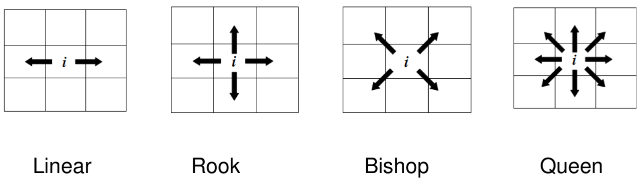

Figure 1. Vicinity criteria types.

economic development of regions (Vilalta, 2003) and electoral behavior (Vilalta, 2005). However, its application to soil degradation patterns has been limited, especially in Mexico. We therefore considered it appropriate to describe the characteristics of the spatial distribution of soil degradation in México, to provide a better interpretation of intrinsic factors that are perhaps not visible in the field. The null hypothesis considered was that the phenomenon of soil degradation is subject to non random autocorrelation.

MATERIALS AND METHODS

Description of the study area

Mexico is located between latitudes of 14º32' and 32º43'N and longitudes of 86º42' and 118º27'W. To the north, it borders with the United States of America, to the south with Guatemala and Belize, to the east with the Gulf of Mexico and to the west with the Pacific Ocean (Figure 3).

Data

The database was obtained from the National Forestry Commission (CONAFOR, 2006) in a shapefile from 2006. This shapefile contains data on the 16,040 terrestrial systems of Mexico, which includes a classification of the degree of soil erosion, evaluated in terms of the reduction in the biological productivity of the land. The classification considers the following levels:

1. Slight degradation: This land is optimal for forestry, agriculture and livestock rearing and shows a slight, perceivable reduction in productivity.
2. Moderate degradation: Land suitable for forestry, agriculture and livestock rearing, although there is also a perceivable reduction in land productivity.
3. Strong degradation: At farm level, degradation of this land is so severe that its productivity is considered irreversible, unless huge restoration efforts are applied.
4. Extreme degradation: Land productivity is unrecoverable and it is not possible to restore the land, even with the best management practices for soil erosion.

Spatial analysis

In order to detect and measure the spatial autocorrelation of the deforested surfaces, *I* Moran's coefficient (1950) was applied. The values of the coefficient vary from -1 to 1, although several authors recognize that it may surpass both limits (Cliff and Ord, 1981; Upton and Fingleton, 1985). The first value implies a perfect negative correlation, whereas the second implies a perfect positive correlation. A value of zero indicates a totally random spatial pattern. To calculate the value of the coefficient, the following equation was applied:

$$I = \frac{N\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}(X_i - \overline{X})(X_i - \overline{X})}{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}\sum_{i=1}^{N}(X_i - \overline{X})^2} \tag{1}$$

where X_i and X_j are the values taken by X at *i* and *j* points, N is the data population and W_{ij} is the weight of the class at distance *d*, which can be 1 if *j* is within the class of distance *d* from the point *i*, or can be 0 if said condition is not fulfilled (Camarero and Rozas, 2006):

$$W_{ij} = \begin{bmatrix} 1\, si\, d_{ij} \le d \\ 0\, si\, d_{ij} > d \end{bmatrix} \tag{2}$$

In the ratio established in 1, the numerator shows the covariance, whilst the denominator indicates variance, which makes it a similar design to the Pearson coefficient of correlation (Pearson, 1896). However, in this ratio, the association of values at the data set is determined by a matrix of distances (2), or by contiguity, which predefines the neighboring values (the values for the coefficient calculation); that is, the weights define the proximity of each point evaluated.

To determine the vicinity within spatial units, the "Queen" criteria was used (Figure 1), because of its contact proximity in all directions (a maximum of eight neighbors).

To test the hypothesis of absence of a spatial pattern, *I* Moran's coefficient was located within a normal curve of probabilities Z(*I*), and a test was carried out to determine whether the spatial distribution of values was random within n possible distributions (Vilalta, 2005). A non-significant value of Z(I) will lead to acceptance of such hypothesis, while a significant positive value reflects a spatial pattern of positive autocorrelation. GEODA software was used to implement this test. In addition, the Scatter diagram of Moran was applied as an instrument of graphical analysis (Anselin, 2003). The Local Indicator of spatial association was also calculated to ensure that each statistic obtained for each section provides information related to the relevance of similar surrounding values. According to Anselin (1995), the statistic used to test the contrast of Local Spatial Association is defined as:

$$I_i = \frac{(X_i - \mu)}{m_0}\sum_{j=1}^{n} c_{ij}(X_j - \mu) \tag{3}$$

with

$$m_0 = \sum_{j=1}^{n}(X_i - \mu)^2 / n$$

and where the added value *j* refers to the cluster of neighboring units of *i* with respect to sample mean μ.

RESULTS

Over the horizontal axis, Moran's dispersion diagram of

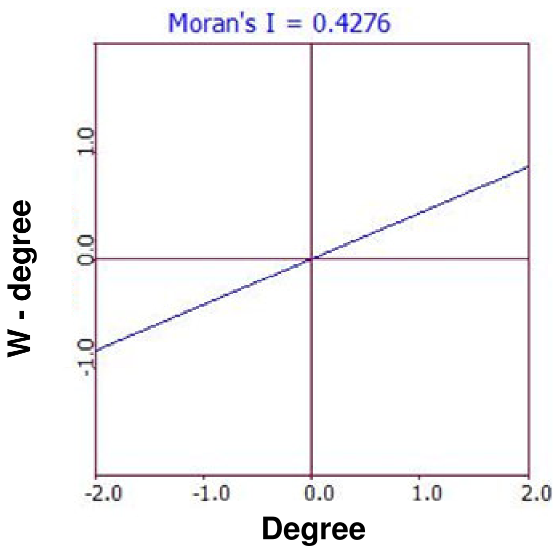

Figure 2. Moran's dispersion diagram for the degree of soil degradation in Mexico.

soil erosion presents the observation of a normalized degree of soil erosion, and over the vertical axis it shows the spatial delay in the same variable, defined as the product between the observation vector of X and the matrix of spatial weights (Figure 2).

Given that most observations are concentrated over the diagonal line that crosses the upper right and lower left quadrants, it is evident that there is a positive autocorrelation of 0.4276, which indicates that the Moran statistic comprises 42.76% of the global structure of linear association between the degrees of soil degradation. Although the coefficient is not very high, the positive trend must be taken into account, given the great diversity in the study area.

The significance map of the local indicator associated with Moran's dispersion diagram (Figure 3) enables identification of regions with numerous highly degraded areas, surrounded by zones with a similar degree of degradation (high-high correspondence at Moran's graph). This correspondence is very common in Baja California and Nuevo Leon, and may be related to the arid conditions in these states, where the highest rates of degradation normally occur (Conafor, 2006; Pompa, 2008).

In some regions, there is also a low degree of degradation associated with similar neighbors (low-low situation); this is particularly common in the Sierra Madre Occidental and the Central highlands. However, low-high (which is a common pattern in the tropics at the Gulf of Mexico) and high-low situations are also encountered. Finally, regions without any association are also found (Figure 3).

The positive association is not observed throughout the entire region, and is restricted to certain regions. The Local Indicator of Spatial Association is shown Figure 4 to reveal those regions with high values of local spatial association. The intensity of this indicator depends on the associated significance of these statistics.

DISCUSSION

The results indicate positive and significant autocorrelation, and therefore a tendency for areas to be aggregated by the degree of soil degradation. We can therefore assert with a confidence level of 99% that this correlation is not random, under the assumption of a normal distribution of Z probable values. Furthermore, the legend of the cluster map in Figure 3 includes five categories: Not significant (Areas that are not significantly degraded at a default pseudo-significance level of 0.05), high-high (Highly degraded areas surrounded by other highly degraded areas), low-low (Slightly degraded areas surrounded by slightly degraded areas), low-high (Slightly degraded areas surrounded by highly degraded areas), and high-low (Highly degraded areas values surrounded by slightly degraded areas).

Soil is an important component of terrestrial ecosystems, which justifies the search for the causes of its degradation. The techniques applied reveal the spatial association in the degree of soil degradation, providing new insight into soil erosion association, as well as the location where said associations are important: regions where the activities of soil recovery and erosion control should be directed, as a function of the spatiality correlated causative variables. The results of the study verify how incorporation of the spatial dimension in the evaluation of soil erosion improves comprehension of the nature of the phenomenon. Further studies are required, according to an observation by Zhang and Chaosheng (2008), who state that spatial analysis of the data at several scales must be a vital part of the search for the underlying reasons for the spatio-temporal distribution of this process.

The results show how spatial association within highly degraded areas is common in arid regions, which indicates the association between climate variation and soil erosion (Conafor, 2006; Pompa, 2008), although further research is required to verify this. On the other hand, low-low associations appeared to be associated with the presence of dense forest coverage, which is an important finding for the design of national soil conservation plans.

The spatial pattern of soil degradation occurrence is a key factor in understanding its dynamics, and presence of soil erosion is determined by several biotic and non biotic factors, however, the effects of each factor vary between ecosystems and within spatial and temporal. Understanding the causal factors and conditions in the geographical areas in which soil degradation occurs is a key step in the development of conservation and rehabilitation strategies.

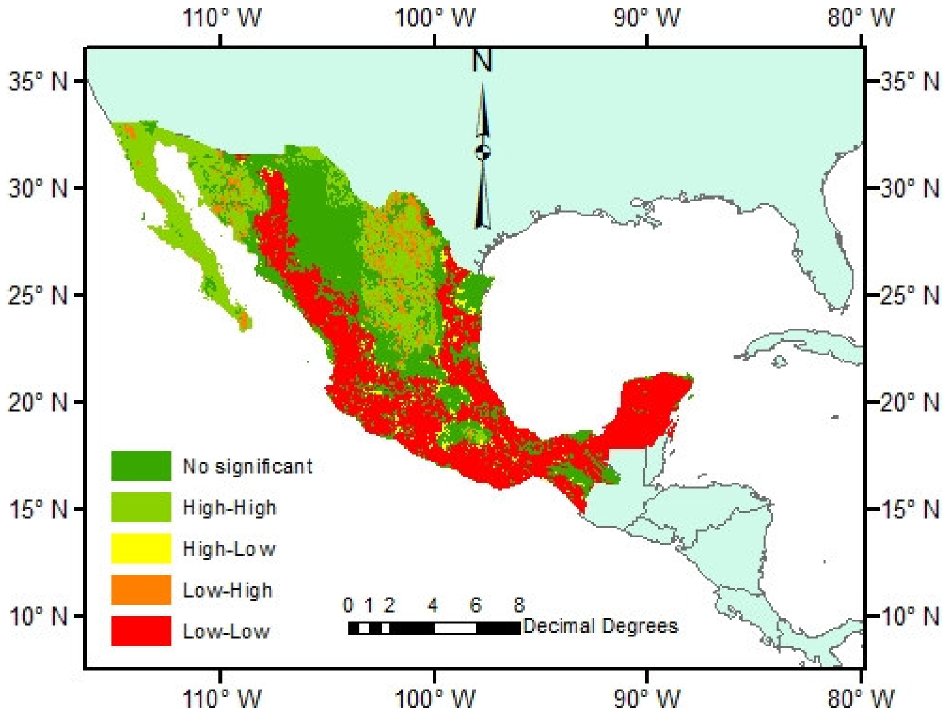

Figure 3. Cluster map showing the associations between different degrees of soil degradation in the study area.

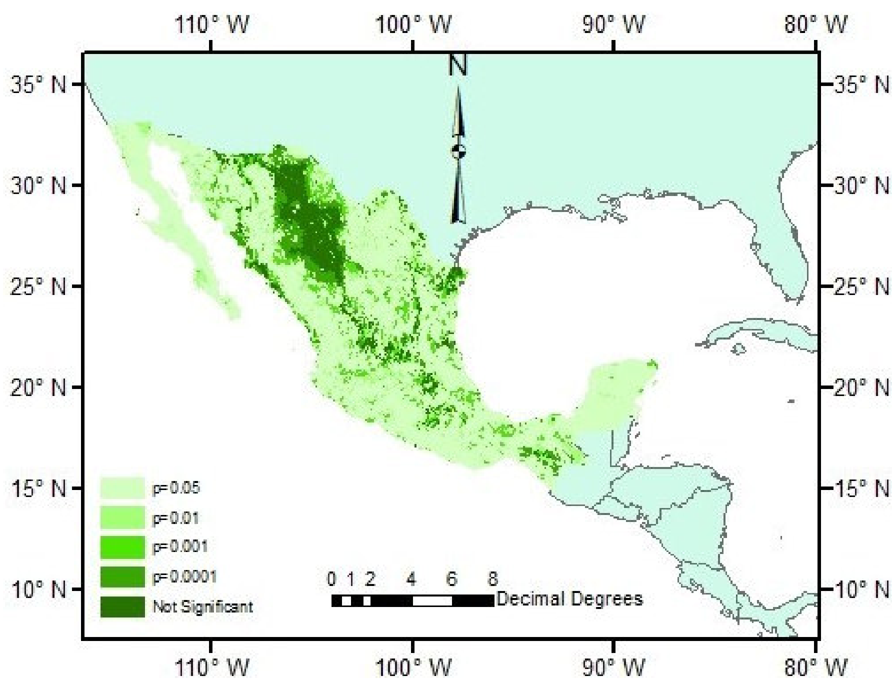

Figure 4. Local Indicator of spatial association for the degree of soil degradation in Mexico.

Spatial analysis has rarely been applied to soil degradation studies and has more often been used to analyze trends in soil pollution (Zhang and Chaosheng, 2008; Chang and Heejun, 2008), spatial autocorrelation of soil properties (Dray and Stéphane, 2008; Iqbal et al., 2005; Buscaglia and Varco, 2003; Ducarme and Lebrun, 2004), soil productivity (Ping and Zartman, 2004), spatial patterns of weeds and plague severity and occurrence in several types of soil (Shaukat et al., 2004; Mueller et al., 2008; Dessaint et al., 1991; Efron et al., 2001; Toepfer et al., 2007). In all these cases, the studied units have shown some type of spatial autocorrelation, thus confirming the law of Tobler (1970). The findings of the present study are consistent with the aforementioned results.

The interactions revealed suggest the need to apply regression procedures to search for the variables that may explain the associations, since only the magnitude and localization of the spatial autocorrelation has been described. This will lead to hypotheses regarding the causal agents of the spatial pattern. Nonetheless, careful revision of the procedure is required, because several ecological processes may produce similar patterns of spatial correlation.

ACKNOWLEDGEMENTS

This work was conducted in the frame of Academic mobility supported by the UJED and Forestry Faculty. We particularly thank the Office of Geo-information of the National Forest Commission (CONAFOR) for providing us with the information required for this study. Also we recognize the support of COCYTED and SRNYMA.

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