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EROSIVITY INDICATORS BASED ON RAINFALL IN NORTHWESTERN MEXICO

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Abstract. This study is motivated by the problem of erosivity (*R*), exacervated in semiarid zones by intense seasonal storms. The purpose was to estimate the spatial variation of *R* in a coastal area covering 37500 km^2 which is one of the most important agricultural areas in northwestern Mexico. Four methods were used. Rainfall data from 11 SMN-CONAGUA weather stations (from 1966 to 2013) were used to calculate *R*. The annual average R_1 was 1181.08, and R_2 was 1084.51 MJ mm ha^{-1} h^{-1} with ranges of 2.35–5220.55 and 2.93–4711.38 MJ mm ha^{-1} h^{-1}. Statistical tests showed that a transformation of the data of the form $y = log(x)$, was appropriate for an ANOVA analysis of the data. The value of the test statistic was $F = 1.77$ with $p = 0.149$, showing interdependence between the indicators *P* ($\alpha = 0.05$). The values of the correlation coefficients for the data were *P* vs. $R_1 = 0.96$, *P* vs. $R_2 = 0.99$, *P* vs. $AI_m = 0.98$, *P* vs. $MFI = 0.99$. The classification of risk in this region showed that 2017.5 km^2 of the study area was at a very high risk of rain erosion, 2407.5 km^2 under high risk, 5662.5 km^2 under medium to high risk, and 14250 km^2 under low risk. The results are shown on 1:10,000 maps. Results are a set of useful information for soil management programs and for cultivation planning that takes the seasonal variation of *R* into account in this region where large volumes of extensive crops are grown.

Keywords: rainfall, risk, indicators, semiarid zones, coastal area.

Introduction

Preventing tillage, wind, and the erosive force of rain from reducing soil fertility and degrading the cultural record depends to some degree on successful management of agricultural and forest resources and of water resources to reduce the loss of sediments (FAO 2015; Morgan 2005). A major factor determining soil erosion processes by water is the erosive potential caused by raindrop impact. This issue is of special interest in the agriculture and forestry industries due to the harmful effects of rain erosion on the soil. It is also a key agent in the process of sediment production. Many models have been developed for studying raindrop erosivity (*R*) and its properties. Parameters such as intensity, speed, size, and kinetic energy are commonly used to develop indexes describing the behavior of R. Among indicators of *R*, the most common algorithms are: (1) the universal soil loss equation (USLE) (R_1), recognized as one of the best parameters for predicting erosive potential by raindrop impact (Muñoz *et al.* 2011; Oñate 2004; De Santos, De Azevedo 2001); (2) regression curves calculated from empirical pluviographic and pluviometric data for each region (R_2) (Martínez 2005; Pérez, Mesa 2002); (3) the modified Fournier index, better known as climate aggressiveness (MFI) (Yuksel *et al.* 2008) and (4) the Lal index (AI_m) or rainfall erosivity (Lal 1976). Throughout the world, determining the behavior of *R* is a problem related to climate, especially in agricultural areas where it implicitly has both an environmental and economic impact (Arshad, Martin 2002).

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In northwestern Mexico, three of the most important agricultural valleys; Guasave Valley, El Fuerte Valley and Mocorito Valley, are intensely cultivated. Erosion produced by misuse of the soil has been reported to be an important environmental problem (Llanes *et al.* 2011).

This, together with the additional factor of intense rainfall (P), motivated the present study. The goal is to estimate R by the four indexes listed above. To date, there have been no studies of the progress of erosion, so it is not known how potential soil loss scenarios might play out in the region. The height of the rainy season (July to September) is a particularly critical period. Furthermore, the absence of any sediment management plans (soil use plans, for example), makes it difficult to counteract erosion and favors factors that promote it. It is important to note that this study was carried out in a region where large volumes of corn, tomatoes, potatoes and other crops of great domestic and international importance are grown. As in other parts of the world, the population explosion and the sharp increase in agriculture and trade in recent years have stimulated a set of environmental problems that have increased erosion levels directly related to structural soil stability (Núñez *et al.* 2007; Llanes *et al.* 2013). The results of this study will provide soil users with a fundamental understanding of the agents that govern sediment production processes. Finding the spatial distribution of R and its risks will enable the development of strategies to reduce erosivity in both coastal and mountain environments in this region which is influenced by the dynamics of climate, topography, vegetation and other factors that favor erosion.

1. Materials and methods

The methodologies for measuring indicators of spatial variation of R were applied to an area covering approximately 37 500 km^2 in northwestern Mexico. The study area included various hydric conditions and extensive coastal plains with typical rainy seasons from July to September. The main water tributaries are the Sinaloa, El Fuerte and Mocorito Rivers. They arise in the Sierra Madre Mountains in Chihuahua State where the Mohinora and Basoapa currents join (Toutcha *et al.* 2005). After approximately 380 km, they empty into the Gulf of California with annual average rates of flow (Q) of 700 to 2,240 m^3 s^{-1}. The high carrying capacities of these rivers readily transport their sediment loads to the final destination. In particular, the sediments of the Sinaloa River are freely carried to its delta due to the dredging carried out by the state government in 2013 that put an end to the problem of accumulated sediments, but increased output of the products of continuous erosion. There are other secondary tributaries; Arroyo De Cabrera, De Ocoroni and De San Rafael, which with their respective flow rates of 18 to 25, 12.3 to 15.2 and 125 to 150 m^3 s^{-1} also transport sediment loads (Fig. 1).

Pluviographic and pluviometric data from 1966 to 2013 were obtained from weather Data Base Northwest México of SMN-CONAGUA (Mexican National Meteorological Service-Mexican National Water Commission). The R_1 index was calculated by the method of Almoza *et al.* (2007), R_2 was calculated using the logarithmic algorithm of Pérez, Mesa (2002). The AI_m index

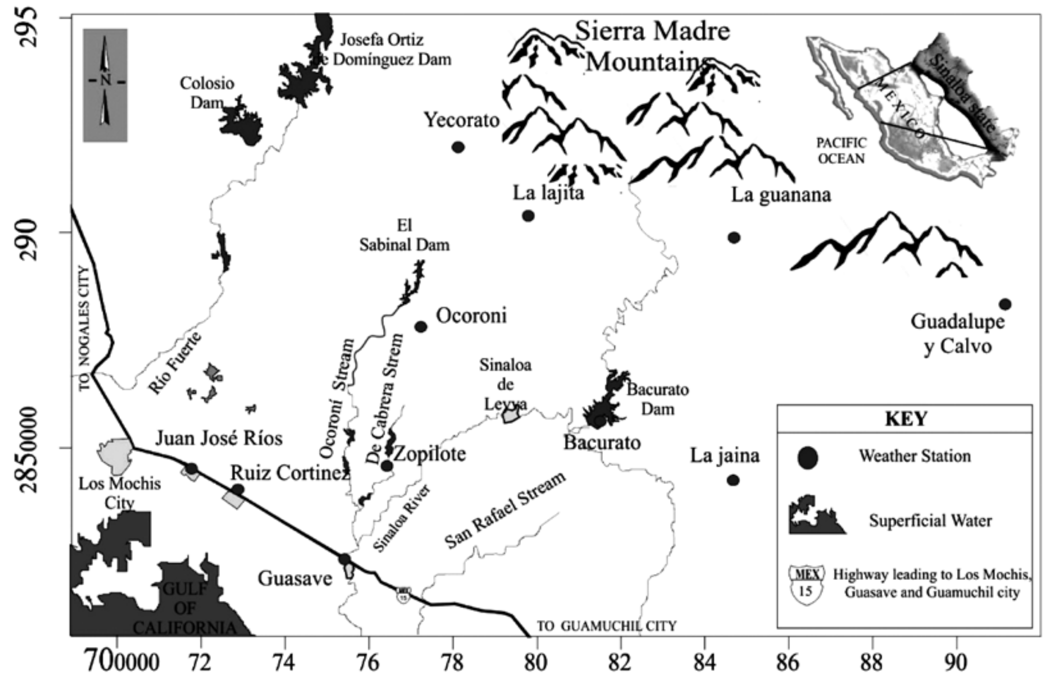

Fig. 1. Location of study area

(rainfall erosivity) was calculated using the method of Lal (1976):

$$AI_m = \sum_{J=1}^{12} \left[\sum_{1}^{n} a I_{\max} \right], \; i = 1, ..., 12 ;$$

where a was daily rainfall (cm), $I_{\max}$ the maximum intensity of rainfall at 7 minutes (cm h^{-1}), n the number of storms in a month and i indicates the month. The *MFI* index or climate aggressiveness was calculated by the method of Yuksel *et al.* (2008):

$$MFI = \frac{\sum_{i=1}^{12} P^2}{P_i}, \; i = 1, ..., 12 ;$$

where P_i was the mean monthly rainfall (mm) and p^2 the mean annual rainfall. The variables used for the estimates R_1 and R_2 were total kinetic energy of rain (E) in MJ ha^{-1} and the maximum intensity of each storm at 30 minutes (I_{30}) in mm h^{-1} (Khosrowpanah, Leroy 2001). R_2 was calculated using the intensity of rainfall and/or a specific increase of rain in pluviophase k (Δik), and the period of increase of the storm or duration of the pluviophase k (Δt_k), both in mm h^{-1} (for more information see Almoza *et al.* 2009). Using pluviographic data, the number of downpours per year (n), the pluviophase of the downpours (q) and unit kinetic energy ($ek = k$); or kinetic energy per mm of rain (MJ ha^{-1} mm^{-1}) were determined. For E, the logarithmic regression $E = a + b \log_{10} I_j$ proposed by Elaheh *et al.* (2012) was used, for which the constants a and b and the intensity of P (I_j) in mm hr^{-1} were estimated. The AI_m index ($cm^2 h^{-1}$) was calculated using daily P (a) in cm, maximum intensity of the rain for 7 minutes in cm h^{-1} (I_{max7}) and the number of downpours per month (n); and for the MFI index, P and its monthly average (p^2), both in mm, were used. The criteria of Da Silva (2004) were used to classify the risk of R by means of R_1 and R_2. The classes were: very low <2452, low 2452–4905, moderate 4905–7357, high 7357–9810, and very high >9810. To compare the annual average of R_1 and R_2 to values in other regions of the world, the ranges shown in Table 1 were used.

To classify risk based on *MFI* values, the categories of Lobo, Gabriels (2005) were applied: 0–60 very low, 60–90 low, 90–120 moderate, 120–160 high, >160 very high. Based on the relationship between the spatial variance of *MFI* and of AI_m (Almoza *et al.* 2007), the following classification was proposed for *MFI*: very low 0–100, low 100–200, moderate 200–450, high 450–1050, and very high >1050.

A statistical analysis was performed to compare the behavior of P with respect to the four indicators. The Shapiro-Wilk test was applied to test for normality in the distributions of the indicators, with significance level $a = 0.05$. As all the distributions were found to be skewed, the transformation $y = log (x)$ was applied to the data in order to make a linear model appropriate and enable estimates of the respective correlations between the dependent variables (R_1, R_2, *MFI* and AI_m) and P to be calculated. To determine whether there were significant differences, a one-factor ANOVA test was applied with five levels, at a significance level of $\alpha > 0.05$. Groups that showed a difference in the ANOVA ($F > 1$, $p < 0.05$), were tested using a Tukey HSD (Honestly Significant Difference) test, using the criterion 0.05 (95 %). For the ANOVA analysis, the PAST 2.17 b program (Hammer *et al.* 2001) was used and corroborated with the IBM SPSS Statistics 2.1 program (IBM 2012).

The maps were drawn on a scale of 1:10,000 in geographic coordinates (UTM), using kriging interpolation in the SURFER 10.0 program (Emery 2007) and a spatial variation in two regions (UTM: Zone 12 and 13). To represent these two zones, the distance between one station in Zone 12 and another in Zone 13 was measured and added to the initial coordinate, to provide continuity to the interpolations. The maps were finished using CorelDRAW X7.

2. Results and discussion

The averages of P, P^2 and a were 753.31 mm $year^{-1}$, 62.77 mm $month^{-1}$ and 2.09 mm day^{-1} respectively, and their ranges of variation were 70.9–2174.5 mm $year^{-1}$,

Table 1. Average annual variation of rainfall erosivity (R) for comparison of R_1 and R_2 with other regions of the world (MJ mm ha^{-1} h^{-1})

Rainfall erosivity (R)				
Country	Region	Maximum Value (MJ mm ha^{-1} h^{-1})	Minimum Value (MJ mm ha^{-1} h^{-1})	Author
Ecuador	Ucabanba and San Cristóbal	1, 140.3	1, 231.4	Suffis 2004
Portugal	Flanders	20	3, 741.8	De Santos, De Azevedo 2001
Brazil	Center of Brazil	20, 000	24, 000	Da Silva 2004
Colombia	Caldas Department	800	860	Ramírez, Hincapié 2009
Chile	Curicó Valley	180	285	Mancilla 2008
Cuba	Cuyaguateje Valley	8, 200	18, 000	Almonza 2007
Spain	Provinces of Córdoba, Jaén and Cadiz	40	600	De la Rosa, Moreira 1987

8.90–181.20 mm month^{-1} and 0.74–6.04 mm day^{-1} respectively. Rainfall in the wettest months, July, August and September, with annual monthly averages of 6.09, 113.27 and 143.97 mm year^{-1}, accounted for 78.8 % of total *P*. February, March, April and May, with 3.6 % average annual rainfall, were the driest months (Fig. 2, part A). During the course of the year, *n* varied and was directly proportional to *P*. The highest rainfall occurred during the wettest months and was moderate to low along the coast, moderately low to high in the agricultural area and highest in the Sierra Madre Mountains.

A total of 70 downpours were recorded at six weather stations in the Sierra Madre Mountains; 25 at three coastal stations and 20 at two stations in the central agricultural region. Given that rain is the main cause of damage to structural stability of the soil during the first few minutes of a downpour, the values of *n* were used as a first approximation of the susceptibility of the soil to erosivity (*R*) (Núñez *et al.* 2007) and thus as a first indicator of the expected value of R_1, R_2, *MFI* and AI_m (Fig. 2, part B). The average annual values of I_{30} and I_{max7} were 20.72 and 4.8 mm year^{-1} and the ranges of variation in daily values were 15–30 and 3.5–7 mm. The ranges of Δik and Δt_k were 2.4–3.45 mm h^{-1} and 1.54–3.22 hours, and the average annual $e_k = k$ per mm of rain was 0.105–114 MJ ha^{-1} mm^{-1}. These environmental conditions in the region produced rainy, stormy weather with spatial variation in *E* from 211 to 4474.60 MJ ha^{-1} and an annual average of 1105.47 MJ ha^{-1}. This indicates high *P* and a high expected value for *R* (Fig. 2, part C). The variation of *E* is shown in part C of Figure 3. In the eastern part of the study region, values of *E* were small; they were larger in the central area and intermediate in the west. The Guanana and Bacurato weather stations recorded the highest values. Note in Figure 3 that the variation of *E* is similar to that of *n* and *P*, suggesting that the spatial variance of these variables is correlated (Chica 2005).

Six stations in hilly country and in the Sierra Madre Mountains had a variance of 0.99 (Yecorato, La Lajita, Guanana, Bacurato, Jaina and Guadalupe y Calvo), three

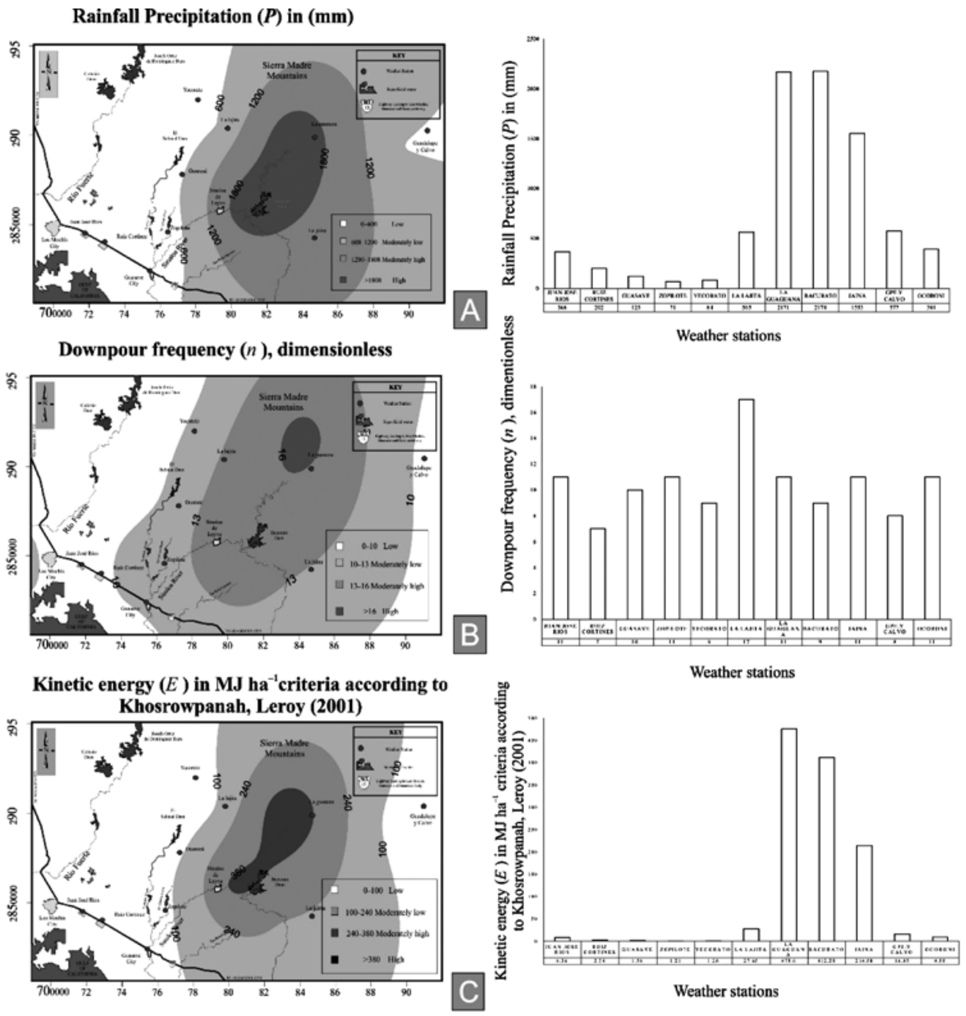

Fig. 2. (A) Spatial variation of annual average rainfall (*P*) in mm, (B) Spatial variation of annual numbers of downpours (*n*) and (C) total kinetic energy (*E*) of rainfall in MJ ha^{-1} in northwestern Mexico

weather stations on the coast had a variance of 0.007 (Juan Jose Ríos, Ruiz Cortínez and Guasave), and two stations in the agricultural region also had a variance of 0.007 (Zopilote and Ocoroni). The high values of *n*, *E* and *P* from localities at higher elevation are 99%, indicative of expected high values for *R*, particularly during the rainiest months. However, considering that *R* is based not only on the amount of rainfall, but also on the intensity of I_{max7}, I_{30} and *E*, high values of *R* in the agricultural and coastal areas cannot be ruled out. The average annual value of R_1 was 1161.30 and of R_2 1084.51 MJ mm ha^{-1} h^{-1}, with ranges 2.4–3701.2 and 2.93–4081.1 MJ mm ha^{-1} h^{-1} respectively. As shown in Table 1, where these results are compared to values from other regions in the world, these results are similar to those found by Suffis (2004) for Ecuador (Ucabanba and San Cristobal) with annual averages of 1140.3–1231.4 MJ mm ha^{-1} h^{-1}. Considering the influence of the climate, which is less influential than *P*, and except for values from Brazil where rainfall amounts are high (Da Silva 2004), the annual averages of R_1 and R_2 from northwestern Mexico can be considered high. The spatial variations of R_1 and R_2 are shown on maps A and B in Figure 4, and it can be seen that with a variance of 0.98 in the indicators, they are quite similar, as are *E, P* and *n*. The small differences between the maps in Figure 4 were attributed to use of the appropriate logarithmic regression equation that determined *E* and which was represented by the constants a = 0.32 and b = 2.08.

The average annual *MFI* was 130.30 cm^2 h^{-1} and AI_m 781.78 mm. Their ranges were 14.1–362.56 cm^2 h^{-1} and 84.50–2175.22 mm respectively. The values of AI_m and *MFI* are shown in Figure 5 A and B. As in the maps of R_1 and R_2, there is a spatial pattern in which values are lower in the east, higher in the central area, and intermediate in the west. The Bacurato and Guanana stations showed the highest values. The fraction of AI_m and *MFI* is analogous to the fraction of R_1 and R_2 in most seasons, as would be expected. The areas where each indicator reached its with the highest risk to the soil as indicated by *R*. These were the places with the highest values of annual precipitation and the heaviest downpours. In the total 37,500 km^2 study area, using the criteria of Da Silva (2004), the risk as measured by R_1 indicates that 5.38% of the region (2017.5 km^2) has a high to very high risk of erosion by rain, 6.42% (2407.5 km^2) a medium to high risk, 15.1% (5662.5 km^2) a low to medium risk, 38.2% (14325 km^2) low risk and 34.9% (13087.5 km^2) a very low risk. In terms of R_2, the percentage of high to very high was 10.2% (3825 km^2), 14.7% medium to high (5512.5 km^2), 13.7% low to medium (5137.5 km^2), 23.2% low (8700 km^2) and 38.2% very low (14325 km^2). The results obtained for AI_m using the territorial classification of Lobo, Gabriels (2009) were 38% very low risk (14250 km^2), 31.2% low (11 700 km^2), 13.5% moderate (5062.5 km^2), 12.3% high (4612.5 km^2) and 5% very high risk (1875 km^2). Using *MFI*, 28% of the area (10 500 km^2) was classified as very low risk, 24.7% low (9262.5 km^2), 20.3% moderate (7612.5 km^2), 15% high (5625 km^2) and 12% (4500 km^2) very high risk. The results of the statistical analysis are presented in Table 2, showing that *P* spatially resembles R_1, R_2, AI_m and *MFI*. The Shapiro-Wilk

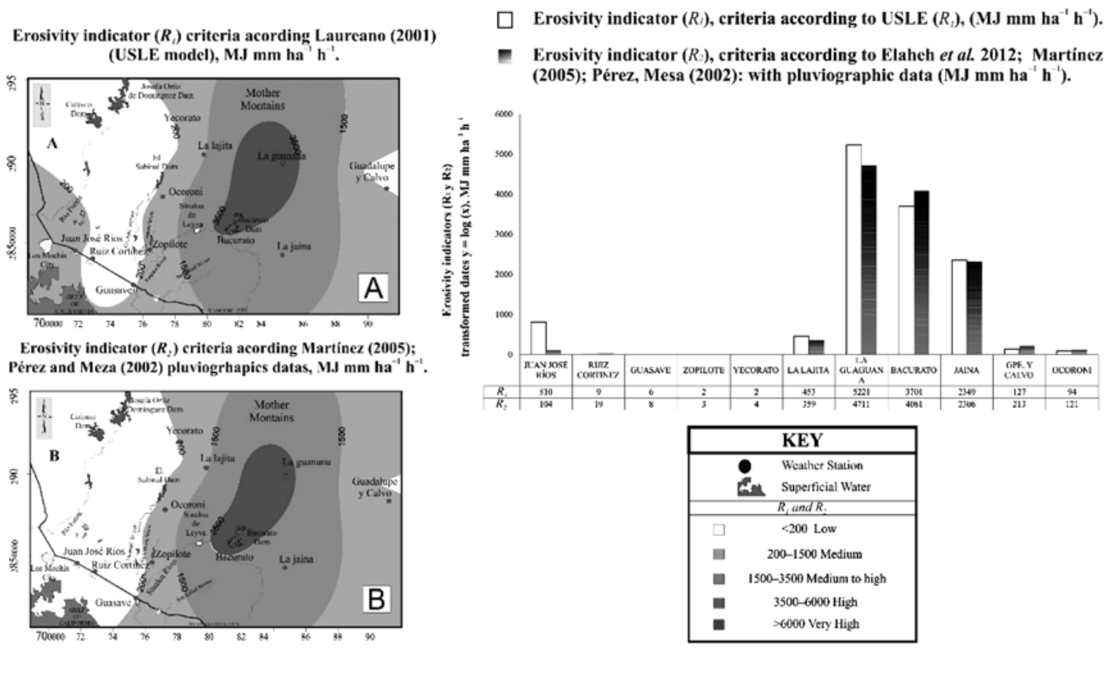

Fig. 3. (A) Spatial variation of annual average factors of rainfall erosivity according to *USLE* (R_1), (B) annual average factor of erosivity according to the curves of logarithmic regressions (R_2) both in MJ mm ha^{-1} h^{-1} and their respective ranges of risks for soils in northwestern Mexico

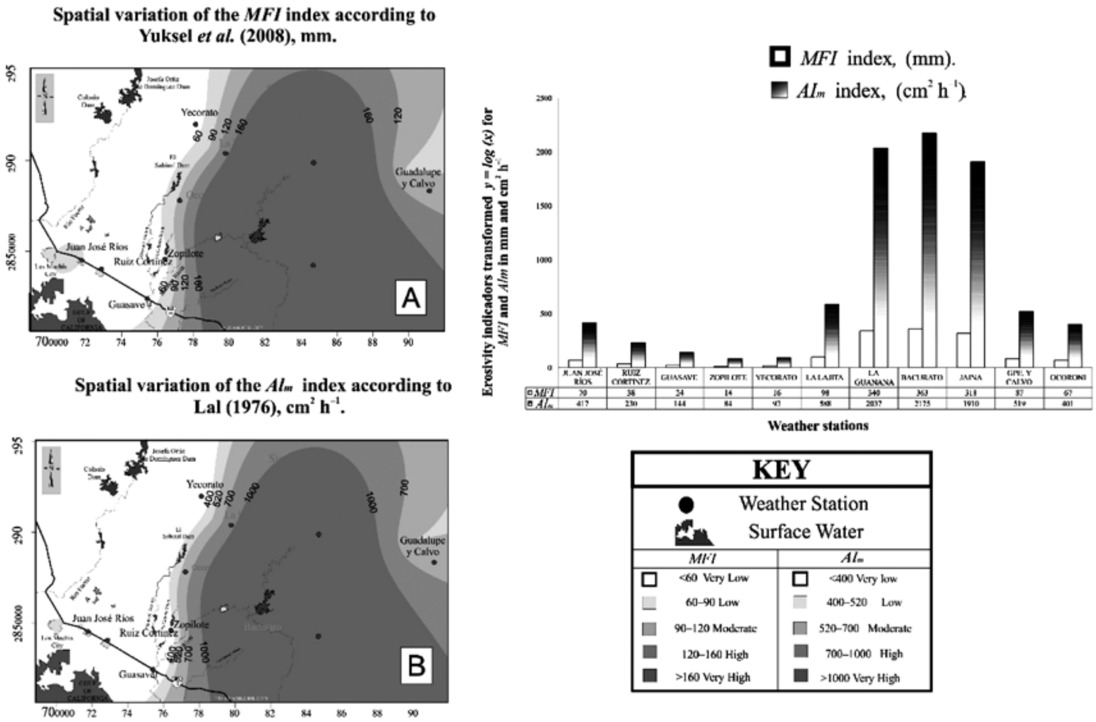

Fig. 4. Spatial variation of the *MFI* index (mm) and AI_m index (cm^2 h^{-1})

Table 2. Magnitude of annual average precipitation (P) in mm, annual averages of indicators of erosivity: R_1 (MJ mm ha^{-1} h^{-1}), R_2 (MJ mm ha^{-1} h^{-1}), AI_m (cm^2 h^{-1}) and MFI (mm) and ANOVA results in northwestern Mexico.

Number	Weather Station	***P*** (mm year^{-1})	$\boldsymbol{R_1}$ (MJ mm ha^{-1} h^{-1})	$\boldsymbol{R_2}$ (MJ mm ha^{-1} h^{-1})	***MFI*** (mm)	$\boldsymbol{AI_m}$ (cm^2 h^{-1})
1	Juan José Ríos	368	810	104	70	417
2	Ruiz Cortínez	202	9	19	38	230
3	Guasave	125	6	8	24	144
4	Zopilote	71	2	3	14	84
5	Yecorato	84	2	4	16	93
6	La Lajita	565	453	359	98	588
7	La Guanana	2171	5221	4711	340	2037
8	Bacurato	2174	3701	4081	363	2175
9	La Jaina	1553	2349	2306	318	1910
10	Gpe. y Calvo	577	127	213	87	519
11	Ocoroni	394	94	121	67	401
			One-way ANOVA			
		Sum of *sqrs*	*df*	Mean Square	*F*	p (same)
	Between groups:	5.469	4	1.367	1.772	0.149
	B Within groups:	38.589	50	0.772		
	Total:	44.058	54			
	Omega^2:	0.0531				

Levene's test for homogeneity of variance, based on means: p (same) = 0.00062

Based on medians: p (same) = 0.00072
Welch F test in the case of unequal variances: F = 3.961, df = 24.45, p = 0.01293

test was applied to test for a normal distribution, $\alpha <$ 0.05. The resulting test statistics and significance levels were: R_1 ($W = 0.714$, $p = 0.0007$), R_2 ($W = 0.663$, $p = 0.0002$), *MFI* ($W = 0.756$, $p = 0.0025$) and AI_m ($W = 0.755$, $p = 0.0024$), indicating that none of the indices were normally distributed. The data were therefore transformed by $y = log(x)$ ($\alpha > 0.05$). A one-factor ANOVA test was applied to the transformed data. The resulting statistics were R_1 ($W = 0.905$, $p = 0.21$), R_2 ($W = 0.925$, $p = 0.36$), *MFI* ($W = 0.917$, $p = 0.29$), AI_m ($W = 0.916$, $p = 0.28$), supporting the *log* transformation for the data.

The value of the ANOVA test statistic was $F = 1.772$ with $p = 0.149$. Considering the established level for significant differences, a test statistic >1 indicated that means of the groups were not significantly different. However, since the F statistic >1, the results of the Tukey HSD test indicated which of the estimated means were different. The results of the HSD test were: t (20) = 4.16, MSE (Mean square error) = 0.77 and HSD = 1.10. The pairwise comparisons of HSD between indices were: [P] vs. [R_1] = 0.553, [P] vs. [R_2] = 0.529, [P] vs. [MFI] = 0.746, [P] vs. [AI_m] = –0.03, [R_1] vs. [R_2] = –0.023, [R_1] vs. [MFI] = 0.193, [R_1] vs. [AI_m] = –0.583, [R_2] vs. [MFI] = 0.216, [R_2] vs. [AI_m] = –0.559, [MFI] vs. [AI_m] = –0.776. Using the criterion of 0.05 (95%) significance level in the pairwise comparisons, [P] vs. [MFI] and [MFI] vs. [AI_m] are the pairs with the highest differences between their averages, with HSD = 1.10. The results of the ANOVA and Tukey tests show that the 80 % of the results are dependent on P, and any differences observed can be attributed to random variation.

The correlation and interdependence between indicators of R in the region are illustrated in Figure 5, where the graphs are the result of applying a multivariate linear model with four dependent variables characterized by the following coefficients of determination: P vs. $R_1 = 0.91$, P vs. $R_2 = 0.95$, P vs. $AI_m = 0.98$, P vs. $MFI = 0.97$.

Taking into account the spatial behavior of the results in this agricultural region of northwestern Mexico, farmers should schedule tillage and irrigation to prevent damage to the soil; that is, mainly during the months when R is highest, which is manifested not only by the value of P, but also by the influence of I_{30}, I_{max7} and E.

The rainfall in the region has a high erosive potential that is highest in the Guanana and Bacurato region, at elevations between 250 and 350 meters above sea level. This range is the source of both surface water and groundwater in the valley. The variations illustrated in the maps are of great utility for farmers since they indicate which places have greater and lesser R risk and enable planning for sustainable agricultural systems, which is of great importance for the regional and national economy.

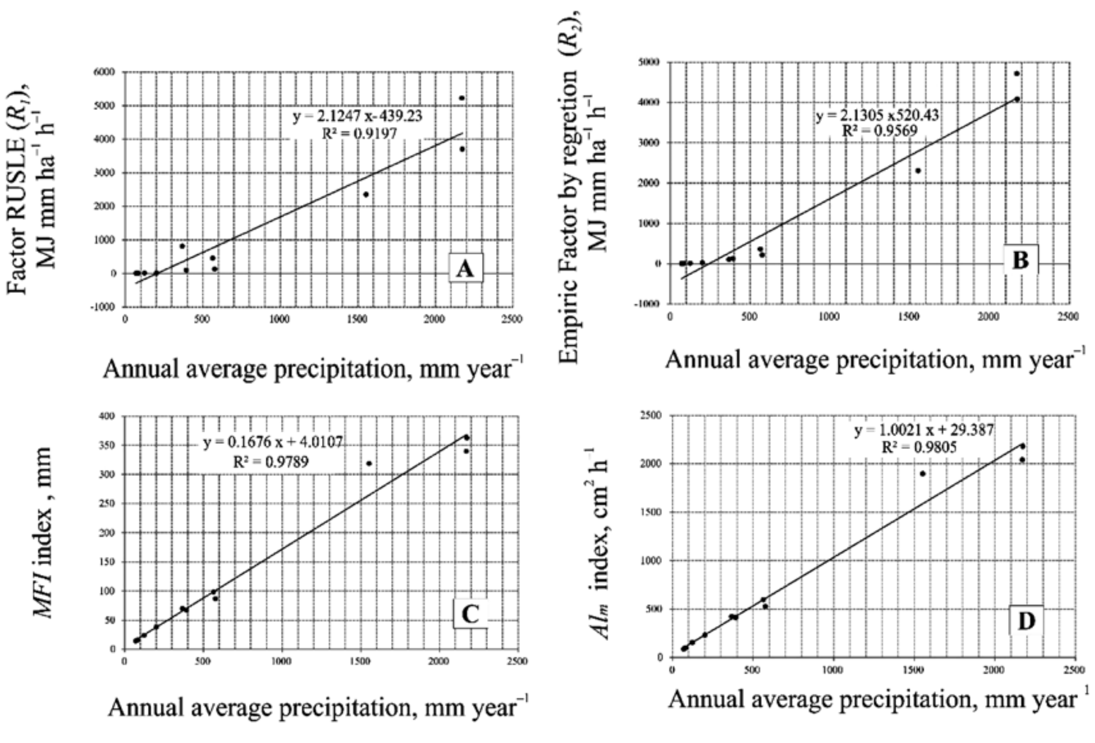

Fig. 5. Linear regression of annual average precipitation (P) in mm with respect to indicators of erosivity: (A) R_1 in MJ mm ha^{-1} h^{-1}, (B) R_2 in MJ mm ha^{-1} h^{-1}, (C) *MFI* index in mm and (D) AI_m index in cm^2 h^{-1}; applied in northwestern Mexico.

Conclusions

The most important cause of degradation that puts soil fertility at risk is erosion caused by water (Zhu *et al.* 2011). It reduces sustainable sources of income in every country and threatens the principles of Conservation Agriculture (CA) (Morgan 2005). Any methodology that can contribute to conserving soil stability is important; and studies such as the present one that can define the erosivity risk of soils in a given agricultural region (here northwestern Mexico) enables management plans that can focus on the first of the three CA principles: (1) Direct planting of crop seeds with minimal mechanical disturbance of the soil; (2) permanent soil cover, especially by crop residues and cover crops and (3) crop diversity.

In spite of increasing interest in CA, there are still sustainable soil management approaches that focus mainly on an input-product approach. Studies such as the present one can help change this by directing attention to a comprehensive vision based on sustainable management. To achieve this, appropriate models and baseline indexes of erosion rates are required, which are rarely considered in developing countries (Seyed, Shahla 2015).

In the context of CA, the results of spatial variation of the four indicators in these agricultural valley regions enabled the areas with the largest values of *R* to be identified. These coincided with the areas showing the greatest erosion problems, and vice versa. This reciprocal behavior between erosion and *R* is attributed to the effect of other factors including the slope of the land, and soil texture and porosity. On the behavior of the slope, note in Figure 3 that in the west where *R* is lower (agricultural area), gentle, rolling hills predominate. In the west where *R* is higher (less erosion), there are steep, rugged slopes (mountainous areas). Integrating information from the four indicators that define soil risk in terms of *R* enabled inference of the spatial nature of a phenomenon that is released in discrete "jumps" and is therefore highly energetic and damaging the longer it interacts with the soil system. Given these properties, the behavior of *R* should be investigated in agricultural valleys around the world and at the same time validated by the methodology described here. The results obtained from applying this methodology can be used as a first indicator of soil loss. However, the reciprocal erosion-erosivity behavior points out the need to take other USLE factors into account in studies predicting total water erosion, as suggested by Wischmeier, Smith (1960). It is urgently recommended that this methodology be applied in areas with gentle slopes where large quantities of rain fall in a short time, in order to develop emerging plans for sites where *R* is high, to recover the dynamic equilibrium of the soil and to conserve dynamic equilibrium where it is low, avoiding losses caused by high *E* when raindrops fall on the soil. This is due to the fact that when *R* is of long duration, the risk of breaking the dynamic equilibrium of the soil is greater than when *R* is frequent and of short duration. When the soil system is broken, it is difficult to restore, and the losses that occur are irreversible. Considering that each system has a different threshold of resistance, that *R* is different in each environment and if *R* surpasses the soil resistance threshold it can result in loss, and that systems tend to evolve, it is important to know and monitor these thresholds in the agricultural valleys of the world. It is therefore important to quantify the risk and the spatial variation of *R* – as in this study – in different scenarios around the world in order to carry out erosion management to control soil loss caused by rain, especially during rainy seasons. In light of this problem, appropriate measures should be taken to minimize the erosive effect of the rainy season, such as maintaining a permanent vegetative cover and refraining from working the land to remove or expose soil during the seasons of heaviest rain. In addition, further studies are needed to estimate *R* at a finer scale. A monitoring network should be established involving more weather stations to provide indexes calculated from rainfall data and/or more complete pluviographic data to create a comprehensive specialized database that will enable numerical modeling of *R* using geographic information systems and specialized software.

In this study, data from eleven weather stations were available, limiting the available data in time and space. Many parts of the world lack a suitable meteorological infrastructure to generate sufficient pluviographic and pluviometric data for such studies, making the necessary data difficult or impossible to obtain. This is commonly the situation in developing countries (Yu *et al.* 2001).

In some countries, the lack of daily and long term data on the intensity of precipitation means that any attempt to model soil erosion and sediment yield based on the USLE-R, USLE and RUSLE factors will be more difficult to calibrate and often inapplicable.

The calculation of actual values of *R* depends on precise estimation of *E* and I_{30}, and the original USLE and USLE-RUSLE method requires pluviographic and pluviometric records from numerous weather stations over a considerable amount of time for calculating EI_{30}. In this context, the present study had data that met these criteria in time but not in geographical distribution, which means that the estimates of *R* are not as precise in space as might be desired. More weather stations should be established and monitored if future studies are to produce better estimates of *R*. The present study was designed following the criteria of Petrovsek, Mikos (2004), who stated that broad approximations can be made with the available data, so it was deemed feasible to proceed with the study and estimate the magnitude and behavior of *R* in space with the existing data. However, it must be acknowledged that the results of this study reflect the variation of the available data in time and space.

González *et al.* (2010) and Taguas *et al.* (2013) report for precipitation regimes in the Mediterranean zone, that high variability in long term records of rain intensity makes the treatment of data less appropriate for calculating the correct values of *R*. Analysis using data ranging over shorter periods tends to result in more accurate estimates of the behavior of *R*. Given this, future work should focus on the use of annual, monthly and daily pluviographic and pluviometric data, which is the form in which these data are normally reported (Shamshad *et al.* 2008). This is the format in which SMN-CONAGUA has always handled the data in Mexico, and if other private and public agencies did so too, it would contribute to soil conservation and CA. Moreover, it would help avoid slow, laborious treatment of long term rain intensity data year after year (Diodato 2005; Da Silva 2004). The application of this methodology to shorter time periods (days, months, one year) would be even better under the recommendations of Ziadat, Taimeh (2013), who state that rain intensity is the most important factor affecting soil erosion, which can occur in relatively small-scale areas of moist soil caused by previous rainfall events. In consequence, locating and identifying areas of moist soil and measuring annual, monthly and daily P can help protect against erosion, and potentially reduce future soil fertility loss and the effects of seasonal dry periods, with resulting benefits to food security and world food subsistence, contributing to meeting the challenges of CA.

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