Journal of Hydrology (2006) **328**, 726–732

available at www.sciencedirect.com

SCIENCE DIRECT®

journal homepage: www.elsevier.com/locate/jhydrol

Evaluation of indices for characterizing the distribution and concentration of precipitation: A case for the region of Southeastern Anatolia Project, Turkey

H. Apaydin [a], G. Erpul [b,*], I. Bayramin [b], D. Gabriels [c]

[a] *Faculty of Agriculture, Department of Farm Structures and Irrigation, University of Ankara, Diskapi, 06110 Ankara, Turkey*
[b] *Faculty of Agriculture, Department of Soil Science, University of Ankara, Diskapi, 06110 Ankara, Turkey*
[c] *Department of Soil Management and Soil Care, Ghent University, Coupure Links 653, B 9000 Ghent, Belgium*

Received 2 November 2004; received in revised form 17 January 2006; accepted 28 January 2006

KEYWORDS
Modified fournier index;
Rainfall variability;
Rainfall seasonality;
Coefficient of variation;
Precipitation concentration index

Summary There is a need to understand and analyze rainfall variability, since it is most variable in time and space, for assessing the erosive potential of rainfall and its impacts on soil erosion and conservation measures. In order to have a spatially realistic surface of the modified fournier index (MFI) and a statistically valid method, two different procedures of calculating the MFI were performed using the daily rainfall amounts recorded for 29 years in the region of Southeastern Anatolia Project (GAP), Turkey and efficiently integrating elevation and GIS. The method that calculated the MFI surface from the monthly rainfall amounts of each individual year and averaged over a number of years ($\mathrm{MFI}_{\bar{j}}$) was compared with the method that calculated the MFI surface from the averages of ith monthly rainfall amounts and averaged over a number of years ($\overline{\mathrm{MFI}}$). Results indicated that the $\overline{\mathrm{MFI}}$ led to the lower-risk MFI classes than the $\mathrm{MFI}_{\bar{j}}$. This was attributed to the fact that the $\overline{\mathrm{MFI}}$ was statistically unable to account for the year-to-year variability in the rainfall data. An analysis with the relationship between the $\overline{\mathrm{MFI}}$ and the coefficient of variation (CV) also suggested the total variability in the data set be better represented to have dependable MFI surfaces because of integration of elevation. Further calculations for surfaces of the precipitation concentration index (PCI) similar to the calculations made for the MFI surfaces conclusively indicated that the $\mathrm{MFI}_{\bar{j}}$ was valuable in determining the potential of the rains for causing soil erosion by providing information on a long-term total variability in the rainfall amount received.

* Corresponding author. Tel.: +90 312 596 1000; fax: +90 312 317 8465.
E-mail address: erpul@agri.ankara.edu.tr (G. Erpul).

0022-1694/$ - see front matter
doi:10.1016/j.jhydrol.2006.01.019

Introduction

There is a need for climatic parameters to analyze and understand hydrologic processes on agricultural fields and watersheds because of their impacts on soil erosion and conservation measures. Of all regular climatic parameters, rainfall is the most changeable in time and space. There are some straightforward measures of the rainfall that can be used to provide information on the variability and hence on the state of the climate. These mainly include monthly rainfall data and annual rainfall totals and averages, which can be used to evaluate the rainfall seasonality and variability, and the frequency of the extreme events. Fig. 1 shows a general illustration of the rainfall data with the totals and averages. The grand total and the grand average of the observations ($p_{\bullet\bullet}$ and $\overline{p_{\bullet\bullet}}$, respectively) can be calculated by

$$p_{\bullet\bullet} = \sum_{i=1}^{a}\sum_{j=1}^{b} p_{ij} = \sum_{i=1}^{a} p_{i\bullet} = \sum_{j=1}^{b} p_{\bullet j} \tag{1}$$

and

$$\overline{p_{\bullet\bullet}} = \frac{p_{\bullet\bullet}}{N} \tag{2}$$

where $N = ab$ (Fig. 1). Variability in the rainfall data is particularly important for a soil erosion research since it could represent the occurrence of the unusual storm conditions with high runoff and soil erosion. Klik and Truman (2003) reported that the knowledge of the temporal distribution of the heavy rainstorms was implicitly necessary for assessing the amount of runoff and soil loss. A good rainfall erosivity index should satisfactorily represent within-year variations and year-to-year variations together with a random variation component that is uncontrolled and generally led by measurement errors. The nature of the rainfall variability in time and space across a region has an effect on the distribution of soil erosion. It directly influences surface runoff and soil transport. Thus, an analysis of the rainfall variability is required to detect the trends in the rainfall amount, and the CV is used to well represent the total variation in the rainfall data:

$$\mathrm{CV} = \frac{\sum_{i=1}^{a}\sum_{j=1}^{b}(p_{ij} - \overline{p_{\bullet\bullet}})^2}{p_{\bullet\bullet}} \tag{3}$$

We statistically know that the nominator of Eq. (3) is equal to:

$$\sum_{i=1}^{a}\sum_{j=1}^{b}(p_{ij} - \overline{p_{\bullet\bullet}})^2 = b\sum_{i=1}^{a}(p_{i\bullet} - \overline{p_{\bullet\bullet}})^2 + a\sum_{j=1}^{b}(p_{\bullet j} - \overline{p_{\bullet\bullet}})^2 + \sum_{i=1}^{a}\sum_{j=1}^{b}(p_{ij} - \overline{p_{\bullet j}} - \overline{p_{i\bullet}} + \overline{p_{\bullet\bullet}})^2 \tag{4}$$

which represents a partition of the total variation in the rainfall data, subsequently expressing the within-year variation, the year-to-year variation, and the random measurement error.

Renard and Freimund (1994) suggested the use of the modified fournier index (Arnoldus, 1977) for determining the rainfall erosivity in the regions where the long-term rainfall intensity data were unavailable:

$$\mathrm{MFI}_j = \frac{\sum_{i=1}^{12}(p_{ij})^2}{p_{\bullet j}} \tag{5}$$

Kai et al. (2002) applied the MFI to calculate the average monthly rainfall erosivity values for the USLE (Wischmeier and Smith, 1978) to provide farmers and conservation planners with a tool to consider necessary measures for preventing erosion in the Andean region of Colombia. A rapid way of deriving seasonal variations was also found in the calculations of the precipitation concentration index (PCI) (Oliver, 1980) as well as the modified fournier index. De Luis et al. (2001) estimated the PCI to analyze the precipitation of the Region of Valencia for the effect of erosion on Mediterranean ecosystems:

$$\mathrm{PCI}_j = \frac{\sum_{i=1}^{12}(p_{ij})^2}{(p_{\bullet j})^2} \tag{6}$$

It can be easily seen from Eqs. (5) and (6) that the MFI and the PCI indices can be related to each other through the common term of $p_{\bullet j}$. Gabriels et al. (2003) gave the relationship between the MFI and the PCI:

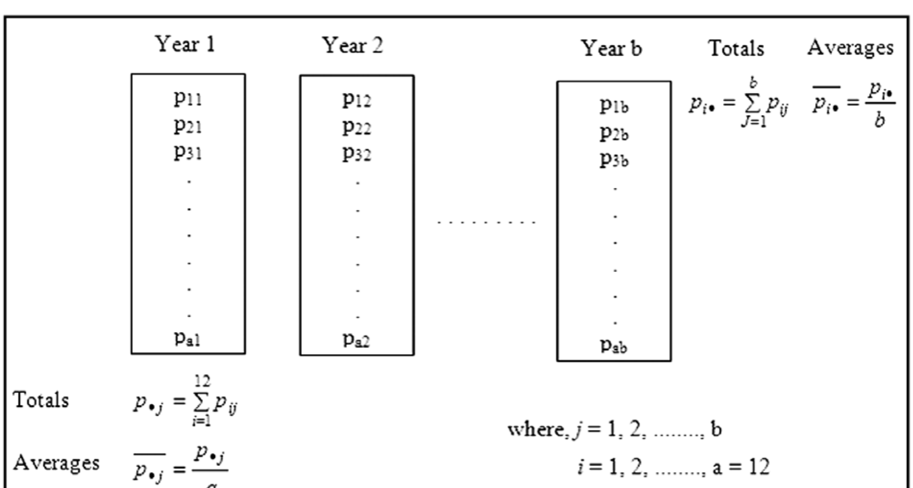

Figure 1 Monthly and annual rainfall totals and averages for statistical parameters.

$$\mathrm{MFI}_j = (PCI_j)(p_{\bullet j}) \tag{7}$$

Eq. (7) could be used as a measure of the rainfall erosion potential. On the other hand, Gabriels et al. (2003) recommended a long-term average value of the $\mathrm{MFI}_j(\mathrm{MFI}_{\bar{j}})$ is estimated by

$$\mathrm{MFI}_{\bar{j}} = \frac{1}{b}\sum_{j=1}^{b}\mathrm{MFI}_j \tag{8}$$

Since the $\mathrm{MFI}_{\bar{j}}$ by Eq. (8) is calculated from the monthly rainfall amounts of each individual year and averaged over a number of years, this index includes the year-to-year variations as well as the within-year variations. Gabriels et al. (2003) stated that according to the available rainfall data sets, two different procedures could be followed to calculate the MFI, first by Eq. (8) and second by

$$\overline{\mathrm{MFI}} = \frac{\sum_{i=1}^{12}(\overline{p_{i\bullet}})}{\overline{p_{\bullet\bullet}}} \tag{9}$$

The $\overline{\mathrm{MFI}}$ is calculated from the averages of ith monthly rainfall amounts $(\overline{p_{i\bullet}})$ and averaged over a number of years. Gabriels et al. (2003) also concluded that the MFI calculated by Eq. (9) would underestimate the potential of the rains to cause soil erosion compared to the MFI calculated by Eq. (8). However, there is a bias to calculate the MFI from the long-term average monthly rainfall, if the monthly data for several successive years are not reported or unavailable.

Calculation of the MFI from the continuous precipitation records should prove valuable in determining the erosive potential of the rainfall by providing information on the long-term variability in the rainfall amount received. Our objective in this paper is to present the result of the MFI calculations by Eqs. (8) and (9) using available data for the region of the South-eastern Anatolia Project (known as GAP), Turkey. These results should provide useful information to projects involving the MFI calculation for climatological erosion risk assessment.

Materials and methods

The study was implemented using meteorological data recorded in the Southeastern Anatolia Project (GAP) region of Turkey. The primary data set includes daily rainfall amounts recorded from 1971 to 1999 in the region by the Turkish State Meteorological Service. The locations of the precipitation data points are shown in Fig. 2, which shows 27 meteorological stations and 85 rainfall gauges. Fig. 3 shows the geographical distributions of long-term averages of annual precipitation amounts in the GAP region, and in general, these are higher than those recorded by the Turkish State Meteorological Service since station data were interpolated as a function of latitude, longitude, and elevation using thin-plate splines (Hutchinson, 2001).

For precipitation surfaces, e.g., the surfaces of the CV and the MFI, procedures from the ANUSPLIN package (Hutchinson, 1991) were used to fit thin-plate spline functions, which were tri-variate functions of longitude,

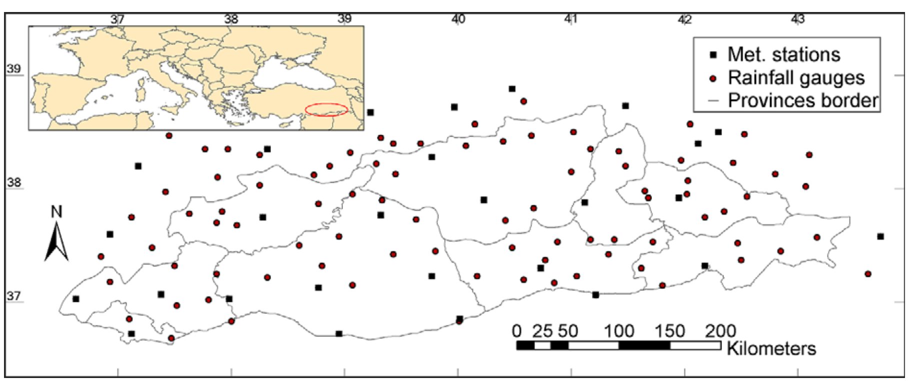

Figure 2 Locations of meteorological stations and rainfall gauges in GAP region.

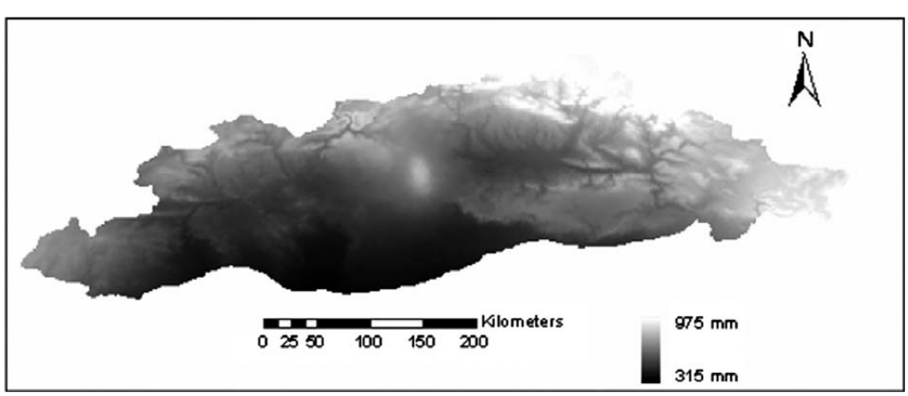

Figure 3 Geographical distributions of long-term averages of annual precipitation amounts in GAP region.

latitude, and elevation. The package supports this aim by providing comprehensive statistical analyses, data diagnostics and spatially distributed standard errors (Hutchinson, 2001). Thin plate smoothing splines can in fact be viewed as a generalization of standard multi-variate linear regression, in which the parametric model is replaced by a suitably smooth non-parametric function. The degree of smoothness, or inversely the degree of complexity, of the fitted function is usually determined automatically from the data by minimizing a measure of predictive error of the fitted surface given by the generalized cross validation (GCV). Theoretical justification of the GCV and demonstration of its performance on the simulated data have been given by Craven and Wahba (1979).

Hutchinson (1995) validated this relative scaling of the longitude, latitude, and elevation, which effectively makes the surfaces 100 times more sensitive to elevation than to horizontal position in precipitation analyses. The resulting spline functions were then applied to a digital elevation model of the GAP region to create maps. The DEM available for the study area is a map converted from a 1/250,000 scale digital topographic map with a resolution of 0.01° extending from latitude 38° 45′N to 36° 30′N and longitude 36° 30′E to 43° 30′E (Fig. 4). MFI surfaces by Eqs. (8) and (9) were finally mapped by calculating monthly rainfall amounts from the daily records formatted in Arc/Info Grid and using ANUSPLIN.

Results and discussion

The MFI surfaces calculated both by Eq. (8) from the monthly rainfall amounts of each individual year and averaged over a number of years and by Eq. (9) from the averages of ith monthly rainfall amounts $(\overline{p_{i\bullet}})$ and averaged over a number of years are, respectively, shown in Fig. 5 (MFI_j) and Fig. 6 ($\overline{MFI}$). Additionally, The MFI classifications from two different calculations are tabulated as a percentage in Table 1.

There were remarkable differences in the MFI surfaces. While Fig. 5 ($MFI_{\bar{j}}$) comprised 0.0%, 44.7%, 50.6%, and 4.7% of the area, Fig. 6 ($\overline{MFI}$) included 17.2%, 52.3%, 28.4%, and 2.1% of the area for very low, low, moderate, and high-risk classes, respectively. Considerably, in the $MFI_{\bar{j}}$ the surface spatial coverage of the moderate and high-risk classes of the MFI increased (55.3%) when compared that in the $\overline{MFI}$ surface (30.5%) (Table 1). It is also noticeable that Fig. 5 contained no low risk (class 1). Since we concluded that the $MFI_{\bar{j}}$, to significant extent, differed from the $\overline{MFI}$ and this can seriously affect assessment of erosion and accordingly implementation of erosion control, for which the $MFI_{\bar{j}}$ required more protective measures, it is of interest to discover the specific nature of the differences. Given Eq. (4) and partitioning of the total variation in the rainfall data, in the $MFI_{\bar{j}}$ represented were the year-to-year

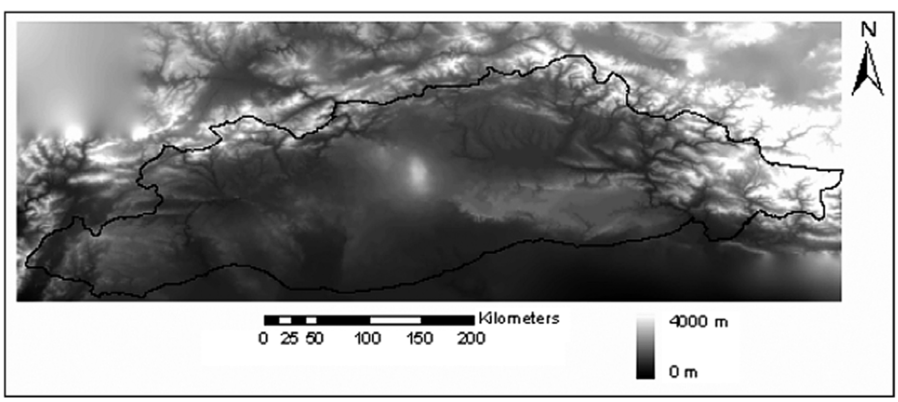

Figure 4 Digital elevation map of GAP region.

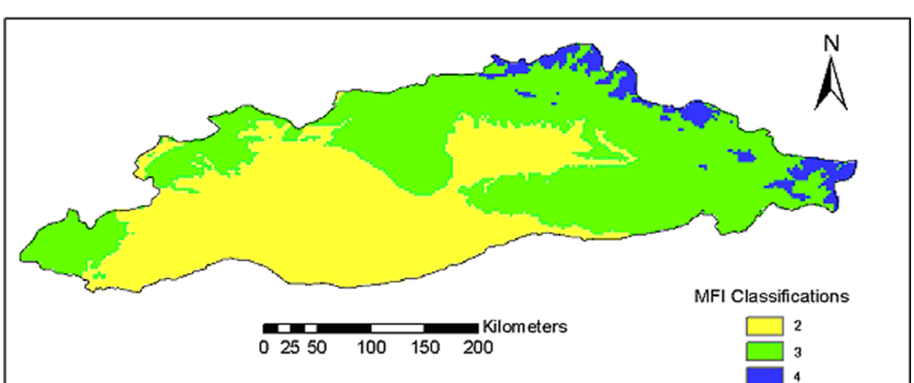

Figure 5 MFI surface calculated by Eq. (8).

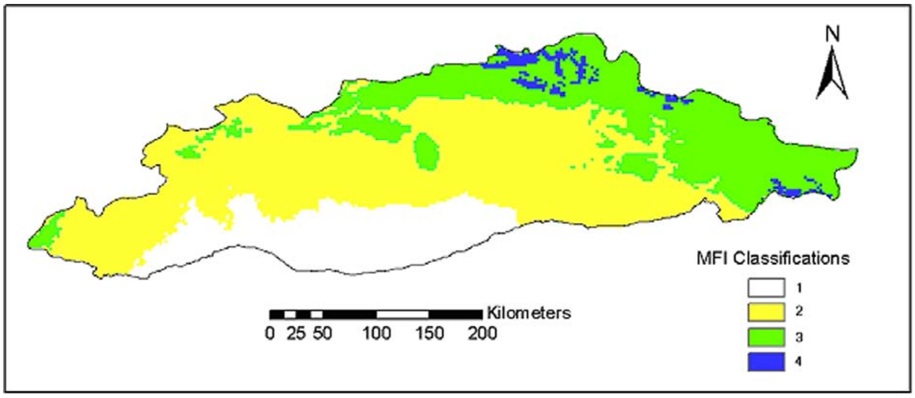

Figure 6 MFI surface calculated by Eq. (9).

Table 1 MFI classifications resulted from three different calculations of MFI by Eqs. (8)–(10)

MFI range	Description	Class	Area (%)			Ratio[d]
			Eq. (8)[a]	Eq. (9)[b]	Eq. (10)[c]	
<60	Very low	1	0.0	17.2	0.0	N/A
60–90	Low	2	44.7	52.3	48.4	0.92
90–120	Moderate	3	50.6	28.4	48.9	1.03
120–160	High	4	4.7	2.1	2.7	1.74
>160	Very high	5	0.0	0.0	0.0	N/A
Total			100.0	100.0	100.0	

[a] MFI calculation from monthly rainfall amounts of each individual year and averaged over a number of years ($\overline{\mathrm{MFI}_j}$).
[b] MFI calculation from averages of ith monthly rainfall amounts ($\overline{p_{i\bullet}}$) and averaged over a number of years ($\overline{\mathrm{MFI}}$).
[c] MFI calculation from the relationship between ($\overline{\mathrm{MFI}}$) and CV.
[d] The ratio of MFI surface by Eq. (8) to MFI surface by Eq. (10).

variations as well as the within-year variations, although the $\overline{\mathrm{MFI}}$ accounted only for the within-year variations (Eq. (9)), overlooking the year-to-year variations in the rainfall data set. Consequently, by isolating different sources of the variability that affect the MFI surfaces using two different procedures, we found out that missing the year-to-year variations resulted in serious underestimation in evaluating the risk classes of the MFI. Gabriels et al. (2003) also observed this in their assessment of the erosive potential of the rainfall and the precipitation concentration in Europe.

From above findings it follows that the CV can be easily introduced to the $\overline{\mathrm{MFI}}$ to better its ability to account for the year-to-year variations, and therefore, we performed a further analysis with the relationship between the $\overline{\mathrm{MFI}}$ and the CV using Eqs. (3) and (9):

$$\overline{\mathrm{MFI}} = \mathrm{CV}\frac{ab\sum_{i=1}^{a}(\overline{p_{i\bullet}})}{\sum_{i=1}^{a}\sum_{j=1}^{b}(p_{ij} - \overline{p_{\bullet\bullet}})^2} \qquad (10)$$

If this analysis is appropriate, the surface obtained by Eq. (10) could show a resemblance with the surface by Eq. (8). The MFI surface calculated by Eq. (10) from the relationship between the $\overline{\mathrm{MFI}}$ and the CV is shown in Fig. 7. The result showed that the MFI surfaces fitted by Eqs. (8) and (10) using ANUSPLIN indicated a significant similarity (Figs. 5 and 7; Table 1).

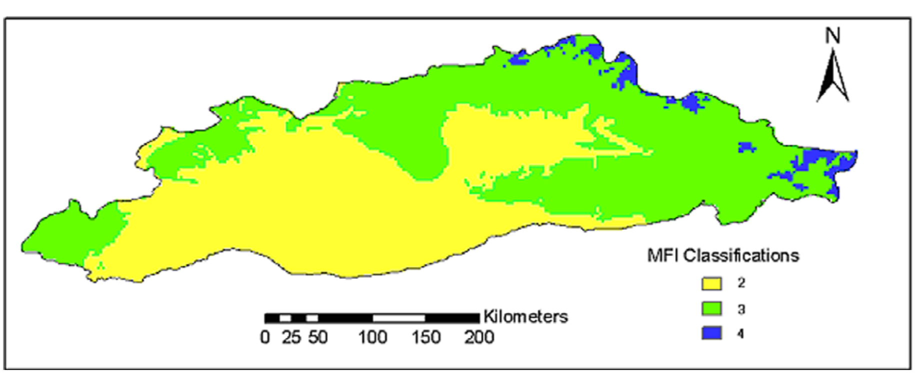

Figure 7 MFI surface calculated by Eq. (10) from the relationship between ($\overline{\mathrm{MFI}}$) and CV.

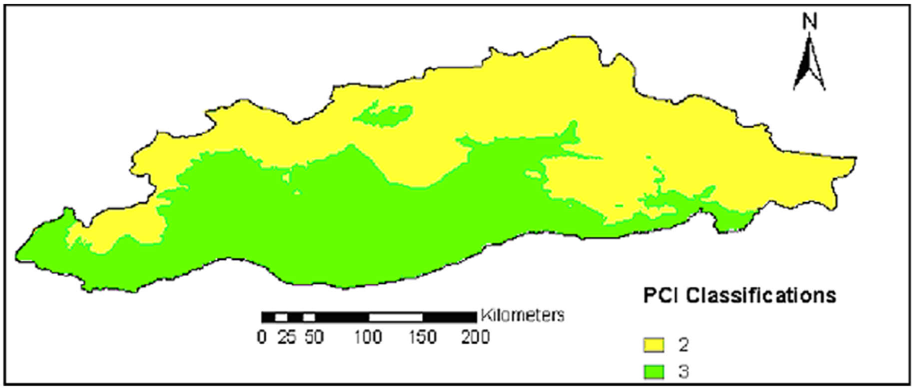

Figure 8 PCI surface calculated by Eq. (11).

That the ratio of the MFI surface by Eq. (8) to the MFI surface by Eq. (10) was very small (Table 1) implied that the ability of the $\overline{\text{MFI}}$ was significantly improved by the CV. However, there is no any advantage of the use of Eq. (10) because it needs the monthly data for several successive years like the $\text{MFI}_{\bar{j}}$ calculations. This only allowed us to examine necessity of knowing the total variability by a component that measures the within-year variation and a component that measures the year-to-year variation.

Similar to the MFI calculations, two different procedures of estimating the PCI were also performed, and these are expressed as $\text{PCI}_{\bar{j}}$ and $\overline{PCI}$ by Eqs. (11) and (12), respectively.

$$\text{PCI}_{\bar{j}} = \frac{1}{b}\sum_{j=1}^{b} \text{PCI}_j \tag{11}$$

$$\overline{\text{PCI}} = \frac{\sum_{i=1}^{12} (\overline{p_{i\bullet}})^2}{(\overline{p_{\bullet\bullet}})^2} \tag{12}$$

where, $\text{PCI}_{\bar{j}}$ is an index calculated from the monthly rainfall amounts of each individual year and averaged over a number of years, and $\overline{\text{PCI}}$ is an index calculated from the averages of ith monthly rainfall amounts $(\overline{p_{\bullet i}})$ and averaged over a number of years. The PCI classification by Eq. (11) $(\text{PCI}_{\bar{j}})$ is shown in Fig. 8, and since the PCI by Eq. (12) $(\overline{\text{PCI}})$ only resulted in a class of 2, its figure is not shown. There was a significant difference between two PCI surfaces. Although the $\overline{\text{PCI}}$ surface only consisted of the PCI range, which corresponded to moderate seasonality ($10 < \text{PCI} < 15$), the surface of the $\text{PCI}_{\bar{j}}$ comprised both moderate seasonality (52.8%) and seasonality ($15 < \text{PCI} < 20$). Since the PCI considers the seasonal aggressiveness of the rains (Oliver, 1980), and it was clear that the $\overline{\text{PCI}}$ could not account the temporal variability of the rainfall distribution within each individual year (Michiels and Gabriels, 1996; Gabriels et al., 2003) like the $\overline{\text{MFI}}$, it failed to appropriately assess the seasonal concentration of the precipitations. It is particularly important to observe that the $\text{PCI}_{\bar{j}}$ was able to better estimate the rain aggressiveness within a given year (Fig. 8) for the regions (47.2%) where the $\overline{\text{MFI}}$ could not denote the year-to-year variability in the rainfall data of the region. This additionally confirmed our conclusion that the calculations made by the long-term averages of ith monthly rainfall amounts might bring about a substantial miscalculation for characterizing the distribution and the concentration of the precipitation.

Conclusions

There could be a number of ways to build the MFI surfaces, and there is a tendency to calculate MFI from the long-term average monthly rainfall data. In order to obtain the spatially realistic MFI surfaces and a statistically valid method that comprises all variability in the rainfall data, two different procedures of estimating the MFI were conducted using the daily rainfall amounts recorded from 1971 to 1999 in the GAP region by the Turkish State Meteorological Service as a case. The result of the MFI surface from the monthly rainfall amounts of each individual year and averaged over a number of years $(\text{MFI}_{\bar{j}})$ is presented and compared with that from the averages of ith monthly rainfall amounts and averaged over a number of years $(\overline{\text{MFI}})$. The findings indicated that the $\text{MFI}_{\bar{j}}$ was significantly different from the $\overline{\text{MFI}}$, which was statistically unable to account for the year-to-year variability in the rainfall data and accordingly resulted in underestimation in the risk classes of the MFI. The analysis with the relationship between the $\overline{\text{MFI}}$ and the CV recommended the total variability in the data set be appropriately represented to have the reliable MFI surfaces. Additionally, calculating the PCI surfaces and comparing those to the MFI surfaces confirmed that the calculations made by the long-term averages of ith monthly rainfall amounts might bring about a substantial miscalculation for characterizing the distribution and the concentration of the precipitation. The development of the better surfaces of the MFI, which provide the year-to-year variations as well as the within-year variations for the GAP region will assist the improved modeling of these areas, and serve in their long-term conservation.

References

Arnoldus, H.M.J., 1977. Methodology used to determine the maximum potential average annual soil loss due to sheet and rill erosion in Morocco. FAO Soils Bulletin 34, 39–51.

Craven, P., Wahba, G., 1979. Smoothing noisy data with spline functions. Numerische Mathematik 31, 377–403.

De Luis, M., Garcia-Cano, M.F., Cortina, J., Raventos, J., Gonzalez-Hidalgo, J.C., Sanchez, J.R., 2001. Climatic trends, disturbances and short-term vegetation dynamics in a Mediterranean shrubland. Forest Ecology and Management 147, 25—37.

Gabriels, D., Vermeulen, A., Verbist, K., Van Meirvenne, M., 2003. Assessment of rain erosivity and precipitation concentration in Europe. In: Gabriels D., Cornelis W. (Eds.), Proceedings of the International Symposium, 25 Years of Assessment of Erosion, 22—26 September 2003, Ghent, Belgium, pp. 87—92.

Hutchinson, M.F., 1991. The application of thin plate smoothing splines to continentwide data assimilation. In: Jasper J.D. (Ed.), Data Assimilation Systems. BMRC Research Report No.27, Bureau of Meteorology, Melbourne, pp. 104—113.

Hutchinson, M.F., 1995. Interpolation of mean rainfall using thin plate smoothing splines. International Journal of Geographical Information Systems 9, 385—403.

Hutchinson, M.F., 2001. ANUSPLIN (version 4.2) user guide. The Australian National University, Centre for Resource and Environmental Studies, Canberra.

Kai, S., Müller-Samann, K., Hilger, T., Leihner, D., 2002. Erosion control and prediction in cassava based cropping systems in the Southern Andean Region of Colombia. In: Proceedings of the 12th ISCO Conference. 26—31 May 2002, Beijing, China, pp. 189—195.

Klik, A., Truman, C.C., 2003. What is a typical rainstorm? In: Gabriels D., Cornelis W. (Eds.), Proceedings of the International Symposium, 25 Years of Assessment of Erosion, 22—26 September 2003, Ghent, Belgium, pp. 93—98.

Michiels, P., Gabriels, D., 1996. Rain variability indices for the assessment of rainfall erosivity in the Mediterranean Region. In: Rubio, J.L., Calvo, A. (Eds.), Soil Degradation in Mediterranean Environments. Geoforma Ediciones, Logrono, 49—70.

Oliver, J.E., 1980. Monthly precipitation distribution: a comparative index. Professional Geographer 32, 300—309.

Renard, K.G., Freimund, J.R., 1994. Using monthly precipitation data to estimate the R-factor in the revised USLE. Journal of Hydrology 157, 287—306.

Wischmeier, W.H., Smith, D., 1978. Predicting rainfall erosion losses. A guide to conservation planning. Agriculture Handbook Number 537, USDA, Washington, DC.