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Analyzing the spatial variability of precipitation extremes along longitude and latitude, northwest Iran

Mohammad Arab Amiri[1,*], Mohammad S Mesgari[2]

[1]*Dept. of Geographic Information System, Faculty of Geodesy and Geomatics Eng., K. N. Toosi University of Technology, Tehran, IRAN*

[2] *Dept. of Geographic Information System, Faculty of Geodesy and Geomatics Eng., and Center of Excellence in Geospatial Information Technology (CEGIT), K. N. Toosi University of Technology, Tehran, IRAN*

**Corresponding author:mohamadamiri89@yahoo.com*

Abstract

Precipitation extremes can have significant impacts on the environment and human activities. The simple precipitation intensity index is one of the most commonly used extreme indices, which can represent the extreme precipitation characteristics in the desired time period. The main objective of this research is to realize a spatial analysis of precipitation extremes in northwest of Iran to investigate spatial trends along longitude and latitude in decadal time scale. Geo-referenced time series from 22 synoptic stations between the years 1991 and 2010 were used. Polynomial fit functions were used for analyzing the spatial variability of extreme precipitation. Besides, the significance of each individual trend surface model order was tested against the F ratio in order to select the most proper polynomial order for each period. The analyses of extreme precipitation identified significant spatial trends to the intercardinal directions, especially to the southwest. The results of the analysis of the magnitude of changes also showed increasing trends over the whole period.

Keywords: Geo-referenced time series; precipitation extremes; simple precipitation intensity index; spatial analysis; surface approximation.

1. Introduction

Climate changes have a severe influence on human society, the economy, ecosystems, agriculture, and the environment. Hence, modeling climate change has become one of the major research topics in contemporary climatology.

Climate extremes can have many impacts on the natural physical environment and human society (Tabari *et al*., 2014). Hence, studying the variability and changes in climate extremes is of great importance.

Climate of more than 80% of Iran was classified as semi-arid and arid; thus, the country experiences both droughts, as well as floods (Madani, 2014; Tabari *et al*., 2014). Previous studies over the northwestern regions of Iran showed a significant decreasing trend in precipitation (Golian *et al*., 2014; Some'e *et al*., 2012; Tabari & Talaee, 2011; Arab Amiri & Mesgari, 2016).

The majority of the previous studies have dealt with temporal analysis of long-term trends of climatological parameters and then interpolating the obtained variations across space (Arab Amiri *et al*., 2016). Estimating a continuous surface from several point samples is called surface reconstruction, and this could be implemented by either interpolation or approximation. Constructing a continuous surface from the samples is not free of error, and it may be desirable to find a surface that approximates the sampled data rather than requiring a surface that interpolates the data points. Surface approximation or surface fitting is like a regression problem, where the model is the surface representation and the data are the sampled points on the surface (Jain *et al*., 1995; Koç, 2016). Consequently, the spatial variability along latitude and longitude could be investigated directly by the approximated surface from the samples.

Bhowmik (2013) investigated the two-dimensional spatial trends along latitude and longitude, and the temporal distribution of the spatial trends of two climate parameters. However, the approximated surfaces were not sufficiently precise. In the present study, different-order polynomial functions are used to investigate the spatial distribution of simple precipitation index in northwest of Iran between the years 1991 and 2010.

2. Materials and methods

2.1.Study area and data

There are three provinces in the study area, including West Azerbaijan, East Azerbaijan and Ardabil. The study area is located in a geographic position between 43° 59’ E to 48° 55’ E longitude and 35° 54’ N to 39° 55’ N latitude, with a total area of about 109, 290 km^2 including Lake Urmia (Figure. 1). The study area also encompasses the rapidly drying Lake Urmia, which is entirely located in the northwestern corner of Iran.

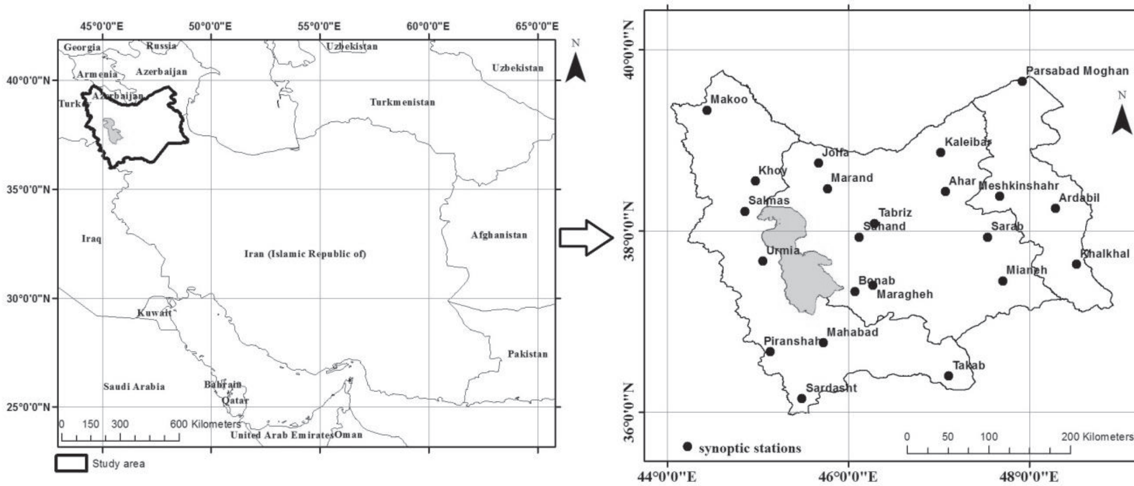

Fig. 1. The location of the study area and the stations located in the study area

We used time series of total monthly precipitation, and the number of wet days (>1mm per day) between the years 1991and 2010 from 22 synoptic stations, recorded by the Islamic Republic of Iran Meteorological Organization (IRIMO). The series comprised records of differing temporal lengths. Four homogeneity tests, including the standard normal homogeneity test (Alexandersson, 1986), the Buishand range test (Buishand, 1982), the Pettitt test (Pettit, 1979) and the Von Neumann ratio test (Von Neumann, 1941) were applied to the time series of the total precipitation amount on wet days and the number of wet days. Finally, the results showed that the series are sufficiently homogeneous and appropriate for variability analysis.

2.2.Methodological framework

2.2.1. Simple precipitation intensity index

Simple precipitation intensity index (SDII) is the ratio of annual total precipitation to the number of wet days (≥ 1 mm) (Peterson, 2005). SDII can be formulated as Equation (1) (Nakayama *et al*., 2012):

$$SDII_j = \frac{\sum_{w=1}^{W} RR_{wj}}{W} \tag{1}$$

Where RR_{wj} is the daily precipitation amount on wet days ($RR \geq 1$mm), and W represents the number of wet days in period j.

Different stations were used in each period, depending on the availability of data records. *SDII* was computed for each decade and for each station to analyze extreme precipitation variability in the study area between 1991 and 2010.

2.2.2. Spatial variations of SDII

The overall distribution of properties throughout space can be modelled by polynomial regression functions, which estimate the property value P_i at any location, based on the X_i,Y_i coordinates of this location. Polynomial regression functions can approximate nonlinear data by successively adding different powers of the dependent variables to the function (Barboux & Collet, 2012). A complete n-th degree polynomial in two dimensions can be expressed as Equation (2):

$$P_n(x,y) = \sum_{k=0}^{n} \beta_k x^i y^j\,, \quad i+j \leq k \tag{2}$$

where the constants β_k are the coefficients, x and y are the geographic coordinates, and n is the degree of the polynomial function.

Climate indices have significant correlations to geographic coordinates, especially to latitudes and longitudes (Bhowmik, 2013). The geographical coordinates were standardized in order to limit their unit of measurement and their influence on regression coefficient values (Barboux & Collet, 2012). To explain whether the regression function expresses a significant amount of the variance or not, significance tests should be conducted. Hence, the most significant polynomial regression function that best explains the distribution of sample values can be selected by computing the F ratio that expresses the proportion of the total variance taken into account by the polynomial regression function. The F ratio value is computed as follows (Equation 3) (Barboux & Collet, 2012):

$$F = \left(\frac{\%R^2}{Dfnum}\right) / \left(\frac{100 - \%R^2}{Dfden}\right) \tag{3}$$

where $\%R^2$ is the coefficient of determination of the fitted surface, Dfnum is degree of freedom associated with the regression function (degree of freedom of the model), which is equal to the number of coefficients in the function less one, and Dfden is degree of freedom associated with the residuals (degree of freedom of the error), which is equal to the number of observations (n) less number of coefficients. According to the *F* ratio, statistically significant surfaces at different confidence levels can be identified.

The extra contribution of the order *n+1* over order *n* can be expressed by the *F*-ratio, which compares the improvement of the fit with the increase in complexity of the fitting model (Davis, 2002). The *F*-ratio can be expressed as follows (Equation 4):

$$F = \frac{(\frac{SSE_1 - SSE_2}{p_2 - p_1})}{(\frac{SSE_2}{n - p_2})} \qquad (4)$$

where SSE_i is the sum of squared errors of prediction of the model i, p_i is the number of coefficients of the model i, and n is the data points to estimate parameters of both models from. The degrees of freedom for checking the significance are p_2-p_1 and $n-p_2$. When the *F* ratio values for the regression functions are computed, the significance of the order *n+1* against order *n* will be specified.

3. Results

Applying each individual regression function in each period, the F values are computed from the coefficients of determination (%R^2) and the degrees of freedom (DF) associated with the fitted surface (Df numerator) and its residuals (Df denominator). The significance of each regression function for each decade is presented in Table 1. The computed F values which are greater than their respective critical F value at the respective confidence level express a significant variation in the considered time period.

Table 1. The significance of each individual polynomial regression function in each period

Time Period	Number of observations (n)	Order of Regression function	Number of coefficients	%R^2	SSE $(mm.day^{-1})^2$	F ratio	Significance (%)
Decade 1 (1991-2000)	16	1	3	55.67	21.58	8.16	99
		2	6	91.12	4.32	20.52	99
		3	10	96.52	1.70	18.49	99
		4	15	98.83	0.57	6.03	-
Decade 2 (2001-2010)	17	1	3	40.50	33.52	4.76	95
		2	6	82.53	9.84	10.39	99
		3	10	97.35	1.50	28.57	99
		4	15	98.85	0.65	12.28	90

The significance of contribution for selecting a regression function withthe order *n+1* over order *n* is expressed by the F ratio value which is presented in Table 2. From Table 1 and Table 2, it was realized that the 2nd order regression function could be the most proper model explaining around 91.12% of overall variations at 99% confidence level over the first decade (1991-2000). Besides, the 3rd order function would be the most appropriate by approximating 97.35% of the point distribution at 99% confidence level for the second decade (2001-2010).

Table 2. The significance of the order n+1 against order n

Period	Number of observations (n)	Order increase	SSE_1 $(mm.day^{-1})2$	SSE_2 $(mm.day^{-1})2$	Δ%R^2	Δ Coef (p_2-p_1)	$n-p_2$	F ratio	Significance (%)
Decade 1 (1991-2000)	16	Order 1 to 2	21.68	4.32	35.45	3	10	13.32	99
		Order 2 to 3	4.32	1.7	5.4	4	6	2.31	-
		Order 3 to 4	1.7	0.57	2.31	5	1	0.4	-
Decade 2 (2001-2010)	17	Order 1 to 2	33.52	9.84	42.03	3	11	8.82	99
		Order 2 to 3	9.84	1.5	14.82	4	7	9.73	99
		Order 3 to 4	1.5	0.65	1.5	5	2	0.52	-

The rate of change of regression functions in the longitude and latitude directions could be investigated by the partial derivatives of the most proper polynomial function with respect to x and y in each period. The spatial patterns of SDII variations in each decade along longitude and latitude are shown in Figure. 2.

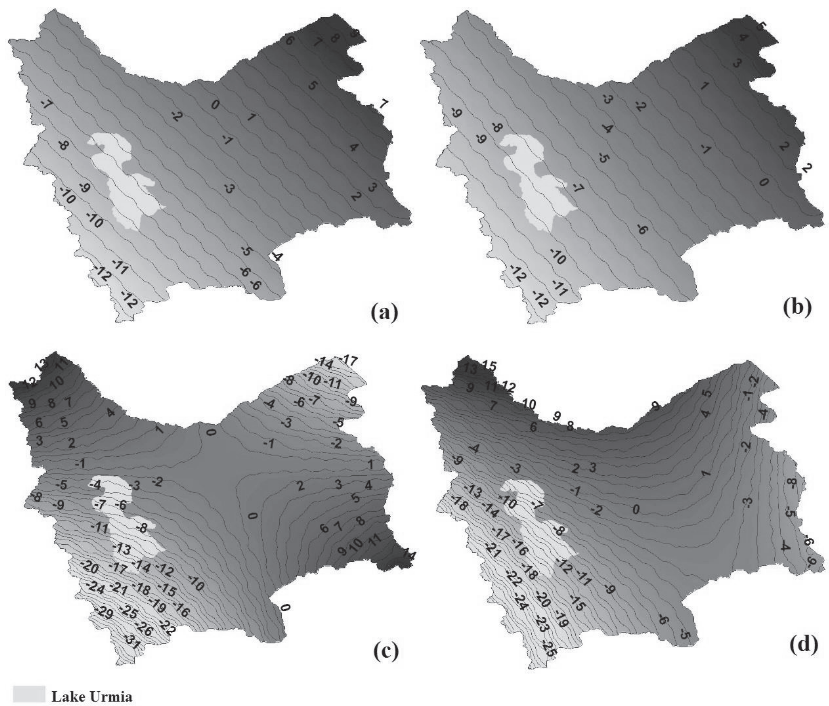

Fig. 2. The variations of SDII in: (a) decade 1 along longitude, (b) decade 1 along latitude, (c) decade 2 along longitude, and (d) decade 2 along latitude

Consider $dz = (\frac{\partial z}{\partial x}, \frac{\partial z}{\partial y})$ as a vector, which represents the rate of changes in the latitude and longitude directions at the point *(x,y)*, then the Euclidean norm of the function could be computed as follows (Equation 5):

$$\|dz\| := \sqrt{(\frac{\partial z}{\partial x})^2 + (\frac{\partial z}{\partial y})^2} \quad (5)$$

where ||dz|| is the magnitude of SDII variations at the point *(x,y)*, and could be obtained by replacing the 2D coordinates of each point (Figure. 3). Note that the Euclidean norm of the function is only the quantity of variations and is always positive.

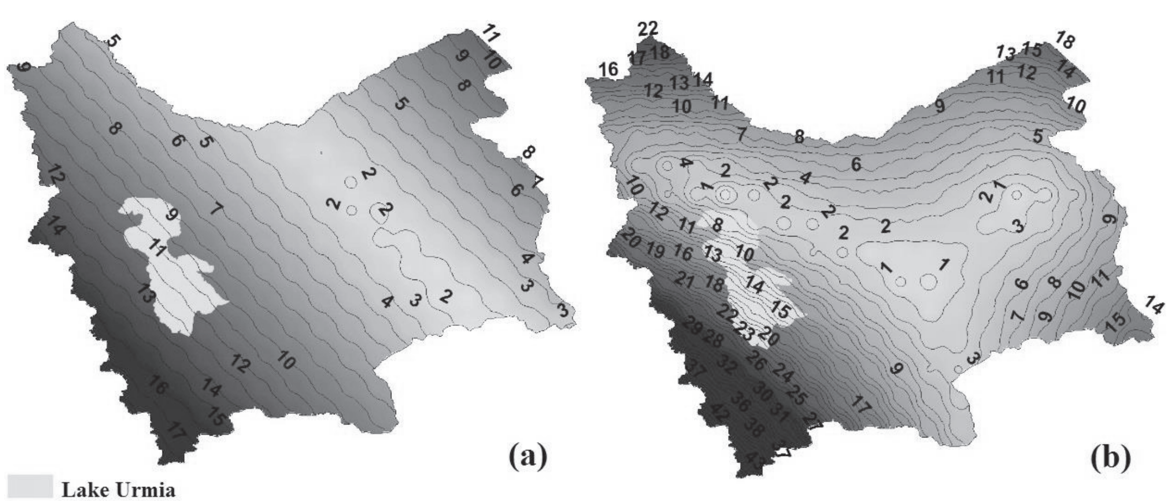

Fig. 3. The magnitude of spatial variations of SDII in: (a) decade 1, and (b) decade 2

4. Discussion

4.1.Spatial variability of extreme precipitation

Figure. 2 shows that the trends in the longitude direction in decade 1 are significant with a maximum increase of 9 $mm.day^{-1}.dd^{-1}$ in the northeastern part and a maximum decline of about -12 $mm.day^{-1}.dd^{-1}$ in the southwestern part. In addition, the trends in decade 2 show that the maximum of positive variations reaches to about 14 $mm.day^{-1}.dd^{-1}$ in northwest and southeast, and the highest amounts of negative variations reach to -16 $mm.day^{-1}.dd^{-1}$ and -32 $mm.day^{-1}.dd^{-1}$ in northeast and southwest, respectively.

The variability of SDII along latitude is also shown in Figure. 2. The latitudinal and longitudinal variations are quite similar for decade 1; and only the magnitudes of latitudinal positive changes were lower in the northeastern part reaching to about 5 $mm.day^{-1}.dd^{-1}$. While, the changes are different in latitude and longitude directions in the east in decade 2. The maximum variations in northeastern part reaches to about -4 $mm.day^{-1}$.dd-1 in y direction, while the maximum variability reaches to about -17 $mm.day^{-1}.dd^{-1}$ in x direction. Moreover, in the southeastern part, the trends were negative reaching -7 $mm.day^{-1}.dd^{-1}$, although the longitudinal variations were positive.

In summary, the studied area could be divided into 4 distinct regions with respect to intercardinal directions. There were negative trends in the southwestern part, which were increasing during the whole period; i.e. the number of days with extreme rainfalls was decreasing throughout the 20 years from 1991 to 2010. The southern part of Lake Urmia, which is drying faster than northern part, is also located in the southwestern part of the studied area. The trends were positive in the northeastern part in the first 10 years, while the variations were negative in the last 10 years; the decreasing trend also continued to be more negative in recent years (Golian *et al*., 2014; Some'e *et al*., 2012; Tabari & Talaee, 2011). There is no specific trend in southeast; and the variations fluctuate in each direction throughout the considered period. Furthermore, it is evident that the latitudinal and longitudinal variations in the northwest were increasing during the whole period.

4.2.The magnitude of the total variability

Having computed the Euclidean norm of the regression function in each point, the magnitude of changes was obtained in each decade (Figure. 3). Generally, there are increasing trends in the magnitude of changes during the years 1991-2010 throughout the study area. It is also remarkable that the least changes took place in the central parts of the region. Whereas, the greatest variations were observed at the inter-cardinal directions. To put it simply, the highest changes were seen in the southwest, which encountered with negative trends in both longitudinal and latitudinal directions in extreme precipitation.

5. Conclusion

The extreme precipitation was investigated in northwest of Iran using monthly precipitation time series from 22 synoptic stations during the period of 1991–2010. In this study, SDII was considered as an index describing extreme precipitation. The spatial variability of extreme rainfall was analyzed by applying the polynomial regression functions to the data. The most proper order of regression functions for each period was identified by means of the results of the statistical tests. The partial derivatives of the most appropriate functions in each period were used to describe the latitudinal and longitudinal variations of SDII. The magnitude of spatial variations was also obtained for each period.

According to the produced surfaces, which show spatial variability of SDII, four specific regions were identified in intercardinal directions as the changes differ from one period to another. During the whole period, negative and positive trends were identified in southwest and northwest, respectively. Trends of extreme rainfall variability were also positive and negative in the first and second halves of the whole considered period in the northeastern region. Besides, in the southeast of the study area, the spatial variability of the SDII varied from one period to another. In short, regions in intercardinal directions showed different trends for the spatial variability of SDII along latitude and longitude.

From the present study, it was also realized that the magnitude of changes in extreme precipitation rose gradually from 1991 through to 2010 across the study area. The greatest variability in SDII was observed in the southwestern regions of the studied area, which had the largest negative trends in SDII variability. It was also concluded that stations with the highest values of SDII were located in the southwest of the region. Therefore, since parts of drying Lake Urmia are located in this region, more studies should be carried out in the southwestern part to investigate relationships between extreme precipitations and drying trend of lake Urmia.

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تحليل التباين المكاني للهطول الشديد للأمطار عبر خطوط الطول والعرض، شمال غرب إيران

محمد عرب أميري[1،2] ، محمد مسغري[2]

[1] قسم نظم المعلومات الجغرافية، كلية الهندسة الجيوديسية والجيوماتكس، جامعة K. N. توسي للتكنولوجيا، طهران، إيران

[2] قسم نظم المعلومات الجغرافية، كلية الهندسة الجيوديسية والجيوماتكس، ومركز التميز في تكنولوجيا المعلومات الجغرافية المكانية، جامعة K. N. توسي للتكنولوجيا، طهران، إيران

*mohamadamiri89@yahoo.com

خلاصة

يمكن أن يكون للهطول الشديد للأمطار تأثيرات كبيرة على البيئة والأنشطة البشرية. فمؤشر كثافة الهطول القليل للأمطار هو أحد المؤشرات الأكثر استخداماً، والذي يمكن أن يمثل خصائص الهطول الشديد للأمطار في الفترة الزمنية المطلوبة. والهدف الرئيسي من هذا البحث هو إجراء تحليل مكاني للأمطار الشديدة في شمال غرب إيران، لبحث الاتجاهات المكانية عبر خطوط الطول والعرض في نطاق زمني عقدي. واستُخدمت السلاسل الزمنية ذات المرجعية الجغرافية من إجمالي 22 محطة بين عامي 1991 و 2010. واستُخدمت دوال تناسب متعددة الحدود لتحليل التباين المكاني للهطول الشديد للأمطار. إلى جانب ذلك، تم اختبار أهمية درجة كل نموذج سطح للاتجاه مقابل نسبة F من أجل تحديد درجة متعدد الحدود الأكثر ملائمة لكل فترة. وحددت تحليلات الهطول الشديد للأمطار اتجاهات مكانية هامة نحو intercardinal، وخاصةً الجنوب الغربي. وأظهرت نتائج تحليل حجم التغيرات كذلك اتجاهات متزايدة طوال الفترة بأكملها.