



The prediction of spatial and temporal distribution of precipitation regime in Iran: the case of Fars province

Saadoun Salimi¹ · Saeed Balyani¹ · Sayed Asaad Hosseini² · Seyed Erfan Momenpour³

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Abstract

Precipitation regime and its spatial and temporal distribution are essential requirements of environmental planning. Precipitation Concentration Index (PCI) and geographical weight regression method are two practical methods for the prediction of the temporal and spatial distribution of precipitation variables. For this purpose, the precipitation regime data for 13 synoptic stations in Fars province in Iran were used since their foundation in 1944. Then, the data were interpolated using Inverse Distance Weighting (IDW) method and precipitation pixels were prepared corresponding to the Digital Elevation Model (DEM), slope and aspect. The results of the study showed that the precipitation regime of the northern, northwest, and western parts of Fars province with PCI values of 13–20 with a maximum rainfall in winter was different from that of the southern and eastern parts of the studied area. In addition, the PCI values higher than 22 ($PCI > 22$) in the southwestern and eastern parts of the region suggested significant changes of rainfall throughout the year. Summer is the dry season of the area, and except for a very small part of southern parts of the province, the other areas were without rainfall. The results of Geographically Weighted Regression (GWR) also indicated that the prediction of precipitation regime with topographic elements shows much better results than the Ordinary Least Squares (OLS) regression, in a way that the relationship between altitude and rainfall in the western, northwestern, and central parts of the province were positive and significant, and the areas of eastern parts of Fars province showed a negative relationship in terms of topographic elements (aspect and altitude). Finally, the results of the prediction of GWR model showed that the mentioned model was able to assess more than 80% of the existing relationship between observe and predict the monthly precipitation amount based on the studied spatial factors successfully.

Keywords Fars province · Precipitation prediction · Precipitation concentration index (PCI) · GWR · OLS

Introduction

Due to their huge impact on the other factors and especially on the human actions, temperature and precipitation have a special importance among climate elements as most of the effects of climatic changes on the planet Earth are centered on these two parameters (Tabatabayi and Hosseini 2003). Any plan or design for water regarding the water resources in drainage basins seems important based on hydrologic data analysis, as one of the most important climate phenomena,

precipitation is no exception, and researchers have paid considerable attention to it (Ahmadzadeh 2005).

Iran is a country whose climate is considered to be dry and semi-dry in comparison with other parts of the world, with an average annual rainfall of about one-third of the average rainfall of dry lands, and less than one-third of the average precipitation of the Earth. On the other hand, the evaporation is three times more than the evaporation of the Earth's dry lands (Jahanbakhsh et al. 2001). Therefore, this parameter must be evaluated in various regions due to its importance. The prediction of precipitation is highly important for countries whose economies are dependent on agriculture. By predicting the precipitation at the appropriate time, it is possible to deal with drought, and reduce the subsequent damages. Precipitation plays an important role in the climate of various regions in a way that it is both influenced by the climate system and influences it. This mutual influence becomes more explicit along with other climate factors

✉ Saeed Balyani
ybalyani52@yahoo.com

¹ Kharazmi University, Tehran, Iran

² Mohaqheqh Ardabili University, Ardabil, Iran

³ Tehran University, Tehran, Iran

and elements; thus adding to the complexity of the subject. One of the most effective ways of understanding these behavioral complexities is to investigate, trace, explore, analyze and interpret the data through modeling. Using statistical models is one of the ways of modeling which has highly been considered so far. In this regard, regression models are the commonly used statistical models dealing with recreating, assessing, and predicting variables in addition to specifying the existing relationships between variables. These models have a superb performance both for temporal and spatial variety analysis (Asakareh and Seifipour 2013). Concerning the investigation of the spatial scattering of climatic elements based on multivariate regression, the studies done by Hansen and Lebedeff (1987) and Jones et al. (1986) can be mentioned. Brunson et al. (2001) examined the relationship between average annual rainfall and altitude in the United Kingdom based on Geographically Weighted Regression (GWR) method. The results of their study showed that precipitation increase with altitude increase (height coefficients) varies from about 4.5 mm/m to about 0 mm/m. Gao et al. (2006) investigated the ability to predict and the performance of three regression models, including ordinary linear regression (OLR) model, prior probability model, and GWR. The results showed the superiority of GWR model estimates. Propastin et al. (2008) studied the relationship between vegetation and rainfall in Indonesia using GWR regression. The results revealed the presence of spatial non-stationary for the vegetation-precipitation relationship. They also showed that the mentioned regression minimized the spatially auto-correlated errors. Using spatial auto-correlation indices, Dai et al. (2010) analyzed the urban surface temperature field in Shanghai, China, spatially and temporally.

In another study, Balyani et al. (2017) examined the spatial analyze of the Iran's annual temperature using OLS model. The results showed the maximum and minimum percentage of distribution of Iran's annual temperature is in the range of 90% and above in the south, southwest, and southeast, and about 50% in the northwest and west of Iran, and Iran's annual temperature have a cluster pattern with a high temperature and a cluster pattern with low temperature. In OLS method, longitude and spatial lag method had a positive and direct relationship, but latitude was positively and directly related to the annual temperature in the spatial lag method. However, the results of spatial regressions showed that spatial error is an efficient model to predict Iran's annual temperature (Balyani et al. 2017).

Buba et al. (2017) made a spatio-temporal analysis of rainfall variations in Savanna Guinea, Nigeria, using mean, standard deviation, coefficient of variation, as well as other inferential statistics such as linear regression and standardized anomaly. The analyzed variables include the monthly and annual precipitation and the number of rainy days, and geostatistical analysis was used for spatial analysis in the

Geographic Information System (GIS). The highest rainy days diversity factor in Northern Guinea is 37% at Yola, and this index is 19.12% in Ilorin, Southern Guinea. The coefficient of determination (R^2) for annual rainfall and rainy days were 66, 56, 63, 73 and 41 percent, for Ibi, Abuja, Lokoja, Makurdi and Lafia, respectively. Overall, the findings showed that time variations were observed in the rainfall (Buba et al. 2017).

Vinay Doranalu et al. (2017) also conducted a study on the spatio-temporal variability of rainfall in Western Ghats and the coastal region of Karnataka, using high-resolution gridded data. The analysis of the findings of the study shows that an increase in seasonal precipitation trend in the southern coastal plains and the western region during time (MAM), and a decline trend in the Monsoon period for the southern coastal plains (JJAS). The daily intensity index of precipitation during monsoon shows an increasing trend in the northern plains and a decreasing one in the medium precipitation. It also shows that the reaction of different regions of Karnataka varies in the process of precipitation, especially in the plains, which is completely different from the higher elevated Ghat region (Vinaly Donaralo et al. 2017).

Spatio-temporal variations on many elements have been studied. In a study done by Mansouri Daneshvar and Abadi (2017) Nitrogen Dioxide was analyzed in the Middle East from 2005 to 2014, and to illustrate distribution in Nitrogen oxide satellite-based data from the ozone monitoring instrument (OMI) was employed, according to which the main areas producing nitrogen are Tehran-Karaj (Iran), Dubai-Ajman (UAE), Kuwait (Kuwait), Riyadh (KSA), Dammam (KSA), Istanbul-Izmit (Turkey), Doha-Rayyan (Qatar), Manama (Bahrain), Cairo (Egypt), Isfahan (Iran), Lahore (Pakistan), Tashkent (Uzbekistan), Baghdad (Iraq) and Beirut (Lebanon). The results also showed that remotely sensed data can be used to determine the temporal and spatial variations of NO_2 concentration.

Using spatiotemporal analysis, Keshtkar and Voiget (2016) attempted to predict the changes of the land in Germany from 2020 to 2050, and applied Markov chain model. The results of their study showed that the forests and rural areas are rapidly changing into urban areas, and it is essential that government officials settle this issue through sustainable development (Keshtkar and Voiget 2016).

Alijani et al. (2013) conducted a spatial analysis of annual precipitation using Moran's I statistic and G^* statistic, the results of which showed a spatial cluster pattern of rainfall in Iran, and high precipitation and spatial auto-correlation were found in the north and northwest belt of Iran on the Zagros axis to the north of Fars province. Balyani et al. (2016) attempted to model the relationships between altitude, longitude, and latitude parameters and precipitation using Moran's I and local statistics and showed that the annual rainfall of Khuzestan province follows a cluster

pattern. Aifeng and Zhou (2016) investigated the accuracy of daily and monthly scale tropical rainfall measuring in the Qaidam basin in China. They applied GWR to estimate the rainfall spatial distribution of measuring the error of altitude, latitude, and longitude and illustrated that GWR model presents a better estimation of tropical areas precipitation. Mahmoodi and Alijani (2013) investigated the relationship between annual and seasonal rainfall and climate factors in Kurdistan province using multivariate regression model. The results of their study showed that combining the two variables of latitude and longitude explains 66 and 46% of spatial variations of precipitation in autumn and spring precipitation, respectively. Therefore, due to the importance of this research, an attempt was made to predict the spatial and temporal distribution of precipitation regime in Fars province in Iran using GWR and OLS.

Data and methods

The case studied in this research is Fars province in the southwest of Iran (Fig. 1). The information of 13 synoptic stations of the region was applied for spatial and temporal distribution of precipitation regime since their foundation until the year 2014.

In order to zone the precipitation regime in the area, inverse distance weighting (IDW) interpolation method was applied.

In this regard, the annual and monthly rainfall regime and Precipitation Concentration Index were drawn on a map with an area of 7 × 7 km and of 2505 pixels. The grid codes related to precipitation values were expanded on the digital elevation model map with a resolution of 90 × 90 m derived from the Aster satellite sensor images. Then, using geographic information system (GIS) abilities, grid codes related to altitude, slope, and aspect values were called by the Sample command to the annual and monthly precipitation base of Fars province. In this regard, 2505 annual and monthly (November, December, January, February, April, March and May) pixels corresponding to 2505 pixels of topographic elements (altitude, slope, and aspect) were evaluated to the spatial prediction of rainfall corresponding to the mentioned elements using spatial regression. In order to illuminate the precipitation distribution throughout various months, the PCI of the stations were calculated. This index, which was introduced in 1980 by Oliver, and was recently modified and applied by De Luis et al. (2000, 2001), in fact, assesses the variations in rainfall during the year or the distribution of rainfall throughout the year. It. In the present study, the modified form of this index shown in the following equation was used.

$$PCI = 100 \frac{\sum_{i=1}^{12} P_i^2}{\left(\sum_{i=1}^{12} P_i\right)^2}$$

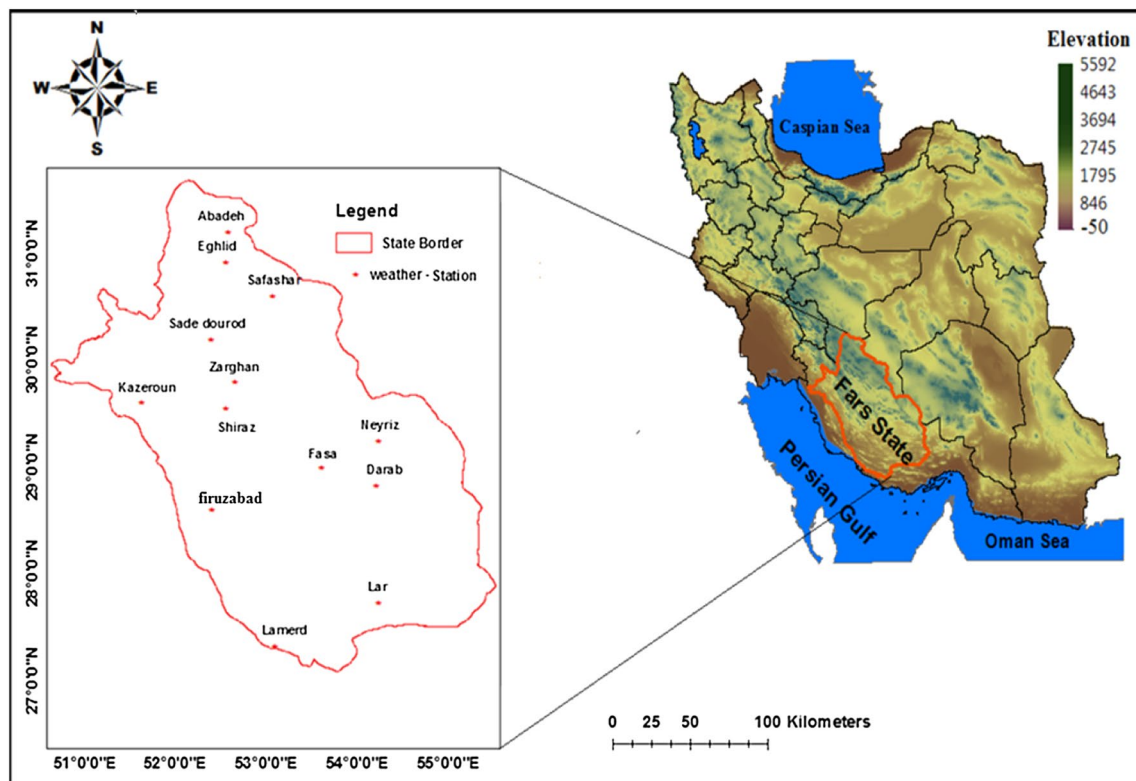


Fig. 1 geographical location of the studied area

Where P_i is the precipitation of the i th month of each station. PCI indicates how the monthly precipitation is distributed throughout the year. The dividing range of this index is from 0 to 100. Values less than 10 ($CPI < 10$) represent a uniform distribution of rainfall in all the months, and a value of 100 ($PCI = 100$) indicates the total concentration of annual precipitation in a particular month. Values of CPI between 11 and 20 ($11 < PCI < 20$) show that precipitation has a determined regime, and values more than 20 represent a severe variation of rainfall and precipitation concentration in a few particular months throughout the whole year (De Luis et al. 2000, 2001). In order to spatially predict the precipitation variation by topographic factors, the geographical weight regression method was applied. To understand the concept of regression, suppose that a variable such as Y has been observed over time or across different units and the corresponding data has been obtained, and now, we aim to explain the variations of this variable. For this purpose, variable or variables which are able to explain these variations are to be selected. Suppose:

$$Y = f(x_{1,t}, \dots, x_{k,t})$$

This is a mathematical model as it only expresses the mathematical relationship between the dependent variable (Y) and independent variable (x). If f is a linear function of x_1 to x_k :

$$Y_t = \beta_0 + \beta_1 x_{1,t} + \dots + \beta_k x_{k,t}$$

Then it is called a linear mathematical model. Selecting the variables which explain the variations depend on the applied theories or model maker's individual perceptions (Balyani and Hakimdoost 2014). Geographical weight regression is a technique used for descriptive analyses of spatial statistics. In ordinary regressions, it is assumed that the relationship which is to be modeled between a dependent and independent variable is uniform throughout the study domain. However, in many cases, this assumption is not correct (Asgari 2011). Different solutions are provided for such cases. Geographical weight regression is one of the most effective and simple methods to conduct these analyses, which is a statistical local approach based on the geographical law of nearness relationship (Asakareh 2012). For ordinary regression in which there is only one explanatory variable, the following equation can be written:

$$Y = \beta_0 + \beta_1 x_1 + \varepsilon$$

Where Y is the dependent variable, x_1 is the independent variable, β_0 and β_1 are coefficients which are to be estimated, and ε is the error term which is assumed to be distributed normally. In this regression, it is also assumed that the coefficients are uniform throughout the study domain. Therefore, if any geographical fluctuations exist in relationships, they should be reflected in each error. Is there a way to calculate

these relationships without being reflected in each error? Assume that there are a number of points with the coordinates of (U, V) in the study domain. In this case, the following model can be expanded for it:

$$Y(U, V)_1 = \beta_0(U, V)_1 + \beta_1 X_1(U, V)_1 + \varepsilon(U, V)_1$$

This model can be fitted by the minimum number of squares to estimate the locus of (U, V) coefficients through geographical weight regression. The weight is adjusted in such a way that the closer data to (U, V) has more weight than the farther data. Usually (U, V) is the place where data has been collected. This allows calculating the regression coefficients for all the points individually. Finally, the estimated coefficients can be illustrated on the map using geographical weight regression.

Results and discussion

General characteristics of precipitation regime in Fars province

Figure 2a, b illustrates the zoning and annual PCI of Fars province located in the southwest of Iran, respectively. As can be seen, rainfall is not uniformly distributed in Fars, and generally, precipitation in this province is in the range of 137 to 474 mm. In addition, the stations located in the north, west and northwest of the province such as Doroodzan Dam, Kazeroon and Eqlid stations have enough precipitation in the province. For example, regions in the east, south, and southwest of the province and around the Persian Gulf, including Lamerd station in the south and Neyriz station in the east have the lowest precipitation in the province. On the other hand, as can be seen in Fig. 2a, an appropriate amount of precipitation in other parts along with the proper time of distribution of rainfall during the year have created a favorable climate for irrigated and non-irrigated cultivation. Figure 2b shows the PCI conditions in Fars province. The presence of high mountainous air masses in the western part of Fars province, known as the Fars Zagros, in zones with 350 mm annual rainfall and more which are often passing the Zagros Mountains, acknowledges this fact. Since spatial distribution of rainfall during the year is one of the key issues in the field of water supply in different regions, an attempt was made to calculate and analyze the PCI values in this study. So, PCI values of all the stations were first calculated, then the variations of precipitation were analyzed using these calculated values. As shown in Fig. 2b, PCI values oscillate in the range of 13 to 22. As mentioned above, PCI values less than 10 ($PCI < 10$) represent a uniform distribution of rainfall in all the months, and a value of 100 ($PCI = 100$) indicates the total concentration of annual precipitation in a particular month. Values of PCI between 11 and 20 ($11 < PCI < 20$)

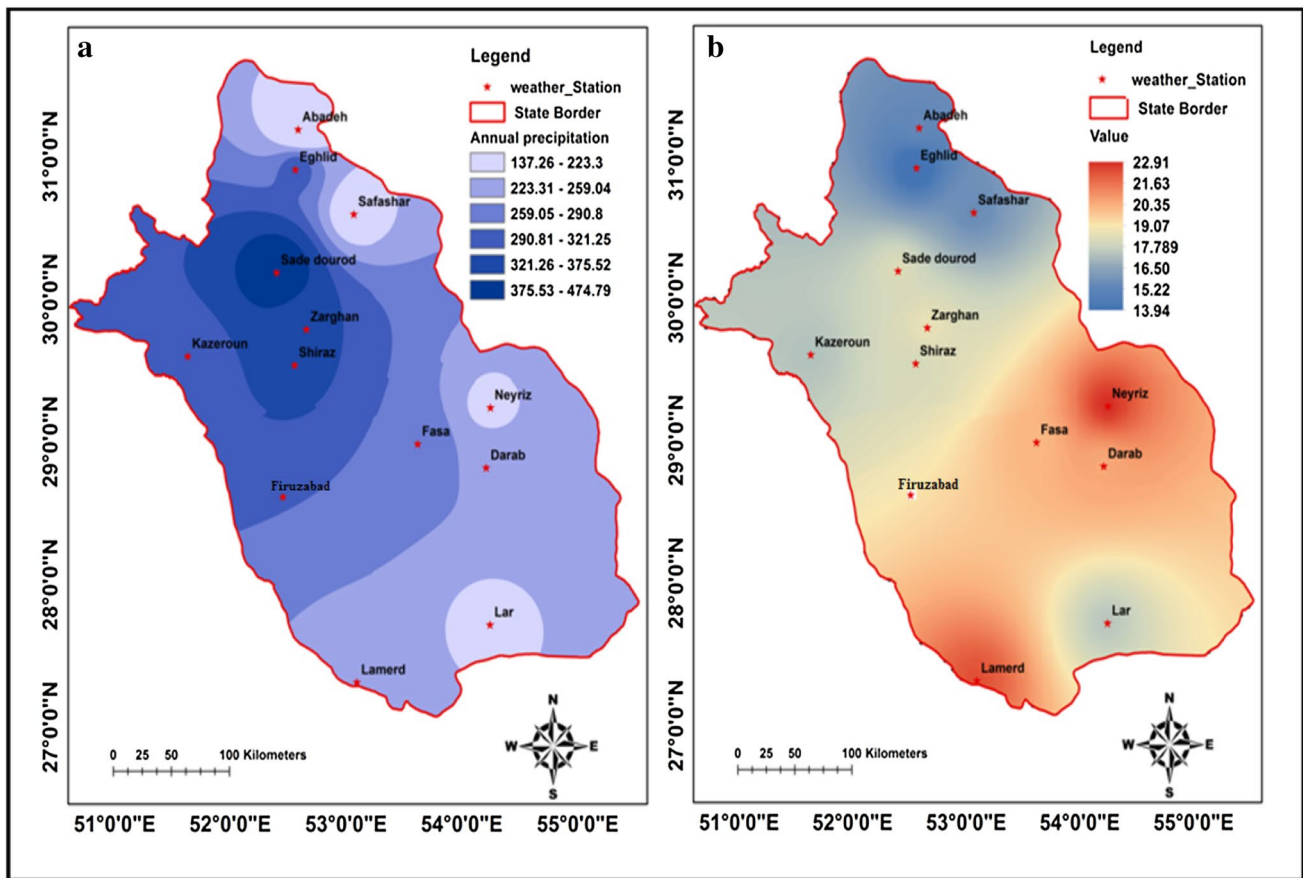


Fig. 2 a Spatial distribution of annual precipitation. b Precipitation concentration index (PCI) in Fars province

show that precipitation has a determined regime and values more than 20 represent a severe variation of rainfall and precipitation concentration in a few particular months throughout the year (De Luis et al. 2000, 2001). Thus, the calculated PCI values show that precipitation does not occur in all seasons, indicating a seasonal regime and severe variations in some areas throughout the year. In other words, the temporal precipitation distribution is distributed in two seasons or in a few particular months throughout the year, so regions with high concentration of PCI face a crisis to carry out agricultural operations. The PCI values in the north, west, and northwest of the province are in a better condition, and these values show that precipitation regime throughout the year is distributed in most months of the year. According to Fig. 2b, the PCI shows values equal to and more than 20. In this regard, northern, western, and central parts of the province can be mentioned as strategic areas for cultivation of agricultural products. These regions have normal values of PCI during the year, and have the highest amount of precipitation. The PCI of Fars province confirmed by researchers is carried out by Masoudian and Qayour (2008). They asserted that precipitation in northern parts of the country is more uniform than central and southern regions. Basically, the

rainfall amount can be explained by the three spatial factors altitude, slope and aspect, and the role of altitude coefficient is known as one of the influential factors on rainfall and its variation in each location. According to the PCI results, it was found that the distribution of precipitation regime in Fars province was seasonal and determined, and its variations during the year were severe. Therefore, in the present study, the geographic regression method is used to spatially predict the amount of precipitation in the months with precipitation in Fars province using topographical factors.

Spatial distribution using factors (topography)

Table 1 shows correlation coefficients of annual and monthly precipitation in Fars province. As can be seen, the relationship between monthly rainfall amount and average annual rainfall is significant for the months in which precipitation occurs and these months have a high correlation. According to table (1), the maximum relationship between monthly and annual rainfall (2505 precipitation pixels) occurs in February and then in December, January, November, and March, respectively. In fact, the total annual precipitation in Fars province receives its highest rainfall in these months. This

Table 1 Correlation matrix of yearly and monthly precipitation on 2505 pixels in Fars province

Correlation matrix	Rainfall	NOV	DEC	JAN	FEB	MAR	APR	MAY
Rainfall	1	0.83 ^a	0.86 ^a	0.84 ^a	0.95 ^a	0.83 ^a	0.69 ^a	0.49 ^a
NOV	0.83 ^a	1	0.61 ^a	0.53 ^a	0.79 ^a	0.55 ^a	0.83 ^a	0.73 ^a
DEC	0.86 ^a	0.61 ^a	1	0.89 ^a	0.78 ^a	0.59 ^a	0.34 ^a	0.24 ^a
JAN	0.84 ^a	0.53 ^a	0.89 ^a	1	0.69 ^a	0.72 ^a	0.29 ^a	0.10 ^a
FEB	0.95 ^a	0.79 ^a	0.78 ^a	0.69 ^a	1	0.76 ^a	0.74 ^a	0.49 ^a
MAR	0.83 ^a	0.55 ^a	0.59 ^a	0.72 ^a	0.76 ^a	1	0.59 ^a	0.40 ^a
APR	0.69 ^a	0.83 ^a	0.34 ^a	0.29 ^a	0.742 ^a	0.59 ^a	1	0.81 ^a
MAY	0.49 ^a	0.73 ^a	0.24 ^a	0.10 ^a	0.49 ^a	0.40 ^a	0.81 ^a	1

^aCorrelation is significant at the 0.01 level (2-tailed)

situation indicates a specific seasonal regime of precipitation in Fars province.

The relationship between annual precipitation and spatial factors indicates that the relationship between precipitation and altitude is direct and significant. In other words, the precipitation increases by 1 mm with an altitude increase of one unit. Similarly, the relationship between precipitation and slope is also direct, and precipitation increases by 0.19 mm with the increase of the slope by one unit. However, there is a negative relationship between rainfall and aspect. In other words, precipitation will decrease by positive variation in aspect; that is, precipitation decreases by 0.008 mm by the variation of aspect. The relationship between the values of statistic *t* and altitude and the slope is significant; however, this relationship is not significant for aspect (Table 2).

As it can be seen in Fig. 3a, b, the ordinary regression is only able to explain 0.041% of spatial precipitation variance. The geographical weight regression, on the other hand, is capable of explaining 0.88% of spatial precipitation variance.

Figures 4 and 5 illustrate spatial prediction and R^2 value maps in geographical weight regression model. As can be observed, spatial factors estimate an amount of precipitation closer to its real values in northeastern regions and a narrow strip of the west to south-west. In fact, it is possible to estimate spatial (topographic) precipitation variations by providing spatial and R^2 value maps.

In ordinary multivariate linear regression, only an overview of the relationship between precipitation and spatial factors can be obtained. Therefore, it is not able to get

effective coefficients maps of precipitation amount. In order to acquire a thorough knowledge and raise the validity of the study, geographical weight regression method was examined to spatially evaluate monthly rainfall. The results indicate that the spatial altitude factor has a positive relationship with monthly precipitation in northern and western halves nearby Zagros Mountains for most of the months in the year. However, this relationship is negative with less value of coefficients for the southern half of the province in most of the months (Fig. 6). Slope and aspect factors also have the highest values of coefficient and positive relationship with monthly precipitation and their coefficients with positive to negative values and are scattered throughout the province. However, their relationship is positive and coefficient values are higher in the north and west (Figs. 7, 8). Slope factor with the value of 0.46 is such an influential factor among the spatial factors that by holding other variables constant, this factor has a significant effect on monthly rainfall increase in the region. As a result, it can be seen that spatial factors in the wind-facing mountain ranges have a positive effect on the monthly rainfall of the area.

One of the interesting achievements of the spatial statistics methods in GWR model compared to ordinary regression is their ability to determine a coefficient for each point and provide the estimated maps resulted by the model (Balyani 2016). Figure 9 illustrates the distribution map of R^2 spatial coefficients and residual values in GWR model. As can be seen, high values of R^2 happened in western and northern parts of the province with high values of coefficients, representing a good estimation of the model in estimating

Table 2 Multivariate linear prediction regression of yearly precipitation using factors (topography)

Coefficients model ^a	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error			
1 (Constant)	253.07	2.66		94.97	0.000
Altitude	0.012	0.001	0.173	8.717	0.000
slop	0.19	0.048	0.080	4.017	0.000
Aspect	−0.008	0.008	−0.020	−1.004	0.316

Fig. 3 Scatter plot of real values and estimated values of ordinary and geographical weight regression

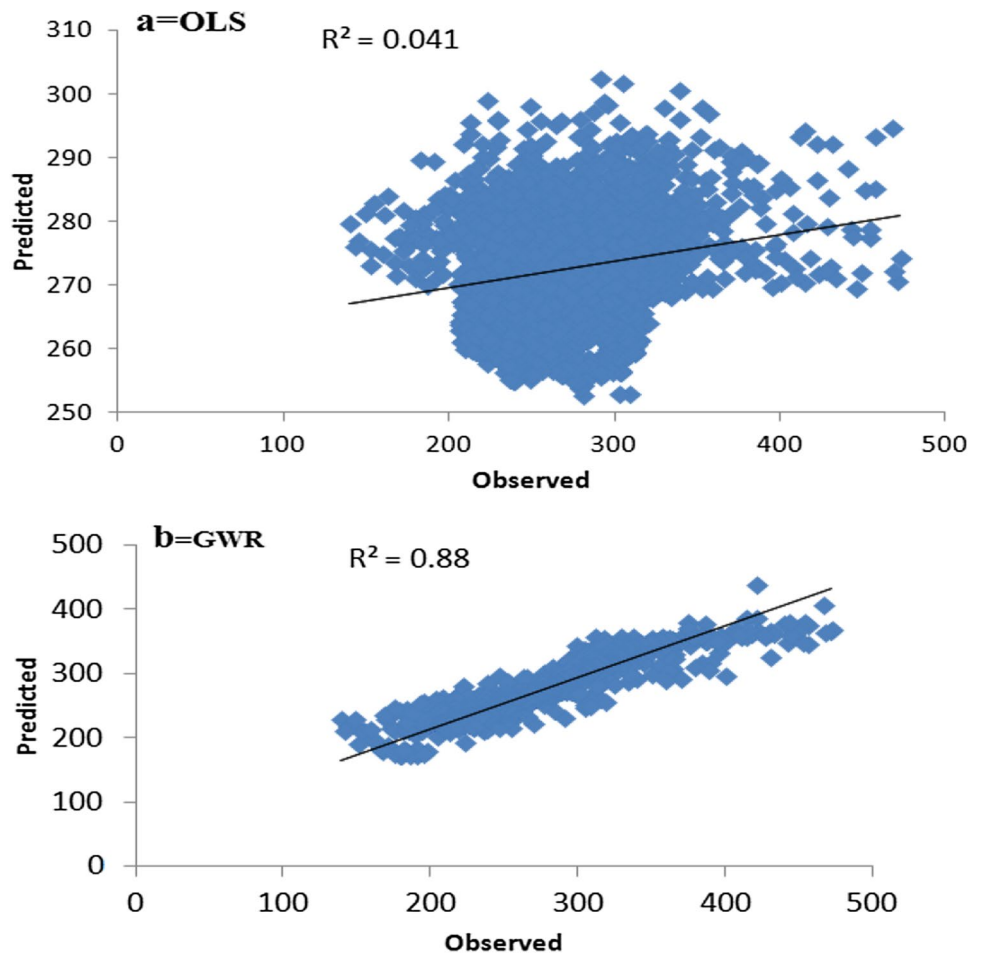


Fig. 4 Spatial prediction of annual precipitation using spatial factors in geographical weight regression

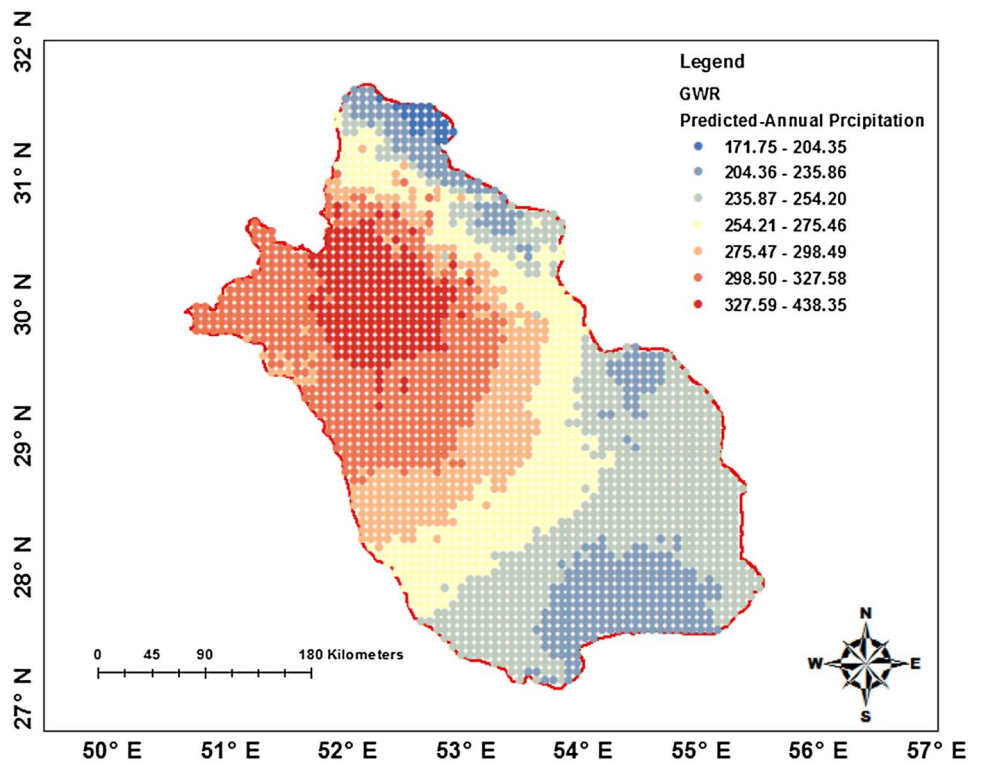


Fig. 5 R^2 spatial map of annual precipitation in Fars province using spatial factors in geographical weight regression

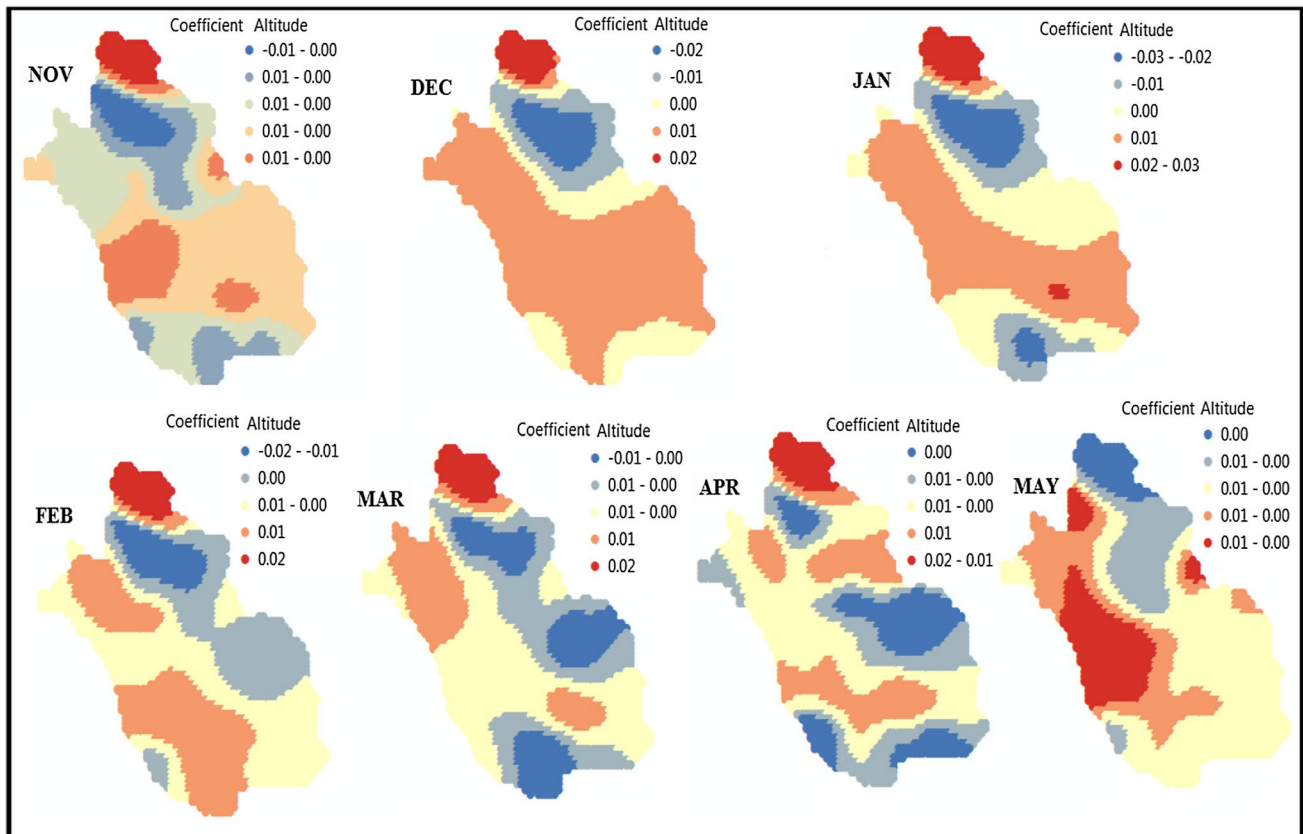
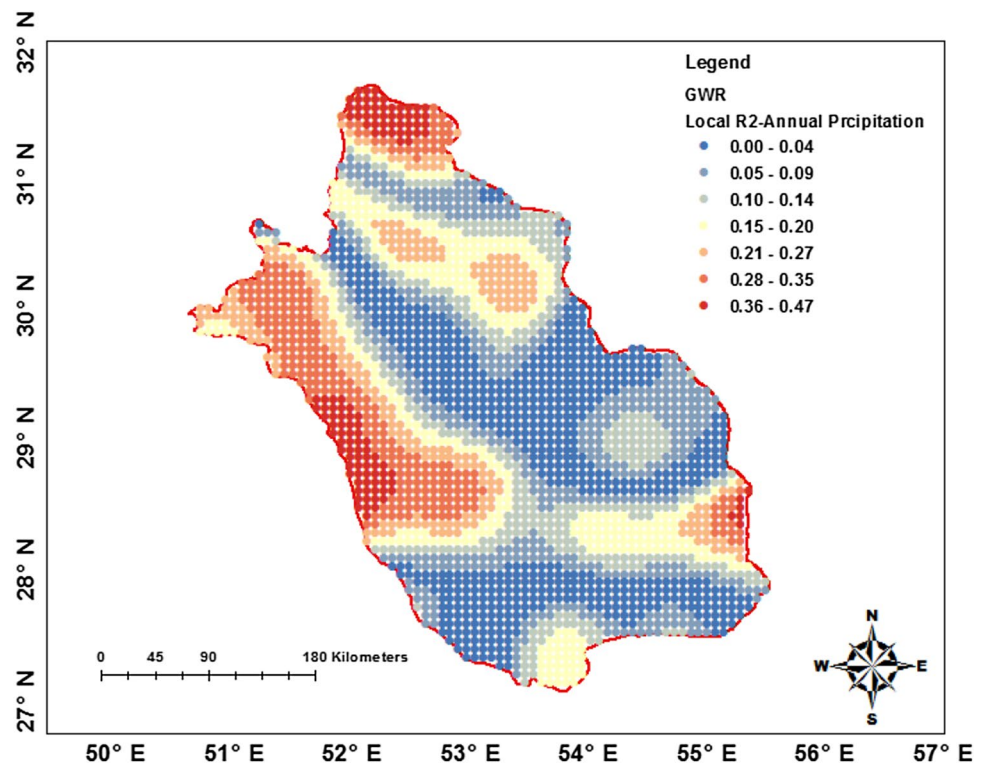


Fig. 6 Altitude coefficients in geographical weight regression of Fars province monthly precipitation

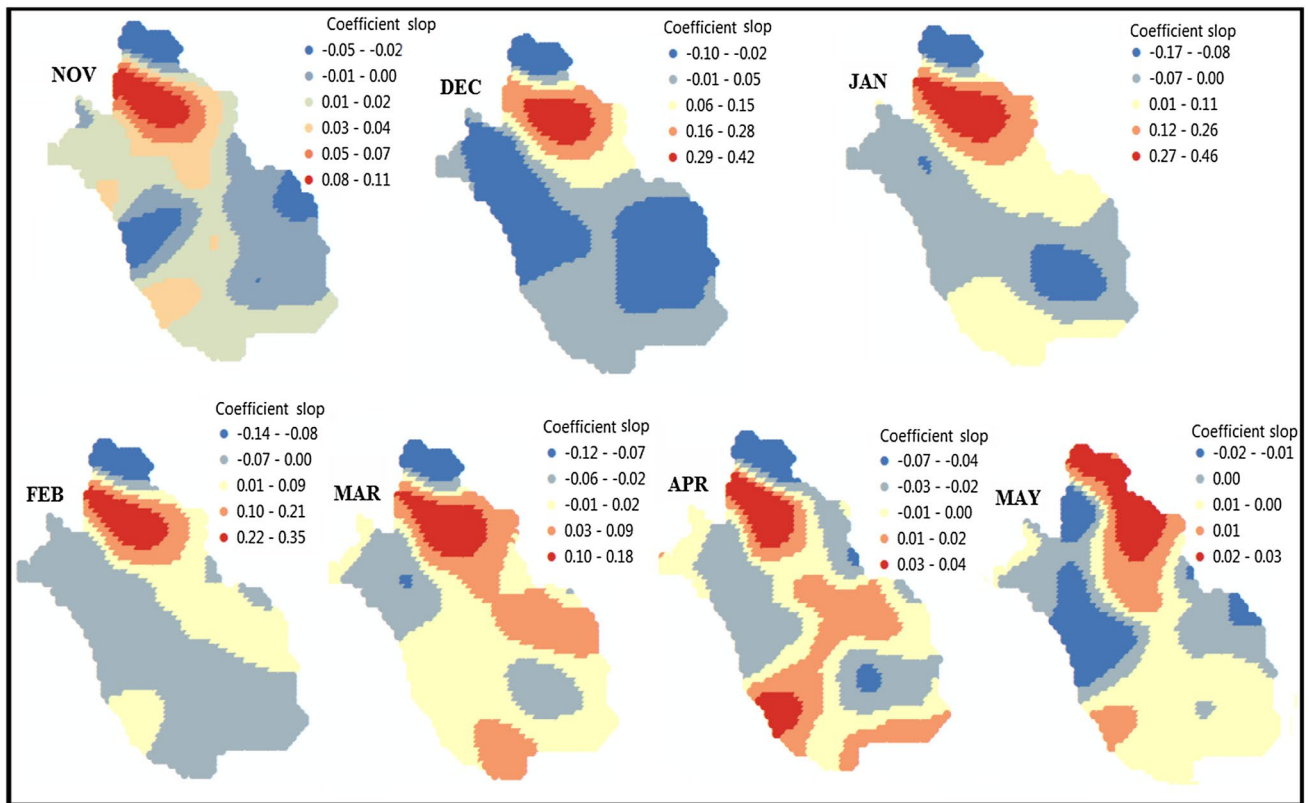


Fig. 7 Slope coefficients in geographical weight regression of Fars province monthly precipitation

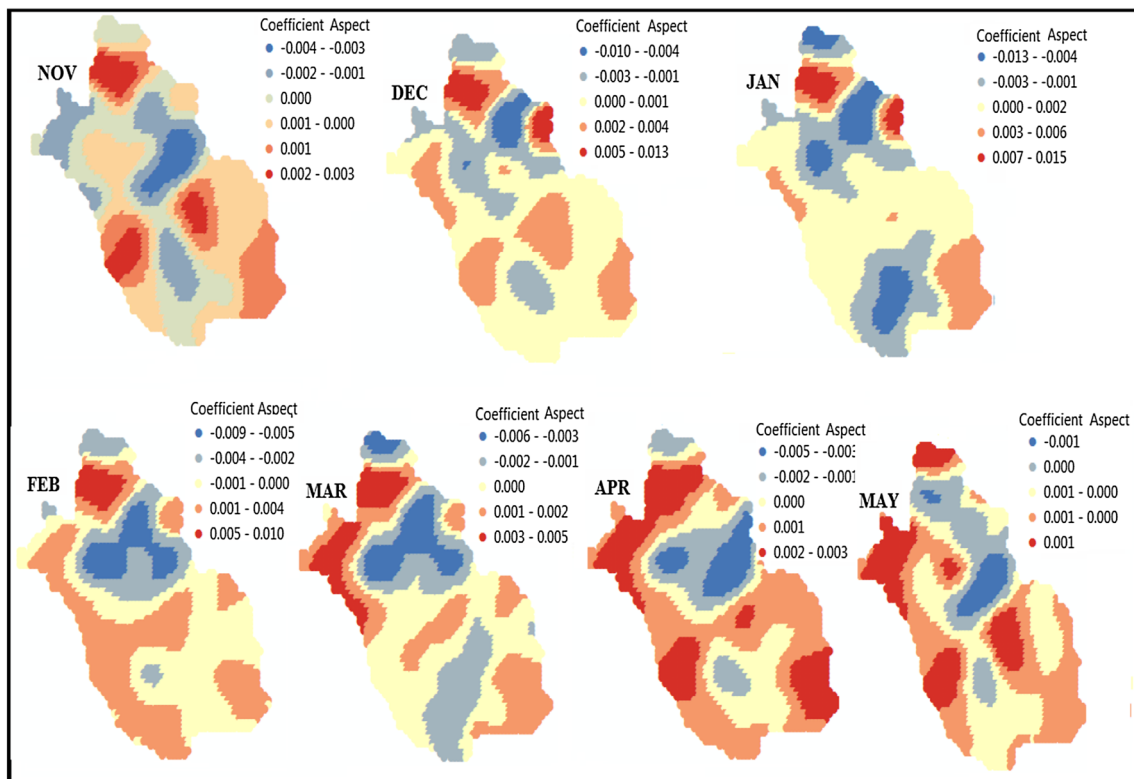


Fig. 8 Aspect coefficients in geographical weight regression of Fars province monthly precipitation

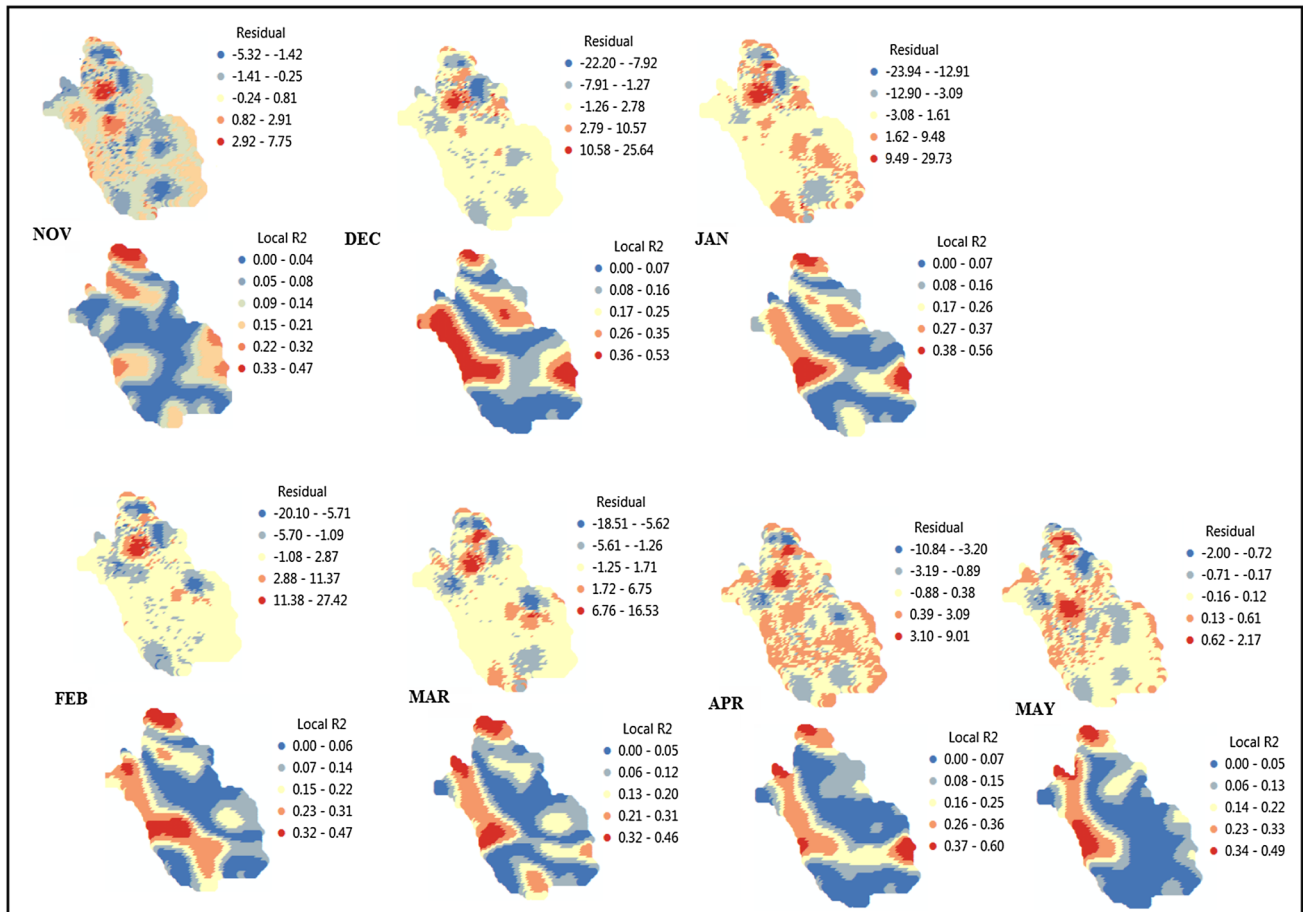


Fig. 9 Residual values and calculated R^2 values in geographical weight regression model of Fars province

dependent variable and predictor independent variable. In addition, lower values of R^2 were located in southern, eastern, and partly central regions. In general, the attempt to estimate the independent variables to predict the monthly precipitation variables was proportionate to the estimation of the model and R^2 coefficients, and the model is well estimated in most parts of the study area. According to residual values in geographical weight regression model, it can be understood that the annual precipitation amount is predicted close to the real values in many regions. If residual values are predicted higher or lower than the real values, the occurrence of spatial auto-correlation is possible. The distribution of spatial residual values in Fig. 9 shows low error values for large areas, indicating a normal distribution.

Figure 10 shows the fitting between observed and predicted values. According to the results, R^2 values were more than 0.8 for most of the months and 0.97 for the other months, meaning that this model properly evaluates more than 80% of the existing relationship. This high value reports that geographical weight regression is adequate

and proper to predict monthly rainfall in the province. This relationship and the closeness of the observed and predicted values indicate that there is no spatial auto-correlation in the residual values of the regression model.

One of the other maps which can be derived from the GWR model is the prediction map resulted from the precipitation amount based on the explanatory variables involved in the spatial prediction. Figure 11 illustrates prediction maps of monthly precipitation in the studied area. As is evident, western and northern parts of the province have high monthly rainfall amounts based on the spatial prediction resulted from GWR model. Southern, eastern, and to some extent, central regions of the province have low precipitation amounts according to this model. This issue was also important in the spatial distribution of the total monthly precipitation of the province. In other words, the spatial and topographic factors could evaluate the prediction of precipitation by GWR model. In fact, the role of these factors is more obvious and more effective in the parts of the province with highest rainfall amounts.

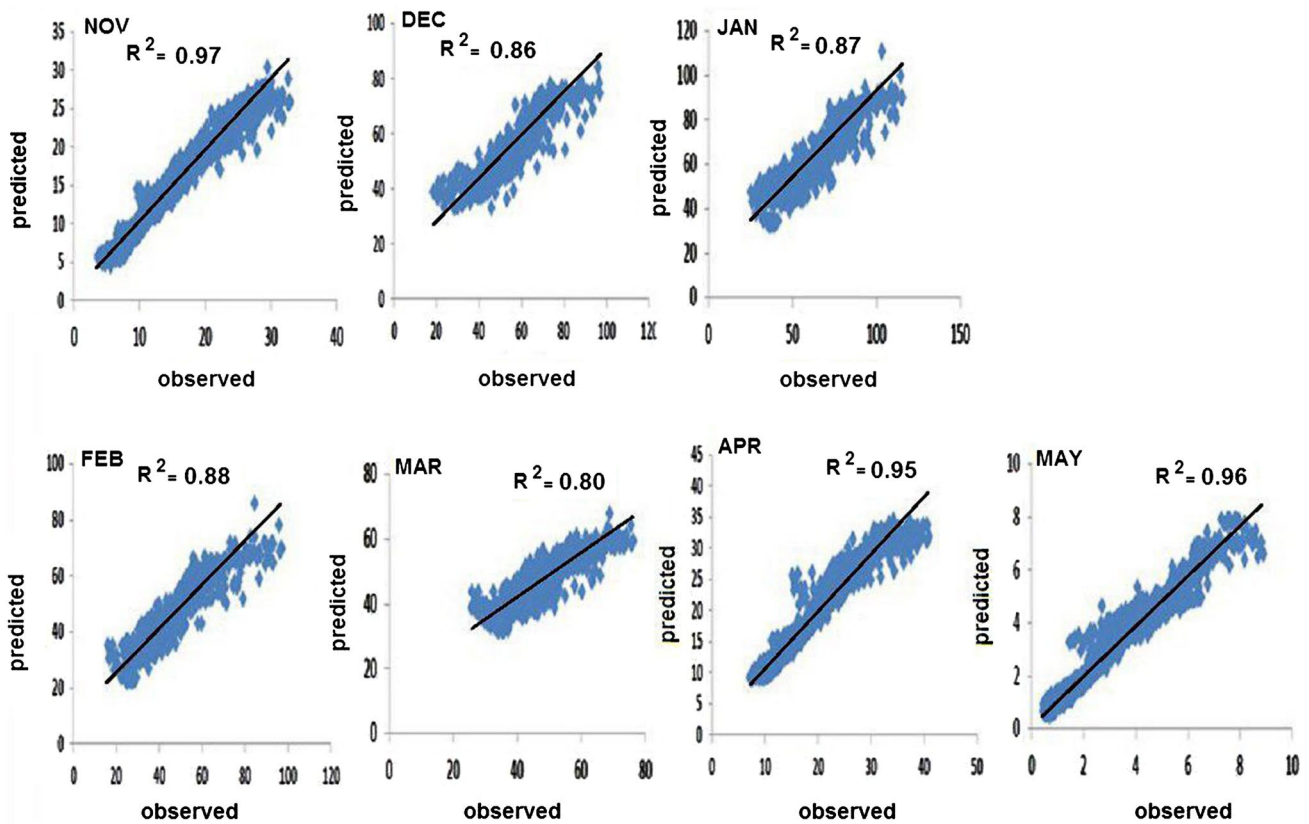


Fig. 10 Scatter plot of observed and predicted values of monthly precipitation using GWR

Conclusion

Spatial statistics techniques are beneficial tools to predict the temporal and spatial distribution of climatic elements. So, in this research, the spatial and temporal distribution of annual precipitation was predicted using the PCI approach and GWR method from the spatial regressions category. For this purpose, to explain the spatial variation of monthly precipitation in Fars province, considering spatial factors and applying 13 synoptic stations, an optimized model called geographical weight regression (GWR) was used.

Results of geographical weight regression (GWR)

The obtained results demonstrate that precipitation regime of northern, northwestern and western parts of the province with PCI values of 13 to 20 and maximum precipitation in winter is different from that of the south and east. PCI values more than 22 in southwestern and eastern parts also indicate severe rainfall variations during the year.

Results of spatial regression (SR)

Spatial regression indicates that the results of monthly and annual precipitation prediction show better results compared to OLS model. Accordingly, it was found that spatial coefficient of altitude has more significant effects on the received rainfall amount in northern and western halves compared to other geographical regions of the province. This strong and direct effect of the altitude coefficient is the combined result of the location of cities in wind-facing mountain ranges and the orientation of rainy systems (including Mediterranean, Sudanese low pressure, Red Sea, Arab, Persian Gulf systems and others) compared to other areas in the province. Therefore, considering that Fars province is a productive area in terms of agriculture and cultivation of irrigated and non-irrigated products for economic and agricultural activities, the precipitation amount is higher in neighboring areas adjacent to the Zagros Mountains.

The effects of slope and direction on rainfall

The coefficients obtained from GWR model for range aspects also show a greater impact by the Zagros Mountains in the north of the province. Thus, these hillside and

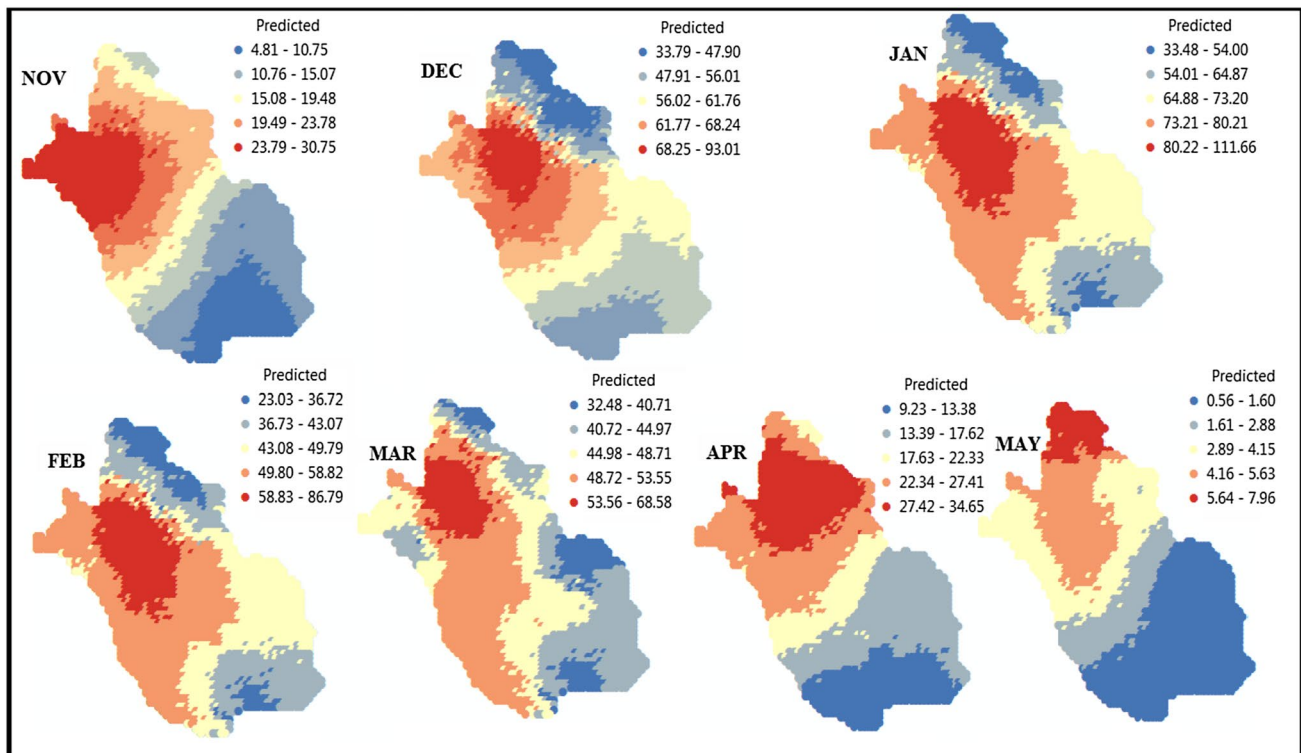


Fig. 11 Predicted monthly precipitation by GWR model in Fars province

their aspects cause a greater impact on the estimation of precipitation in these areas and this impact is positive on the amount of precipitation. In examining the spatial distribution of slope coefficients, the positive and negative values are scattered in most of the province areas. However, in areas where altitude and range aspects have a positive relationship, this factor also has a positive relationship in these areas. The other parts of the province had less negative or positive values compared to northern and western parts which are adjacent to the Zagros Mountains because of the influence of spatial factors on the spatial prediction of annual precipitation. Therefore, it was observed that spatial coefficients in wind-facing ranges of Zagros Mountains in northern and western parts of the province have a major impact on the amount of monthly precipitation. The fitting plot between observed and predicted values also indicates that R^2 values are more than 0.8 for all the months, indicating that geographical weight regression is adequate and proper to predict monthly rainfall of the province. The rainfall prediction maps of the case study also show that western and northern province regions have higher values of precipitation based on spatial prediction resulted from GWR model, and the model has properly predicted monthly precipitation amount based on spatial factors of the case study.

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