

Modeling the spatial structure of annual temperature in Iran

Saeid Balyani¹ · Younes Khosravi² · Fardin Ghadami¹ · Maryam Naghavi¹ · Ali Bayat¹

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Abstract Understanding temperature and its spatial and temporal variations can prepare the ground for developing climate planning. One of the good approaches to understanding temperature variations is to use statistical information across time and space. Spatial statistical techniques are one of the practical approaches for gaining a deep and scientific understanding of the behavior of the spatial variables. The present study was an attempt to model the spatial structure of Iran's annual temperature. For this purpose, the data gathered from 320 weather stations in Iran including synoptic and climatologic stations from their establishment time to the 2014. In line with this goal, OLS, spatial lag and spatial error models were used to determine the temperature structure and predict its spatial variation based on geographic features (elevation, slope, and aspect). The results showed that the maximum and minimum percentage distribution of Iran's annual temperature respectively lie in the range of 90% and above in the South, Southwest, and Southeast and in the range of 50% in the Northwest and West of Iran. Moran's I value for annual temperature was found to be 99%, which is indicative of a positive spatial autocorrelation. Scatter plot and the local Moran's I map showed that the highest pixel values (temperature points) and their neighbors lie at the subgroups with high–high and low–low values. In other words, Iran's annual temperature follows a cluster pattern with a high–high temperature value and a cluster pattern with low–low temperature

value. Finally, spatial regression modeling on Iran's annual temperature showed that variables such as latitude and longitude, elevation, slope and aspect show positive and negative correlations with annual temperature at different significance levels in all three methods, i.e., OLS, spatial lag and spatial error. In the OLS method, longitude and in the spatial lag method, latitude were found to have a positive and direct correlation with annual temperature. However, the results from spatial regressions showed that the spatial error is a better model for predicting Iran's annual temperature.

Keywords Temperature · Moran's I · Ordinary least square (OLS) · Spatial lag · Spatial error · Iran

Introduction

As a measure of thermal energy, temperature is one of the determining factors for knowing about climate and weather. Considering the changes in the solar energy received in different parts of the world, temperature, as a consequence, undergoes a lot of changes which can, in turn, lead to changes in other factors involved in weather forecasting and influences the general climatic conditions of an area (Balyani et al. 2011). Numerous studies have been conducted all over the world to examine the variations and changes in temperature. For instance, Kothiyari and Singh (1996) analyzed the precipitation and temperature trends. The results of their study were indicative of an increase in temperature and a decrease in precipitation. In another study, Niedzwiedz et al. (1996) examined the day and night temperature trends in Central and Southern Europe and found that there has been an increase in both day and night temperature in these parts. Tuerkes et al.

✉ Saeid Balyani
Ybalyani52@yahoo.com

¹ Faculty of Geographical Science, University of Kharazmi, Tehran, Iran

² Faculty of Science, Department of Environmental Science, University of Zanjan, Zanjan, Iran

(1996) focused on the variability of the average annual temperature in Turkey. The results of their analysis at the local level revealed an increase in the rate of temperature in Anatolia but a decrease in the coastal areas in Turkey during the last two decades. Unal et al. (2003) conducted another study in Turkey. After standardizing the data from 113 weather stations including the data related to average temperatures, average maximum, average minimum and precipitation from 1951 to 1998, they used five hierarchical cluster analysis techniques for climate zoning and finally recognized seven climate zones using the ward method.

Using the temperature indices in Canada, Przybylak and Vizi (2005) examined the frequency of the daily and annual average temperatures and the level of temperature variation and the frequency of occurrence of different daily temperature characteristics (very hot, hot, very cold and cold) and then analyzed and compared the status of temperature from 1819 to 1859 with the temperature conditions from 1955 to 1961. The results of their comparison showed that temperature has been low on average in the nineteenth century in this country and the average annual temperature has been 3 °C lower than the average annual temperature in the twentieth century. Grieser et al. (2002) also examined temperature in Europe in 100 years and found that it has been shifted downwards in Western Europe but upwards in Eastern Europe; there has been a significant increase in annual temperature variation across Eastern Europe and the temperature trend has increased almost in all this region. By examining the range of daily temperature and cloudiness in the Northern Europe countries, Kaas and Frich (1995) introduced different models of temperature trends in this region and predicted its future range of temperature variation. Stafford et al. (2000) investigated the night temperature, daily temperature and day-and-night temperature and also the extent of temperature variation in 25 meteorological stations from 1949 to 1998 in Alaska using least squares regression. Their analysis revealed that temperature has followed an increasing trend in all the stations with the highest increase being 2.2 °C in the middle of Alaska in winter in the time range examined in this study (i.e., 50 years).

Shirgholami and Ghahraman (2005) carried out a comprehensive study in Iran; they examined the trend of changes in the average annual temperature in Iran. Based on the results of their study, from the 34 weather stations examined in this study, an increasing trend was observed in 44% and a decreasing trend in 15% and the remaining 41% showed no sign of variation. In another study in Iran, Heydari and Alijani (1999) classified Iran into different climate zones using multivariate techniques. They studied nine climatic variables in 43 synoptic weather stations using factor analysis and cluster analysis. Then using this approach they identified six homogeneous climate zones.

Spatial statistics techniques have been normally unheeded in the climatic studies in Iran although they have received a lot of attention from the urban geographers all over the world. Except for a study by Asakereh and SeifiPour (2012), few studies, if any, have used this method. However, it should be noted that there have been some meteorological studies carried out by researchers in the field of statistics. Among them, the study by Yaghoubian (2008) can be mentioned, which examined precipitation in Hamedan province in Northwestern Iran using Kriging method.

Etminan (2006) and Shafiee (2008) predicted the groundwater level of the catchment area in Birjand, Eastern Iran, using spatial statistics and spatial prediction. Brunson et al. (2001) examined the relationship between annual precipitation and elevation in Britain based on Geographically Weighted Regression (GWR). Accordingly, regression parameters were identified and estimated and their spatial distribution was presented in the form of a map. Mahmoudi and Alijani (2013) modeled the relationship between annual and seasonal rainfall and Earth's climate parameters in Kurdistan, Iran. Their findings showed that the combination of the two variables of latitude and longitude accounted for 66 and 46% of the spatial variations of precipitation respectively in Autumn, annual precipitation and spring rainfall. Combination of the two factors (i.e., latitude and elevation) explained about 63% of the spatial variations in summer rainfall and combination of the three factors including longitude and latitude and elevation accounted for 47% of the variation in winter precipitation. Alijani et al. (2013) classified Iran's annual precipitation in 176 synoptic stations using Ordinary Kriging and conducted a spatial analysis of annual precipitation for the pixel on annual rainfall using Moran's I and G-Star statistics (hotspots and coldspots). The results of their study revealed that rainfall in Iran follows a cluster pattern. Besides, analyzing the hotspots and cold spots, they identified high-value precipitation clusters and spatial autocorrelation in the Northern half of Iran and Northwest of Iran along Zagross mountains up to the north of Shiraz province. They also confirmed the existence of cold spots with low precipitation in central, Southern and Southeastern Iran.

The present study further attempts to examine and model spatial structure of Iran's annual temperature and, in line with it, present the advantages of spatial statistics methods and spatial regression (ordinary least squares, spatial lags and spatial errors) over the commonly used methods in classic statistics.

Data and methods

The data related to average annual temperature from 320 synoptic and climatology stations from the beginning of their establishment to 2014 were used for the purpose of the present study (Fig. 1). Accordingly, Iran’s annual temperature was interpolated using the ordinary Kriging method. Then for creating the raster map (pixels) of Iran’s annual temperature, all the area under study was prepared in the dimension 15×15 km in Lambert conformal conic projection. It should be noted that this dimension was selected after a trial and error on the whole area of Iran. Following that, based on the provided explanations, all the area under study were filled with 7241 temperature pixels. To match and coordinate the number of temperature pixels with the independent variables (i.e., elevation, slope, aspect, latitude and longitude), Digital Elevation Model (DEM) was also prepared on each pixel. Finally, database of the dependent variable, i.e., annual temperature, and the explanatory variables was extracted for spatial prediction of Iran’s annual temperature in the framework of a shape file in the ArcGIS 10.

Clearly when the sample data have a spatial component, one of the issues to be considered is spatial dependence.

Therefore, in the present study, the major focus was on spatial autocorrelation in the residuals of spatial regression models. The possible autocorrelation in the residuals of spatial regression models violates the assumption of independence of the residual errors in the classic multivariate regression model, an implicit assumption in Gauss–Markov theorem (Fox 1997; Greene 2000). Since spatial autocorrelation has been known in the last few decades, different measures have been presented for estimating it. The most commonly used one is Moran’s I statistics which is defined as:

$$I = \left(\frac{n}{\sum_i \sum_j w_{ij}} \right) \left(\frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \right) \tag{1}$$

(Cliff and Ord 1981; Moran 1950) in which x represents the dependent variable, i and j are the indexes for spaces or spatial units and n is the number of observations or areas. w_{ij} is a spatial weight lower than 1 which defines the relationship between the spatial unit i and the spatial unit j . w_{ij} is a component of spatial weights matrix, W , with $n \times n$ dimensions and has been standardized mainly as a series.

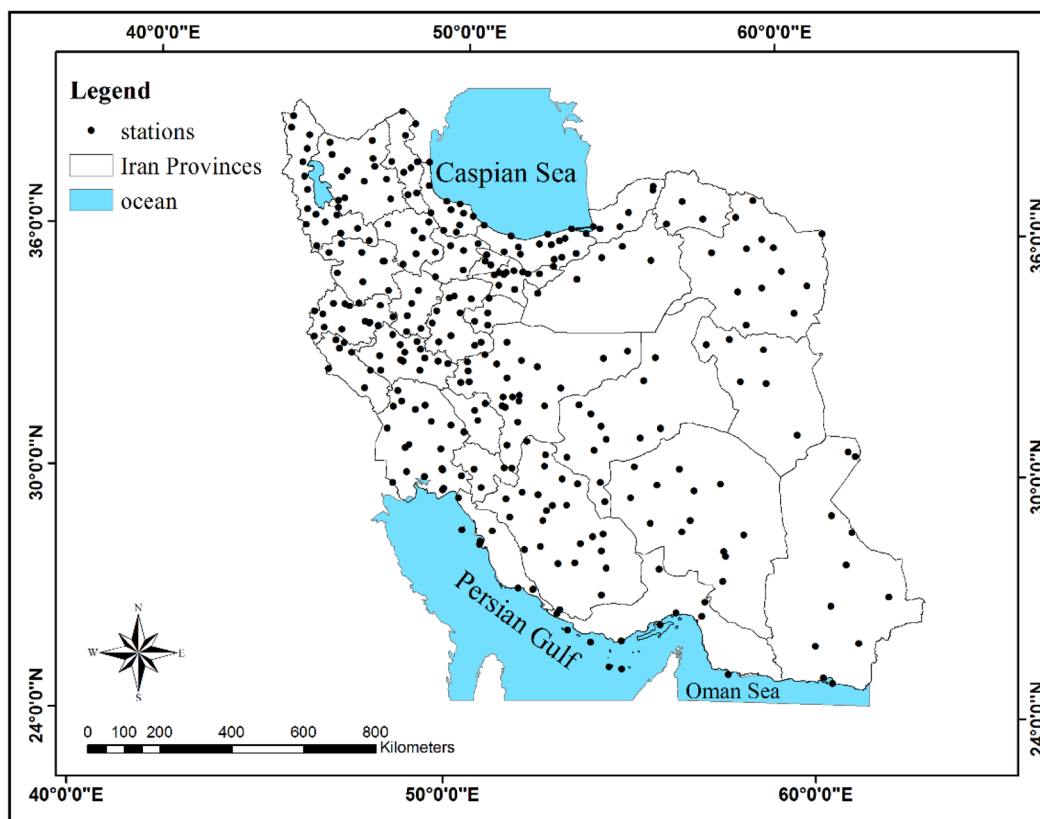


Fig. 1 Digital elevation model of study area

Moran's I statistics is equal to Pearson correlation coefficient. However, the values of the minimum and maximum number for this statistic do not necessarily fall within the -1 and 1 range (Bailey and Gatrell 1995; Griffith 1996). There are logical and appropriate solutions for estimating the regression model including the following:

1. First, we fit the data on a standard OLS method and examine the diagnostic regression tests including multicollinearity, test of normal distribution of residual errors, heteroskedasticity test, and then a spatial dependence test using Moran's I statistics and Lagrange multiplier.
2. Then, based on the accepted theories related to spatial autocorrelation and using the guide for OLS regression diagnostics, an appropriate spatial regression model is fitted.
3. If the results of spatial regression confirm the existence of spatial autocorrelation, we may have to get back to the first phase of the study and select a better model.

Accordingly, two models have been presented for examining spatial autocorrelation. Equation (2) is a spatial error regression model:

$$y = X\beta + u \quad (2)$$

$$u = \lambda Wu + \varepsilon$$

and Eq. (3) is a standard spatial lag regression model:

$$y = \rho Wy + X\beta + \varepsilon \quad (3)$$

in which y is a $(n \times 1)$ vector of the observations of the dependent variable. W represents the observations of the spatial dependence related to observations of y $(n \times n)$. X and u denote a $(n \times k)$ matrix and a $n \times 1$ vector of the observation of the explanatory variables and the error vector respectively. Wu is a $(n \times 1)$ vector of the spatial lags and a component of the u error, λ is a variant of the spatial error and ρ a factor of spatial lag which should be estimated. Accordingly, Wy represents the weighted average of the dependent variable for the neighboring positions. The model used in this study will be examined based on the aforementioned theoretical foundations and the purpose of the study as represented in Eq. 4. In fact, Eq. 4 shows the factors influencing annual temperature:

$$y = \alpha + \beta_1 x_1 + \dots + \beta_n x_n + u \quad (4)$$

In this equation, the relationship between (y) as the dependent variable or annual temperature and (x) as the independent variables including latitude and longitude, and geographic parameters (elevation, slope, and aspect). To achieve the goals of the study, first Eq. 4 was estimated using the OLS method and then diagnostic tests were

carried out. Diagnostic tests including Breusch–Pagan test and Jarque–Bera test were implemented for examining homogeneity of variance and normal distribution of the residuals of the spatial regression model. Furthermore, Moran's I was used for analyzing spatial autocorrelation of the regression residuals. The most important statistic to be considered is the spatial autocorrelation test. If Moran's I statistics confirms the existence of spatial autocorrelation, the results of standard regression from the OLS method will be no longer reliable. Thus, the problem of spatial autocorrelation needs to be resolved. For this purpose, two models including 'spatial error' and 'spatial lag' can be used. The results of diagnostic tests of LM and Robust LM will reveal which of the two models is better. Significant Lm (lag) and LM (error) values on each of the two models will be indicative of the existence of spatial autocorrelation and of a significant difference between that model and the results of estimation obtained by the OLS method. In addition, other statistics such as R^2 , Log Likelihood and AIC in these models (Anselin 2005) should also be noted. Besides these statistics, LM-SARMA is also a combinational statistics which indicates the high value of a model estimated by OLS with the two spatial lag and spatial error models. Therefore, with the spatial autocorrelation being confirmed, Eq. 4 can be replaced by Eqs. 5 and 6 for estimating spatial error and spatial lag models respectively after selecting the basic model:

$$y = \alpha + \lambda e_w + \beta_1 x_1 + \dots + \beta_n x_n + u \quad (5)$$

$$y = \alpha + \rho y_w + \beta_1 x_1 + \dots + \beta_n x_n + u \quad (6)$$

In these two equations, y and x are the same dependent and independent variables defined in Eq. 4. e_w denotes the weighted error of spatial autocorrelation or Wu , y_w denotes dependent variable of the spatial lag or Wy and λ and ρ represent the coefficients of the spatial autocorrelation (Anselin 2000, 2001a, b; Anselin and Bera 1998; Kelejian and Prucha 1997).

Research findings

First, map of the spatial distribution of Iran's annual temperature will be analyzed. Figure 2 demonstrates the map of the spatial distribution of annual temperature. As shown in Fig. 2, the highest annual temperature is for South, Southwest and Southeast of Iran. The lowest annual temperature, on the other hand, is for Northwest of Iran with 724 temperature pixels at the range of 10% or lower (first percentile). According to the distribution map of annual temperature, cluster distribution of Iran's annual temperature can be seen in two regions, one with a cold cluster and low annual temperature and one with

Fig. 2 Distribution of Iran’s annual temperature

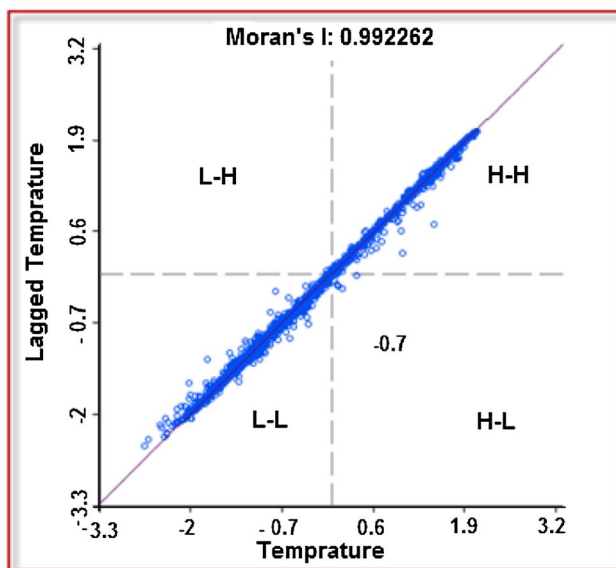
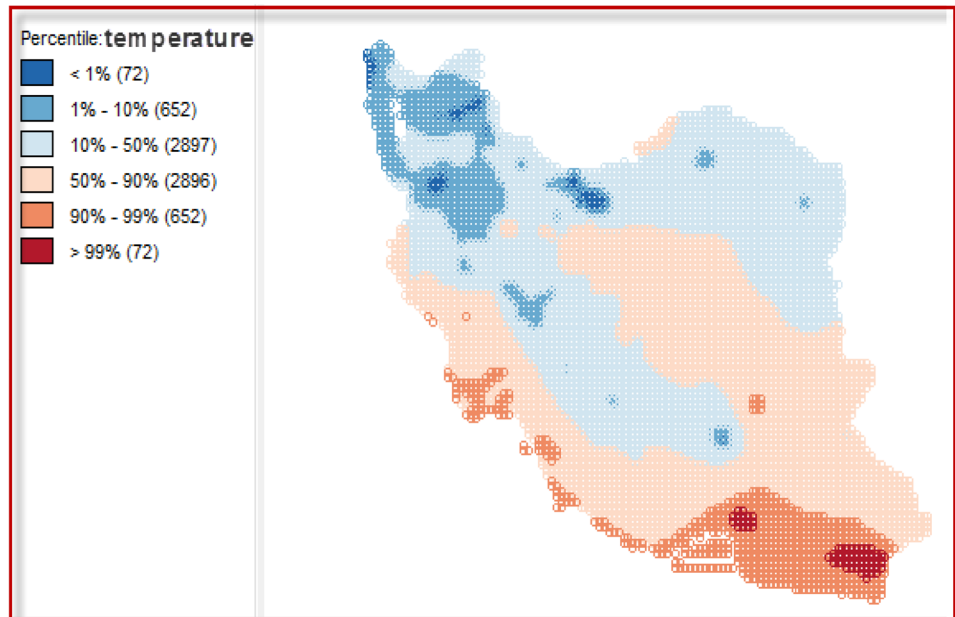


Fig. 3 Global Moran’s I’s distribution of Iran’s annual temperature

hot cluster and high annual temperature. Therefore, it seems that the existence of spatial autocorrelation is not unexpected in Iran. It should be pointed out that different mountainous regions and Zagros mountains from Northwest to Southwest of Iran moderate the temperature conditions in Iran. Therefore, these results are indicative of an initial relationship and the existence of a cluster pattern in the annual temperature of Iran and can reveal the level of spatial autocorrelation. Figure 3 shows the Log-normal distribution of Iran’s annual temperature. Moran’s

I value was found to be +0.99%, which is indicative of the existence of a pattern with cluster spatial structure in Iran’s annual temperature pixels (temperature points).

On the inside of the graph, the H–H, L–L, H–L and L–H signs indicate that the four quarters from the log-normal distribution of spatial autocorrelation of Moran’s I statistics in annual temperature can be interpreted as follows:

High–high points: include the points in which both pixels (temperature points) or each neighboring geographic parameter (annual temperature) have/has a high value and have been surrounded by points that has a high temperature.

Low–low points: include the points where both pixels (temperature points) or each neighboring geographic parameter (annual temperature) have/has low value and have/has been surrounded by spots which have low temperature.

Low–high points: points or neighborhoods in which a low temperature has been surrounded by high temperatures.

High–low points: points or neighborhoods in which a high temperature has been surrounded by low temperatures.

Anselin (2005) also showed that slope of the regression line passing from the middle of these points in global and local Moran’s lognormal distribution shows Moran’s I value. The value of this measure was found to be +0.99 for Iran’s annual temperature as the dependent variable of the study, which shows that the existing pixels in neighborhood to each other form a cluster pattern. In other words, one of the cluster patterns with high–high values and a cluster pattern with low–low values are concentrated in the study area. Figure 4 demonstrates local Moran’s I statistics for annual temperature.

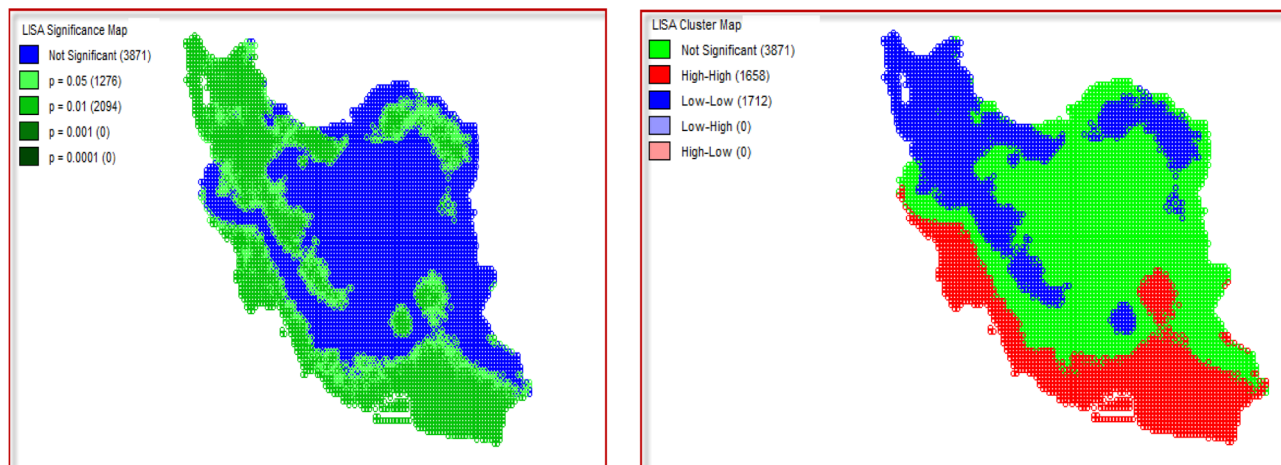


Fig. 4 Local Moran's I value of Iran's annual temperature and its significance at different levels

As shown in Fig. 4, the pixels that have high–high values with positive spatial autocorrelation can be observed in the South, Southwest and Southeast of Iran. Besides, the pixels with low–low values are located in the North, Northwest, Northeast and West of Iran. As it can be seen in local Moran's I map, a spatial cluster with a low–low value can be observed in a part of Southern Iran, Kerman province. Basically, the number of pixels with high–high values that have spatial autocorrelation is 1658 cells which are concentrated in the North, Northwest and Northeast of Iran. In this figure, only the clusters with high–high values ($n=1658$) and the clusters with low–low values ($n=1712$) were found to be meaningful at 0.05 and 0.01 levels of significance.

Local Moran's I values were not meaningful for the pixels that have been distributed in a non-cluster form on the map. As it was mentioned, assuming that there is no spatial dependence in Iran's annual temperature pattern and particularly in spatial variables, spatial modeling of the annual temperature was carried out. Accordingly, the first step in spatial regression analysis was to make an estimation using the standard OLS method and run regression diagnostic tests. Table 1 presents the results related to the OLS regression estimates.

As shown in the table, independent spatial statistics (latitude, elevation and slope) were found to be meaningful at 95 and 99% levels of significance respectively and

Table 1 The results of regression estimates from OLS, spatial lag and spatial error models for Iran's annual temperature

Estimation method	OLS	ML (spatial lag)	ML (spatial error)
Width of the origin	270.55***	- 0.126*	47.81*
Longitude	+./00024***	- 0.000126**	-./0000419*
Latitude	-./00079***	+./000092*	-./000333**
Elevation	- 0.0047***	-./00070***	-0.0041***
Slope	- 0.71***	- 0.0020***	- 0.059***
Aspect	+0.0012***	-./0000097*	0.000100***
R^2	.90	.99	.99
Log likelihood	- 12836.2***	1191.08***	2402.67***
Breusch–Pagan test	407.78***	3282.98***	9960.48***
Moran's I (error)	0.95***	.38	.36
Lagrange multiplier (lag)	13296.07***	-	-
Robust LM (lag)	18.78***	-	-
Lagrange multiplier (error)	13384.01***	-	-
Robust LM (error)	106.72***	-	-
Lagrange multiplier (SARMA)	13402.79***	-	-
Jarque–Bera	625.63***	-	-
Likelihood ratio test	-	28054.57***	30477.75***

*, ** and *** indicate significance at 90, 95 and 99 percent levels

have a negative correlation with temperature. Longitude and aspect, on the other hand, have a positive correlation with annual temperature. In other words, when there is a one-unit increase in these two variables in longitude from west to east of Iran, annual temperature will also increase. Having the highest coefficient in the related spatial models, slope seems to be the most influential spatial factor. Undoubtedly, this situation is indicative of the fact that the slopes towards the North, West, Northwest and shadow slopes have a lower annual temperature compared to other domains. Distribution of elevation in 83% of Iran is lower than 2000 m and in the remaining 16%, it is more than 2000 m (Jedari Oyuzi 1995). This wide scope of changes brings height into prominence as the main influential factor in climatic variables and annual temperature. Hence, considering the wide range of elevation in Iran, this factor will have a considerable role. One of the interesting findings of the present study was the multi-parameter spatial distribution that cannot be seen in classic statistics in a way that a significant coefficient or value could be calculated for each pixel. As the Figs. 5, 6, 7, 8 and 9 show, there are different positive and negative relationships between Iran’s annual temperature and variables such as latitude and longitude and topographic factors on the multi-parameter spatial distribution. In fact, with a one-unit change in any of the independent variables, the dependent variable or annual temperature will have positive or negative relationships with them. For instance, as shown in Fig. 5, there is a reverse relationship between elevation and annual temperature. In other words, an increase in elevation or altitude will influence

temperature conditions negatively. Slope, as another example, has a negative relationship with temperature in eastern areas of Iran. There is also a reverse relationship, based on Fig. 7, between aspect and temperature in some parts of the South and Southwest of Iran. The figures related to the relationship of longitude and latitude with temperature can be also inferred by referring to Fig. 7.

Now the assumption of heterogeneity of variance and non-normality of the OLS model residuals is confirmed based on Table 1 and Breusch-Pagan test and Jarque–Bera test. Furthermore, Moran’s I value was found to be +99%, which is meaningful at 1% level of significance and confirms the existence of spatial autocorrelation. LM SARMA value was also found to be 13402.79 and significant. Therefore, based on the significance of the mentioned statistics, spatial lag and spatial error models were used as an alternative to the OLS regression model. As demonstrated in the second column of Table 1, LM (lag) statistics is meaningful and LM (error) is also meaningful at 99% level of significance. In other words, there is a significant difference between the OLS and spatial lag and spatial error models. Therefore, if spatial lag and error models are used, spatial dependence will be either lowered or totally eliminated. On this basis, spatial error and lag models were selected. Then by preparing and comparing the spatial autocorrelation graphs of the residuals and standard deviation error map, we found out which model would yield better results in estimating the dependent variable of the study. According to the second and third column of Table 1, there was no significant difference between the spatial lag and the OLS

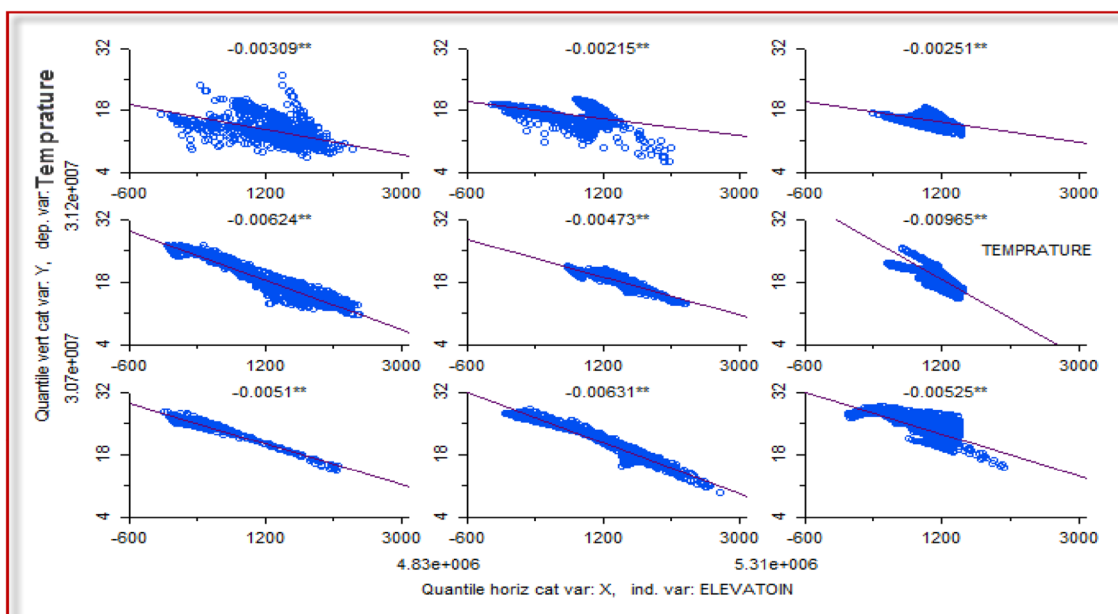


Fig. 5 Multi-parameter spatial distribution for the spatial relationship between elevation (independent variable) and annual temperature (dependent variable)

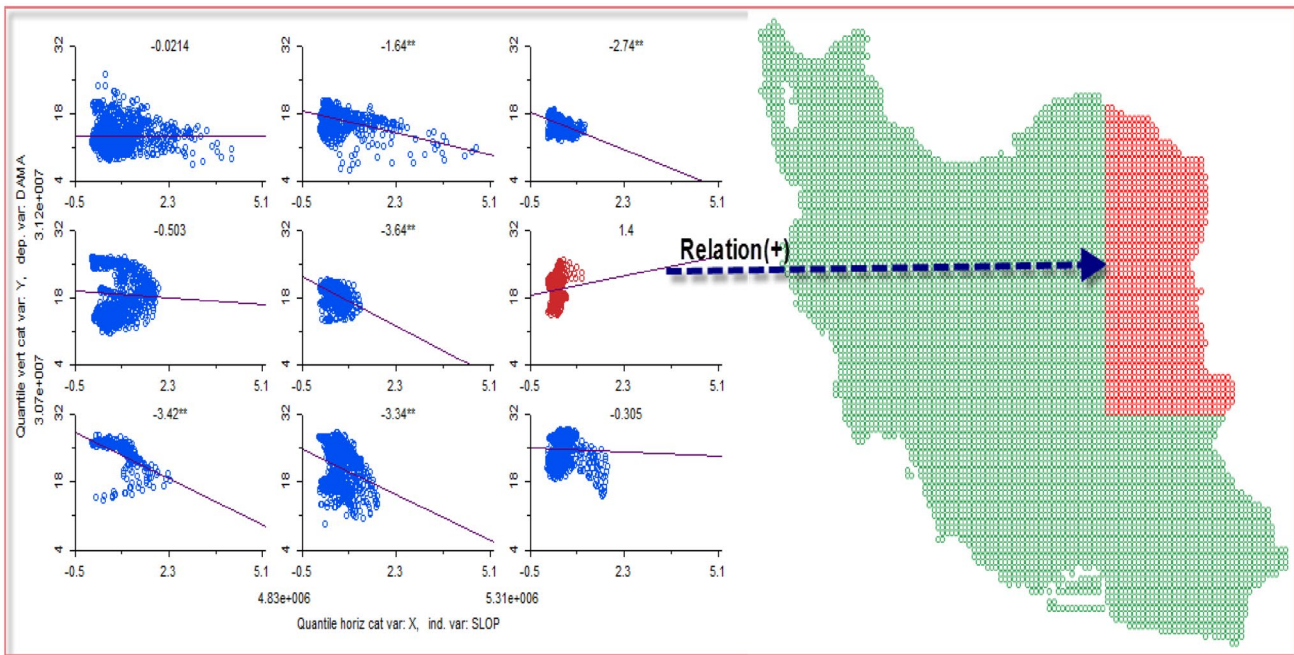


Fig. 6 Multi-parameter spatial distribution for the spatial relationship between slope (independent variable) and annual temperature (dependent variable)

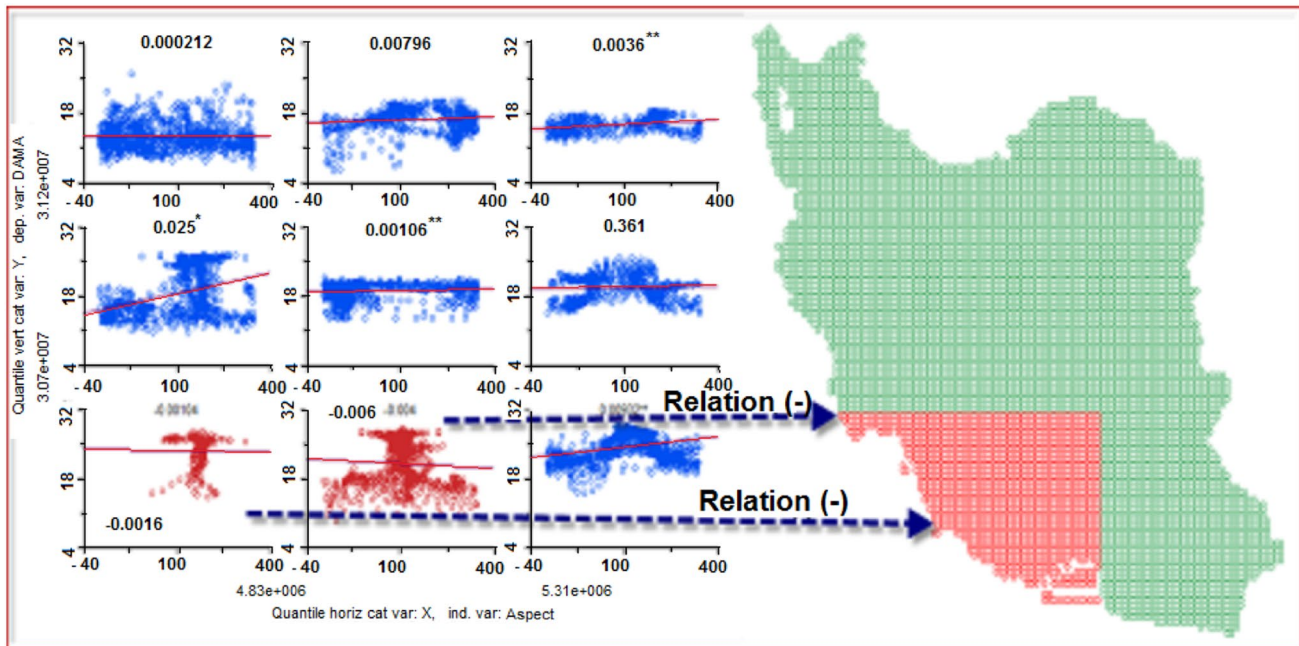


Fig. 7 Multi-parameter spatial distribution for the spatial relationship between annual temperature (dependent variable) and aspect (independent variable)

models. however, significant values were found for the variables in the spatial error model. As it was mentioned, the coefficients of the topographic factors particularly ‘elevation’ were negative in all three models, which is indicative

of its reverse relationship with and its effect on annual temperature. For instance, concerning the relationship between spatial variables and annual temperature in the spatial lag model, longitude was found to be (-), latitude

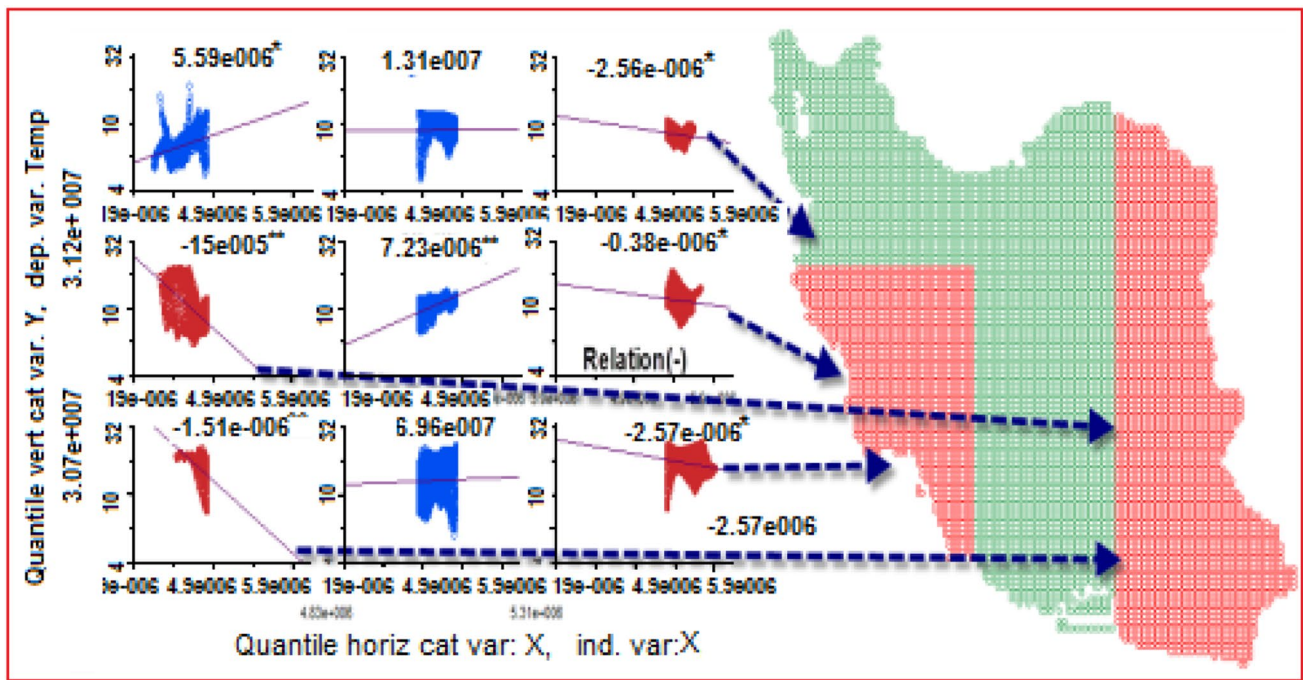


Fig. 8 Multi-parameter spatial distribution for the spatial relationship between annual temperature (dependent variable) and longitude (independent variable)

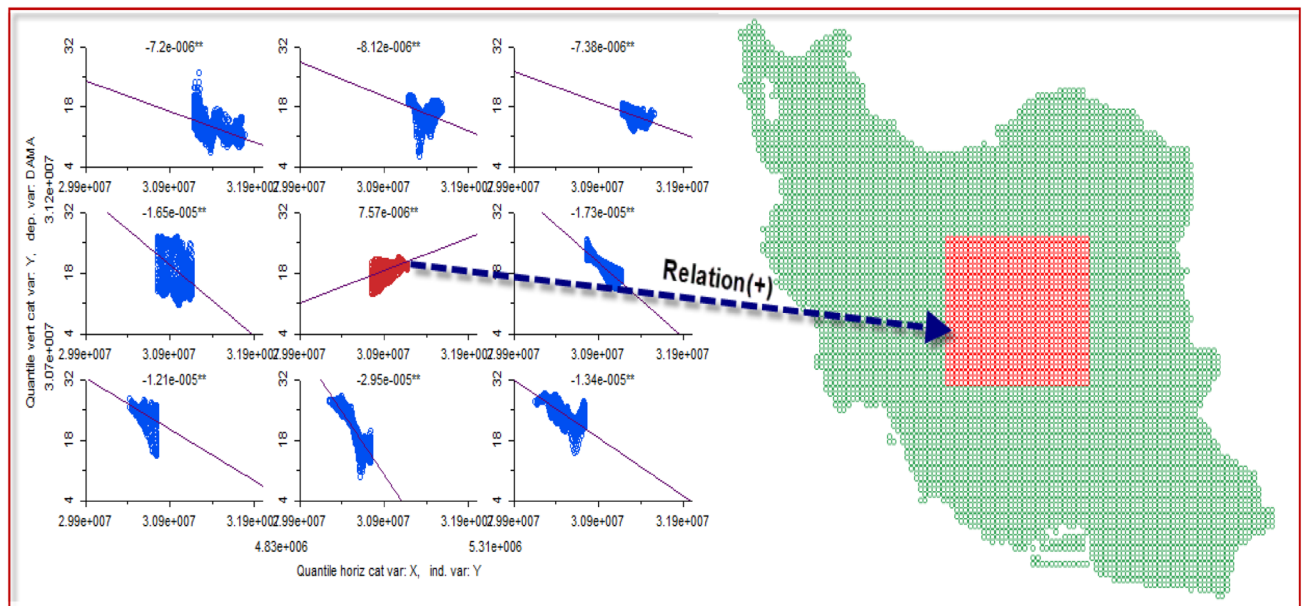


Fig. 9 Multi-parameter spatial distribution for the spatial relationship between annual temperature (dependent variable) and latitude (independent variable)

was (+), elevation, slope and slope were all (–). R2 was found to be 90% in the OLS model. In other words, spatial factors accounted for 99% of the variations in Iran’s annual temperature. The value of R2 in the spatial lag and

error models was 99% which is higher compared the OLS method. On the other hand, Log Likelihood is higher for the spatial error model (2402.67) compared to the other two models. Breusch–Pagan statistics in both spatial lag

and spatial error models as the selected models show that there is no heteroskedasticity; in other words, spatial variance has been distributed homogeneously in the residuals of the models. Overall, implementation of spatial models have yielded better results compared to the OLS model.

However, a comparison between spatial lag and spatial error models shows that spatial error control has yielded better results in terms of controlling spatial dependence and residual error of error regression model has been normally distributed on the map shown in Fig. 10; spatial

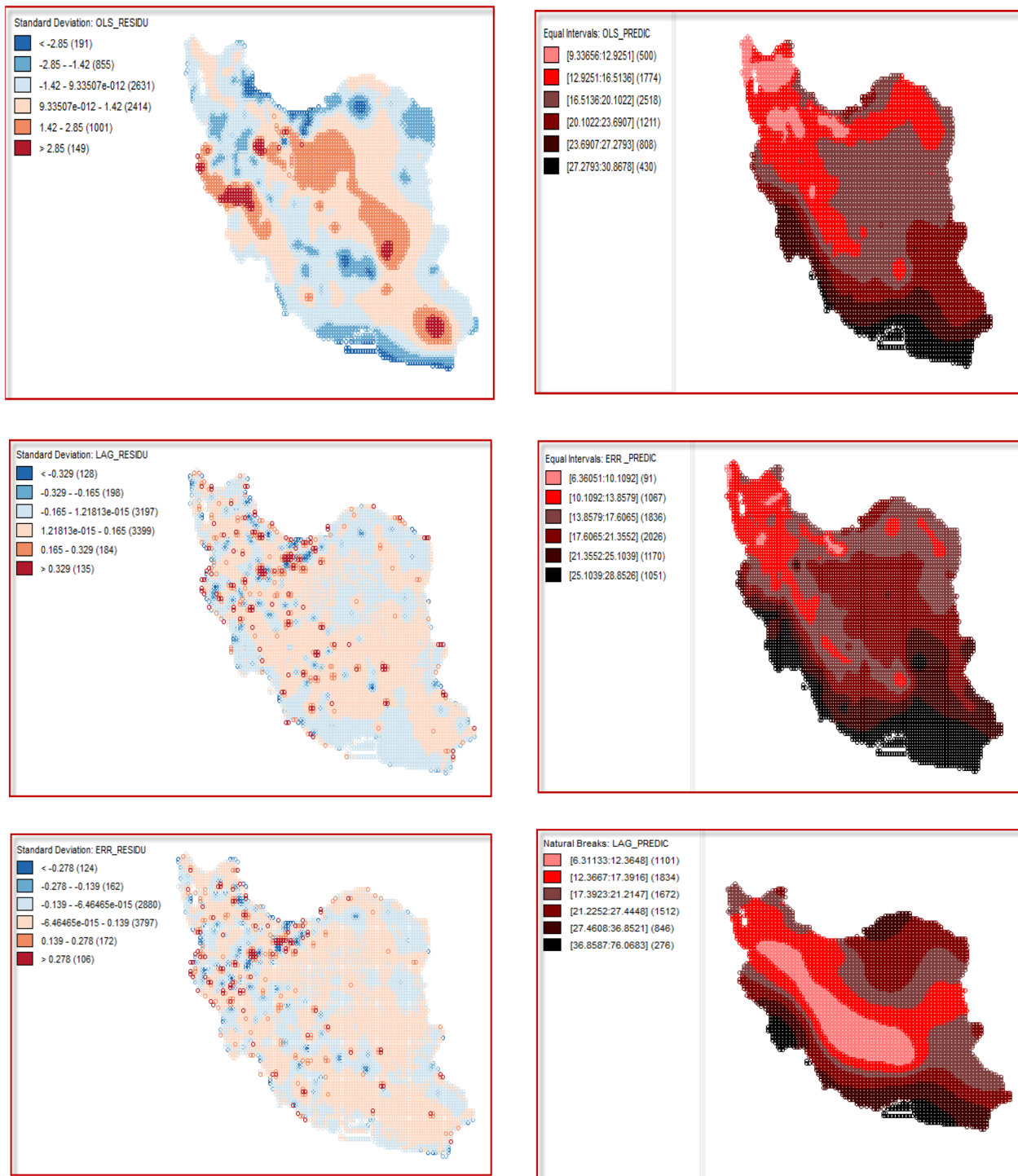


Fig. 10 Maps of the standard deviation of the residuals and estimates made by ordinary least-squares (OLS) regression, spatial lag and spatial error models

dependence of the residuals in the area of Iran varied from -0.27 to $+0.27$. What can be inferred from the graphs obtained from spatial regression model is (A) where the value of the residuals of the model are unusually high or low and (B) whether the values of the residuals have spatial autocorrelation or not. In the present study, the areas with a large number of standard residuals (StdResid 2.5) will be more likely to have spatial autocorrelation (Asgari 2011). Low standard deviation values are indicative of an appropriate prediction of the spatial error model but in the OLS model a spatial cluster pattern can be observed in the residuals of the model. This was also found to be 95% and meaningful in the spatial autocorrelation error value of Moran's I.

It should be pointed out that the spatial error model has a relative superiority over the spatial lag model. Therefore, this model was selected for the purpose of the study. The vectors in Fig. 11 show the lognormal distribution of the residuals of the spatial models.

Error regression model shows the best estimation result with the lowest Moran's I value for the residuals. In other words, spatial autocorrelation was much lower in this model compared to the OLS model, which is indicative of the normal distribution of its residuals. Based on these results which led to the selection of spatial error model as the best model, now the factors affecting Iran's annual temperature will be examined and analyzed. As shown in Table 1, except for the 'aspect', all the other spatial factors had a negative correlation with annual temperature. latitude and longitude, elevation and slope correlate negatively but aspect, only with the assumption that these variables have fixed values, correlates positively with annual temperature. As it was already mentioned, with the highest coefficient value, slope was found to be the most effective spatial factor in all the three models. Furthermore, the relationship between geographic parameters (longitude and latitude) and annual temperature was reverse, as shown in Table 1; with a decrease in longitude and latitude along the

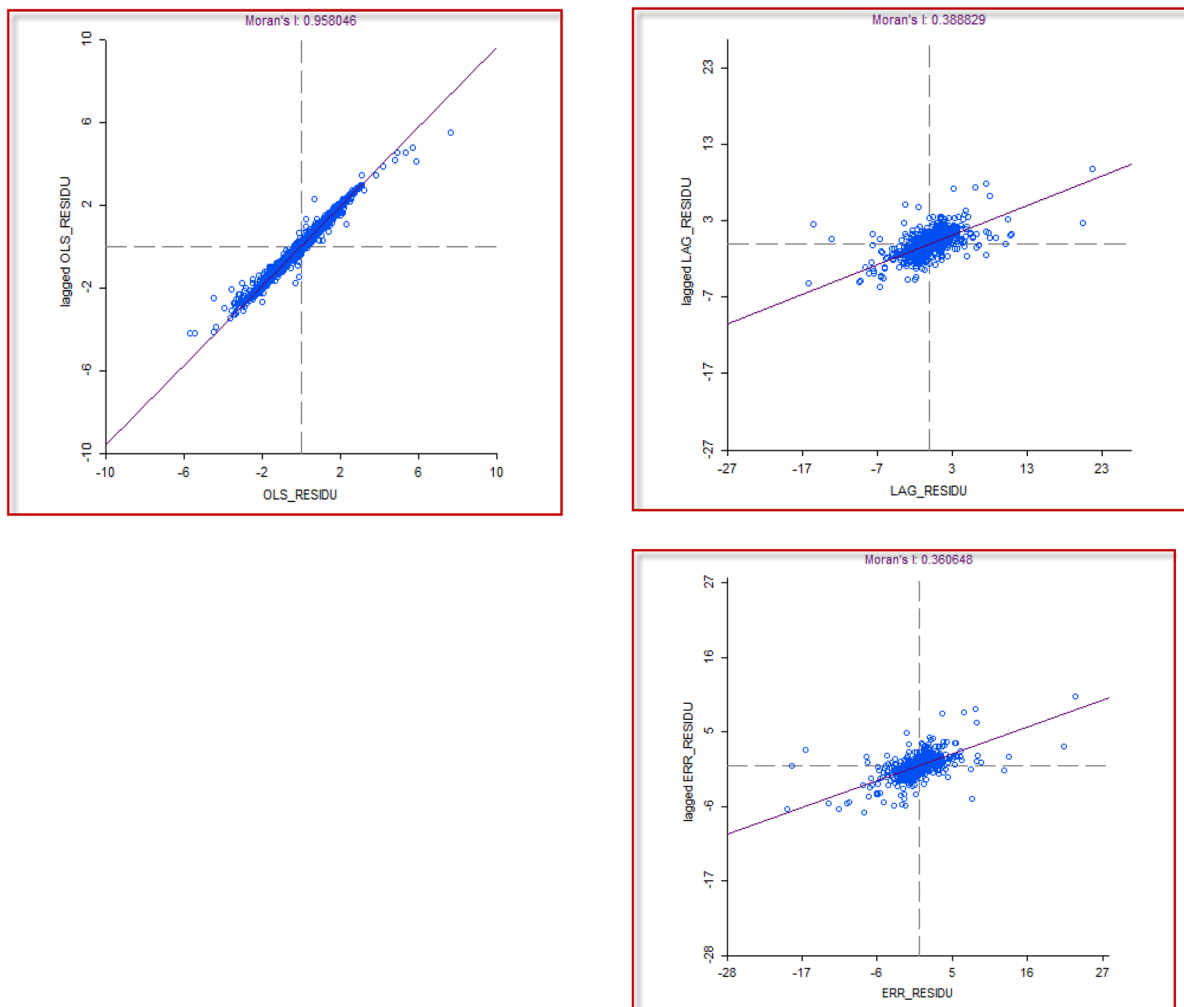


Fig. 11 Lognormal distribution of the residuals of the OLS, spatial lag and spatial error models for Iran's annual temperature

north–south axis (latitude) and with a decrease in longitude from the East to the West of Iran, Iran's annual temperature also decreases. Elevation also showed a negative correlation with annual temperature in all the models. That is, the relationship between elevation and temperature is negative in all areas of Iran and with a decrease in elevation, annual temperature will increase. In the spatial error model, only 'aspect' had a positive relationship with annual temperature meaning that the domains that are exposed to sunshine are more likely to have high temperatures. Average annual temperature maps could also properly help to evaluate temperature values in Iran based on spatial and topographic factors. According to Fig. 10, it can be observed in the spatial error model that low annual temperatures in Iran are mainly in the West and Northwest of Iran and across the Zagros mountains. High temperatures, on the other hand, are common in the South, Southeast and Southwest of Iran and along the coasts of the Persian Gulf and Oman Sea.

Conclusion

One of the good approaches to understanding temperature variations is to use statistical information across time and location. Spatial statistics techniques are among the useful approaches for gaining a scientific understanding of the spatial variables. Therefore, in the present study an attempt was made to model the spatial structure of Iran's annual temperature using spatial statistical methods. In line with this purpose, the spatial relationship between annual temperature and the independent variables of the study including latitude and longitude, elevation, slope and aspect was investigated. The percentage distribution of annual temperature in Iran, as it was mentioned, was found to be 90 and 50% in two high- and low-temperature domains in the South, Southwest and Southeast of Iran and in the North, Northwest, Northeast and West of Iran respectively. General Moran's I value was also found to be +0.99, which is indicative of the existence of a positive spatial autocorrelation in the data related to Iran's annual temperature. The lognormal distribution plot and local Moran's I map showed that the largest number of pixels (temperature points) and their neighbors lie in the subgroups with high–high and low–low values. In other words, Iran's annual temperature follows a cluster pattern with high–high and low–low temperature values. The results pointed to the need to use a model that took into account the reverse relationship of some of the geographic parameters in all the spatial regression methods. This relationship in any of the three models in some cases showed that some of the independent variables of the study had positive relationship with annual temperature. For instance, in the OLS model, longitude and aspect correlated with annual temperature; with a one-unit change in

longitude from West to the East of Iran, annual temperature also increases and with the change of the aspect, the temperature will also increase. With the highest coefficient value in the spatial models, slope was found to be the most influential spatial factor. Furthermore, elevation is 2000 m in 83% of the area of Iran and more than 2000 m in 16% (Jedari Auzi, 1995: 11). This wide range of variation leads elevation to be considered as the primary factor influential in climatic variables and annual temperature. Accordingly, considering the wide range of variation in elevation in Iran, the explanatory power of this variable will be quite high. In the present study, the relationship between elevation and annual temperature was found to be reverse in all areas of Iran. To put it differently, an increase in elevation or altitude above sea level affects temperature conditions and correlates negatively with it. Finally, a comparison was made between the spatial regression models the results of which showed that spatial error model is a good alternative to the OLS regression methods. Spatial autocorrelation in the residual error of the OLS model confirmed this fact. In addition, the R² value (R² = .99) in the spatial lag and spatial error models provided further evidence for the replacement of the mentioned models. Overall, improvements were observed after using spatial models as a replacement for the OLS model. However, a comparison between the spatial lag and spatial error models revealed that the spatial error model could better control spatial dependence. Maps of the model predictions and standard deviation of the residuals of the spatial error model were indicative of a better performance and better estimations of annual temperature by this model. Unlike the spatial error model, in the OLS model a kind of spatial clustering was observed in the residuals of this model. Finally, based on the predictions of the spatial error model, high temperatures are common in the South, Southwest and Southeast of Iran and low temperatures are common in Northeast, West and Northwest of Iran.

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