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Comparison of interpolation methods for modeling spatial variations of Precipitation in Iran

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ABSTRACT

In this study, represents a new climatic modeling of monthly rainfall for Iran (1975-2014), presented with the spatially variability, patterning monthly rainfalls series available in the 140 stations and rainfall points. Eight special interpolation methods were estimated and considered: the inverse distance weighting (IDW), the ordinary kriging (OK), the simple kriging (SK), the universal kriging (UK), the indicator kriging (IK), the probability kriging (PK), the disjunctive kriging (DK) and the empirical Bayesian kriging (EBK). The results of the several methods were studied and assessed by the validation indicators, evaluating the outcomes from the methods with the actual rainfalls series and predicting various residuals amounts. The eight methods presented suitable for IDW, OK, UK and EBK than for other methods with the least RMSE (IDW=0.497, OK=0.37, UK=0.398 and EBK=0.189), and for the spatial variability, rather than another patterns, as well at 31200 rainfall points in January than 37261 points for another series. The suitable and best outcomes were realized with EBK and OK utilized for the actual rainfalls series in the Iran. The EBK and OK perfected the precision of the rainfall spatial variability analysis with respect to IDW and UK. We present a method of rainfall monthly patterns, using the EBK and OK to predict any spatial variations in the monthly rainfall for the period of 2014-2064 over Iran.

KEYWORDS interpolation methods, spatial variations, precipitation patterns and Modeling ARTICLE HISTORY Received 20 January 2017 Revised 28 March 2017 Accepted 9 April 2017

Introduction

Rainfall spatial variability express distribution values of rainfall and are utilized as an essential climatic element in various subjects, such as environmental planning, hydrology and natural and water resource management among others elements. (Benavides, Montes, Rubio, & Osoro, 2007;

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Fand et al., 2014). In addition, rainfall spatial variability modeling are an important element in predicting for rainfall distribution and climatic classification, to predict environmental patterns and to analysis how the precipitation relates with other climatic elements (Fares et al., 2014; Feizizadeh, Shadman Roodposhti, Jankowski, & Blaschke, 2014; Keshavarzi, Ebrahimi, & Moore, 2015). Hence, environmental management and research need this rainfall change as a rule for realizing many processes, as it is the main factor affecting precipitation patterns, in the sense that its action thought to be at the earth's surface process (Machiwal & Jha, 2014; Martínez-Cob, 1996; Masoud, 2014). Therefore, spatial variation modeling of monthly precipitation, are of interest for climatologists and hydrologist (Benavides et al., 2007; Celik, 2015; Dummer, Yu, Nauta, Murimboh, & Parker, 2015). Different interpolation methods have been used for modeling the geostatistical patterns of monthly precipitation. The most widely used interpolation methods are deterministic and geostatistical methods, deterministic interpolation techniques, global and local models, Inverse Distance Weighting (IDW), kriging interpolation and spatial least squares analysis methods (Elbeih, 2015; Feizizadeh et al., 2014; Haberlandt, 2007; Jinliang Huang, Huang, Pontius Jr, & Zhang, 2015; Javari, 2015). Several researchers have compared different methods (splines, inverse distance weighting, Kriging and Cokriging and types of kriging) for monthly precipitation in various parts of world (Jinliang Huang et al., 2015; Karacan, Olea, & Goodman, 2012; Karagiannis-Voules et al., 2015; Mentis, Hermann, Howells, Welsch, & Siyal, 2015; Odeh, Crawford, & McBratney, 2006). These methods can be used to produce the maps of kriging predicted values, maps of kriging standard errors associated with predicted values, maps of probability, indicating whether or not a predefined critical level was exceeded and maps of distribution for a predetermined probability level. In the monthly-based interpolation, different results can be inferred from the various methods a plied in the same environmental condition, such as include inverse distance weighting (IDW), global polynomial interpolation (GPI), local polynomial interpolation (LPI), radial basis functions (RBF), ordinary kriging (OK), simple kriging (SK), universal kriging (UK), indicator kriging (IK), probability kriging (PK), disjunctive kriging (DK) and empirical Bayesian kriging (EBK). Some studies showed that the accuracy of OK, UK and EBK in the study area are higher than that of another methods (Babak, 2014; Cheng, Hsieh, & Wang, 2007; Ford & Quiring, 2014; Plouffe, Robertson, & Chandrapala, 2015; Shahbazi, Aliasgharzad, Ebrahimzad, & Najafi, 2013; Verdin, Rajagopalan, Kleiber, & Funk, 2015; Wang et al., 2014; Xu, Zou, Zhang, & Linderman, 2014). In view of the spatial-temporal variation patterns on the geostatistical interpolation, this paper takes eleven interpolation methods that IDW, OK, UK and EBK selected to interpolate based on the monthly, seasonal and annual rainfall from observation in 140 stations and 37261 points of rainfall in 1975-2014 and forecasting of spatial variations for future (2014-2064). We also investigated the precipitation trend spatial variations. Geostatistical interpolation methods can be employed as a versatile GIS technique to provide a suitable framework for the spatial variation analysis of precipitation patterns and precipitation variations. The rest of the paper is organized as follows: in Section. 2, we briefly introduce the geostatistical model and the geostatistical interpolation methods to provide a description of our proposed spatial effects framework of precipitation that is explained in the next section. Section. 3 presents the new modeling of

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precipitation variations in detail. The experimental results and conclusions are presented in Sections. 4 and 5, respectively.

Materials and methods

Materials

Iran, situated in the southwest of Asia, ranges from 25° 3' to 39° 47' N and from 44° 5' to 63° 18' E. The case study deals with the identification of geostatistics and spatial statistics effect on precipitation to better forecast the precipitation variations in Iran. Precipitation variations can be defined from various aspects, such as effectiveness of precipitation formation factors or even climatic events such as drought. With regard to precipitation changes in Iran, we chose rainfall indices, namely. The chosen indices were obtained from meteorological organization and included the monthly, seasonal and annual information of 140 stations and 37261 rainfall points in Iran for the period 1975-2014 (Fig. 1).



Figure1. Location of Stations

In this study, the distribution of the 37261 rainfall points were evaluated with a digital elevation model (DEM) extracted from the ASTER-based global digital elevation model(Hayakawa, Oguchi, & Lin, 2008; Peña-Angulo, Brunetti, Cortesi, & Gonzalez-Hidalgo, 2016). All the observed precipitation data have been subject strict quality control obtained from to http://www.irimo.ir/englwd/720-Products-Services.html. The study focused on monthly, seasonal and annual variations. The rainfalls series includes 90% of primary and 10% of reconstructed series from stations at a correlation further than 0.7. Obviously individual station data varies, depending on the area and decade, with original data showing an increase in the 1981-2010 period. For this

purpose, a harmonic analysis was applied to all data, and data were studied with respect to the time defaults, normality, missing data, outliers etc. at different phases of the research.

Methods

This paper employs the geostatistical interpolation methods for comparing and investigating the variations in precipitation spatial patterns. The next subsections provide a brief introduction to these one algorithms to make this paper more reader-friendly and self-contained. The geostatistics interpolation methods include the following three steps: (Ahmadi & Sedghamiz, 2008; Arslan, 2012; Babak, 2014; ESRI, 2014a; Hengl, 2009; Henley, 2012; Johnston, Ver Hoef, Krivoruchko, & Lucas, 2001; Pohlmann, 1993; Wu & Li, 2013):

Geostatistical models for investigating the precipitation spatial variations:

The geostatistical models include the following three steps:

Exploratory of precipitation spatial patterns

Before using the Geostatistical models, should explore rainfall using the exploratory precipitation spatial analysis tools (EPSAT). (Dumitrescu, Birsan, & Manea, 2015). Six different EPSAT methods were used: (1) the histogram plots, (2) the normal QQ plot, (3) the trend analysis tool, (4) the semivariograms / covariance cloud tool, (5) the Cross covariance cloud tool and (6) Prediction performances were assessed by cross-validation. With rainfall measurements done at 140 stations and 37260 rainfall points, according to ESRI (2014) the Quantile-quantile statistics (QQS) can be calculated using the following equation:

$$f(p,h) = \operatorname{Prob} \left\{ \mathbf{Z}(s) \pounds z_{p}, \mathbf{Z}(s+h) \pounds z_{p} \right\}$$
(1)

where f(p, h) is the joint probability density function of Z(s) and Z(u) and Given a geostatistical model, Z(s), its variogram g(h). For each rainfall points, we delineated and analyzed the histogram, normal QQ plot, the trend analysis (Polemio & Lonigro, 2015), the semivariograms/covariance cloud (Jingyi Huang, Shi, & Biswas, 2015), the Cross covariance cloud and cross-validation using the methods described by ESRI. With rainfall measurements done at 140 stations and 37260 rainfall points, the semivariograms / covariance cloud equation is(I. B. Gundogdu, 2015):

$$g(h) = \frac{1}{2n(h)} \bigotimes_{i=1}^{n(h)} \bigotimes_{i=1}^{n(h)} \bigotimes_{i=1}^{n(h)} \bigotimes_{i=1}^{n(h)} \bigotimes_{i=1}^{n(h)} \sum_{i=1}^{n(h)} \sum_{i=1}^{n(h)}$$

where *h* is the distance separating sample locations x_i and x_i+h , n(h) is the number of distinct data pairs. In some circumstances, it may be desirable to consider direction in addition to distance. In an isotropic case, *h* should be written as a scalar *h*, representing magnitude. The Cross covariance cloud can be used to examine the local characteristics of spatial correlation between rainfall stations, and it can be used to look for spatial shifts in correlation between rainfall sets. A cross covariance cloud (Suparta & Rahman, 2016), with

rainfall points to predict the spatial variability as a function of the cross covariance, was estimated as follows:

$$CV = (t,s) = (Z(s_i) - \overline{Z})(Y(t_j) - \overline{Y}) (3)$$

where CV is the cross covariance locations x_i and a geostatistical model, $\mathbb{Z}(s_i)$, its forecast values (\overline{Z}) .Cross-validation uses all the stations and rainfall points to estimate the trend and autocorrelation models. Cross-validation indexes were estimated as follows: (Kisaka et al., 2015; Pereira, Oliva, & Misiune, 2015):

$$MSE = \mathbf{\hat{a}} \left(\mathbf{Z}_{i^{*}} - \mathbf{Z}_{i} \right)^{2} / n \quad (4)$$
$$RMSE = \sqrt{\mathbf{\hat{a}} \left(\mathbf{Z}_{i^{*}} - \mathbf{Z}_{i} \right)^{2} / n} \quad (5)$$

where \boldsymbol{Z}_{j*} is the measured values at locations and \boldsymbol{Z}_i is the forecasted values at locations.

Explanation of Iran Monthly Precipitation

The important explanation of the methods are to predict the relationship between rainfall series and rainfall points separately for each cell of the DEM, creating more significance to analysis spatial variations with geographical features comparable to those of the cell patterns. Explanation of Iran monthly precipitation spatial variability techniques can be used to describe and model spatial patterns (variography), predict amounts at rainfall spatial distribution and variations and assess the patterns associated with a rainfall predicted value at the unmeasured locations. The analyses of model spatial patterns versus model temporal patterns show important distinctions between rainfall variability in Iran. Here we describe methods employed in the following:

-In Inverse distance weighted (IDW) interpolation the rainfall points are weighted during interpolation such that the influence of one point relative to another decline with distance from the unknown point want to create(Barbulescu, 2015). To predict a value for any unmeasured points, IDW uses the measured values surrounding the predicted point. The measured values closest to the predicted point have more influence on the predicted value than those farther away. Inverse distance weighted was estimated as follows (Zhang, Vaze, Chiew, & Li, 2015):

$$\hat{Z}(\boldsymbol{u}_{o}) = \overset{n}{\underset{i=1}{\mathbf{a}}} z(\boldsymbol{u}_{i}) \boldsymbol{w}_{i} / \overset{n}{\underset{i=1}{\mathbf{a}}} \boldsymbol{w}_{i} \quad (6)$$

where $Z \, \rm is \, the \, measured \, values \, at \, locations \, and \, \, w_{i} \,$ is the weight for measured values at locations.

-The analysis of Iran monthly precipitation offers several types of kriging and Cokriging interpolation models, which are suitable for interpolation different types of data and have different underlying methods: 1- Ordinary method: Ordinary method of the main issues concerning ordinary kriging is whether the assumption of a constant mean is reasonable. However, as a simple prediction method, it has remarkable flexibility (Paparrizos, Maris, & Matzarakis, 2016). According to ESRI (2014) the ordinary method can be calculated using the following equation:

$$Z(s) = m + e(s)$$
 (7)

where μ is an unknown constant and ϵ (s) is residuals at interpolation.

Simple method: After predicting the mean value over a station, we want to predict the value of our underlying random function Z(x) at any arbitrary point in Iran. For simple kriging, because we assume that we know μ exactly, also know $\varepsilon(s)$ exactly at the data locations(de Amorim Borges, Franke, da Anunciação, Weiss, & Bernhofer, 2015). According to ESRI (2014) simpler method can be calculated using the following equation:

$$Z(s) = \mathbf{m} + \mathbf{e}(s) \quad (8)$$

Universal method: We want to introduce the spatial prediction method universal kriging, whose aim is to predict Z(s) at un-sampled places as well (Htwe, Brinkmann, & Buerkert, 2015). A second-order polynomial is the trend which is $\mu(s)$. If we forecasted data subtract the second-order polynomial from the original data, you obtain the errors, $\varepsilon(s)$, which are assumed to be random. According to ESRI (2014) simpler method can be calculated using the following equation:

$$Z(s) = \mathbf{m}(s) + \mathbf{e}(s) \quad (9)$$

where μ is an unknown constant and ϵ (s) is residuals at interpolation.

Indicator method: We want to introduce the spatial prediction method universal kriging, whose aim is to predict I(s) at un-sampled places as well. Indicator method the creation of binary series may be through the use of a threshold for continuous data, or it may be that the observed data is 0 or 1(Barbulescu, 2015). Using binary variables, indicator kriging proceeds the same as ordinary kriging. A variable that is continuous can be made into a binary (0 or 1) variable by choosing a threshold. In Geostatistical Analyst, if values are above the threshold, they become a 1, and if they are below the threshold, they become a 0. This method can be compared to ordinary kriging. As with ordinary kriging, you assume that $\varepsilon(s)$ is autocorrelated. Notice that because the indicator variables are 0 or 1, the interpolations will be between 0 and 1, and predictions from indicator kriging can be interpreted as probabilities of the variable being 1 or being in the class that is indicated by 1. If a threshold was used to create the indicator variable, the resulting interpolation map would show the probabilities of exceeding (or being under) the threshold (Mirzaei & Sakizadeh, 2015). With rainfall measurements done at 140 stations and 37260 rainfall points, the indicator method equation is (ESRI 2014):

$$I(s) = \mathbf{m} + \mathbf{e}(s) \quad (10)$$

Probability method: Use probability kriging to produce a probability or standard error of indicators map. The rainfall points need to be sampled from a climatic condition that is continuous spatially. Probability kriging can use either <u>semivariograms or covariances</u> (the mathematical forms used to express autocorrelation) and <u>cross-covariances</u> (the mathematical forms used to express cross-correlation). The Probability kriging function is calculated as follows (I. B. Gundogdu, 2015; Johnston et al., 2001):

$$I(s) = I \not Z(S) > C_t \stackrel{\text{line}}{=} m_1 + e_1(s), Z(s) = m_2 + e_2(s)$$
 (11)

where μ_2 is an unknown constant and $\epsilon_2(s)$ is residuals at interpolation.

Disjunctive method: In rainfall analysis, we can predict either the rainfall value itself or an indicator with disjunctive kriging. Disjunctive kriging requires the <u>bivariate normality assumption</u> and approximations to the functions the assumptions are difficult to verify, and the solutions are mathematically and computationally complicated (Dokou, Kourgialas, & Karatzas, 2015). We want to introduce the spatial prediction method Disjunctive kriging, whose aim is to predict g (Z(s)) at un-sampled places as well. The Disjunctive kriging function is calculated as follows(Haberlandt, 2007; Johnston et al., 2001; Pohlmann, 1993):

$$\hat{g}\left(Z\left(s_{o}\right)\right) = \mathop{\mathbf{a}}\limits_{i=1}^{n} f_{i}\left(Z\left(s_{i}\right)\right), fZ\left(s\right) = \mathbf{m} + \mathbf{e}(s), \quad (12)$$

where Z is the measured value at the location and μ is an unknown constant and $\epsilon(s)$ is residuals at interpolation.

Cokriging method: Cokriging uses rainfall on climatic pattern types. The rainfall variable of interest is Z_1 , and both autocorrelation for Z_1 and cross-correlations between Z_1 and all other climatic period types are used to make better predictions (de Amorim Borges et al., 2015). We want to introduce the spatial prediction method Disjunctive kriging, whose aim is to predict $Z_1(s)$ at un-sampled places as well. The Cokriging function is calculated as follows(ESRI, 2014b):

$$Z_1(s) = \mathbf{m}_1 + \mathbf{e}_1(s), \ Z_2(s) = \mathbf{m}_2 + \mathbf{e}_2(s)$$
 (13)

Empirical Bayesian kriging (EBK) is a geostatistical interpolation method that interpolated the rainfall difficult aspects of spatially a valid kriging model(Baker, Kröger, Brooks, Smith, & Czarnecki, 2015). Other kriging methods in rainfall analysis require us to manually adjust parameters to receive accurate results, but EBK automatically calculates these parameters through a process of submitting and simulations(Mirzaei & Sakizadeh, 2015). Empirical Bayesian kriging also differs from other kriging methods of accounting for the error introduced by estimating the underlying semivariogram. We want to introduce the spatial prediction, Empirical Bayesian kriging, whose aim is to predict Z_1 (s) at un-sampled places as well. The Empirical Bayesian kriging is calculated as follows(ESRI, 2014b; Goovaerts, 2005):

$$\mathbf{g}_{ebk}\left(\boldsymbol{u}_{\mathbf{a}}\right) = \mathbf{I}\left(\boldsymbol{u}_{\mathbf{a}}\right) Z\left(\boldsymbol{u}_{\mathbf{a}}\right) + \boldsymbol{\mathbf{g}} - \mathbf{I}\left(\boldsymbol{u}_{\mathbf{a}}\right) \boldsymbol{\mathbf{y}} \boldsymbol{n} \quad (14)$$

where m is the population-weighted sample mean, $\lambda((u_a))$ is the weight assigned to the rate observed at location (u_a) .

Semivariograms/Covariance modeling:

The semivariograms and covariance functions quantify the assumption that rainfall series nearby tend to be more similar than rainfall series in various stations that are further apart. Semivariograms and covariance both measure the strength of statistical correlation as a function of distance (de Amorim Borges et al., 2015). The process of modeling semivariograms and covariance functions fits a semivariograms or a covariance curve to rainfall series. In this paper is to achieve the best fit, and also incorporate our forecast of the rainfall series in the model. The model will then be used in rainfall variations predictions. When fitting a rainfall variation, explore for <u>directional autocorrelation</u> in every station. The <u>sill, range, and nugget</u> are the important characteristics of the modeling by using the semivariograms. The semivariograms, covariance and correlation functions are theoretical quantities that estimate them from rainfall series, using tool is called the empirical semivariograms, empirical covariance and correlation functions. The empirical semivariograms, empirical covariance and correlation functions are calculated as follows (Bohling, 2005; I. Gundogdu, 2015; Oliver & Webster, 2015; Scheuerer & Hamill, 2015). Given a geostatistical model, Z(s), its variogram g(h) is formally defined as:

Correlation function:
$$R(h) = \frac{C(h)}{\sqrt{s_0's} + h}$$
 (15)

Covariance function:

$$C(h) = \frac{1}{n(h)} a_{a=1}^{n_{e}^{a} h_{\frac{a}{2}}^{a}} Z(u_{a})' Z(u_{a} + h) - m_{0}' m_{+h}^{(16)}$$

Semivariance function: $\mathbf{g}(h) = \frac{1}{n(h)} a_{\mathbf{a}=1}^{n_{\mathbf{a}}^{\mathbf{a}} h_{\mathbf{a}}^{\mathbf{b}}} \left(\mathbf{u}_{\mathbf{a}} + h \right) Z(u_{\mathbf{a}})_{\mathbf{a}}^{\mathbf{a}}$

where m_0 and m_{+h} are the means of the range values:

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$$m_{0} = \frac{1}{n(h)} \frac{n_{t}^{*}h_{\frac{1}{6}}^{*}}{a=1} Z(u_{a}) \quad (18) \quad m_{+h} = \frac{1}{n(h)} \frac{n_{t}^{*}h_{\frac{1}{6}}^{*}}{a=1} Z(u_{a} + h)$$
(19)

and \mathbf{S}_0 and \mathbf{S}_{+h} are the corresponding standard deviations:

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$$s_{+h} = \frac{1}{n(h)} a_{a=1}^{n_{b}^{e} h_{a}^{b}} (u_{a} + h) - m_{+h_{u}^{e}}^{2} (20)$$

$$s_{0} = \frac{1}{n(h)} a_{a=1}^{n_{b}^{e} h_{a}^{b}} (u_{a} - m_{0}) (21)$$

Where u is vector of spatial coordinates , z(u) is variable under consideration as a function of spatial location, h is lag vector representing separation between two spatial locations and z(u+h) is lagged version of variable. If the empirical semivariograms continues increasing steadily beyond the global variance value, this is often indicative of a significant spatial trend in the series, resulting in a negative correlation between rainfall series separated by large lags. In this study, types of interpolation methods, including include inverse distance weighting (IDW), global polynomial interpolation (GPI), local polynomial interpolation (LPI), radial basis functions (RBF), ordinary kriging (OK), simple kriging (SK), universal kriging (UK), indicator kriging (IK), probability kriging (PK), disjunctive kriging (DK) and empirical Bayesian kriging (EBK), were used to analysis and forecasting precipitation spatial variations over Iran. These methods in format the Geostatistics wizard tool in ArcGIS_{10.3} were divided into two groups: deterministic (IDW, GPI, LPI and RBF) and geostatistical (OK, SK, UK, IK, PK, DK and EBK) methods(ESRI, 2014a). The basis for interpolations by both geostatistical and deterministic in this analysis procedures was a digital mosaic model of Iran which consists of regular cells or pixels of 44.2338 km2. The deterministic interpolation methods create 37261 cells from rainfall points by taking spatial relationships functions that determine spatial extent of rainfall, whereas the geostatistical interpolation methods utilize spatial statistical functions that nature the spatial relationships among rainfall points and stations. Rainfall spatial variability was evaluated through semivariograms estimation, model fitting and comparison for each variable. The cross-validation index was used to check the analysis accuracy. Mean Square Error (MSE) and Root Mean Square Error (RMSE) indexes were the main criterion for deciding which fitted model was the best one for each monthly rainfall(Ford & Quiring, 2014; Yang, Xie, Liu, Ji, & Wang, 2015). Inverse distance weighting (IDW) method was used as an interpolation method that estimates precipitation values from a set of weighted sample points with measurement values (Babak, 2014; Wu & Li, 2013). In this paper it was twofold. Firstly, we aimed to determine the deterministic methods for rainfall data for application to wide climatic modelling in Iran. To investigate this, four different spatial interpolation methods were evaluated: IDW, GPI, LPI and RBF types. Secondly, we used geostatistical methods to compare values of the forecasted precipitation variations at different stations. We used cross validation of IDW to compare and evaluate the values of the monthly and seasonal precipitation variations at different methods. We used cross validation of interpolation methods, first, we can estimate that the value of a station rainfall is general values and is estimated by the value of its neighboring stations, as forecast values, then calculate the deviation (error values) between actual rainfall values and forecasted values. Evaluated indexes, mean square error

(MSE) and the root mean square error (RMSE) are estimated to assess the accuracy of the interpolation. Secondly, we can estimate that the values of forecasted rainfall and are estimated by the spatial least squares method, as forecast values. Various geostatistical interpolation types can be obtained from the linear model by applying the generalized least-squares estimation of the expected values. The type of kriging method depends on the model assumed for the expected values. Kriging methods depend on mathematical and statistical models. Kriging assumes that at least some of the precipitation spatial variations observed in natural conditions can be modeled by random processes with spatial autocorrelation, and require that the spatial autocorrelation be explicitly modeled. The geostatistical analysis offers several types of kriging, which are suitable for different types of data and have different underlying assumptions: Ordinary, Simple, Universal, Indicator, Probability, Disjunctive and Empirical Bayesian. Interpolation by ordinary kriging (OK) was the geostatistical method applied to these rainfall data. Kriging interpolation methods provide each cell with a local, optimal prediction and an estimation of the error that depends on the accuracy and on the spatial nature of the data.

Results and discussion

As pointed out, geostatistics interpolation methods study the variations of climatic variables or the elements which are not directly observable. These variations, patterns are measured by several models. Concerning the effects of temporal-spatial factors on precipitation, two indicators that is, geostatistical models and spatial models, were found to influence precipitation. In Iran, the best presenting models is for all time the EBK and OK, and the worst is the IDW. The results showed that IDW, OK, UK and EBK are the suitable methods with the least MSE (IDW=0.247, OK=0.137, UK=0.158 and EBK=0.0357) and RMSE (IDW=0.497, OK=0.37, UK=0.398 and EBK=0.189). The results proved that pointed methods were suitable for the estimation of rainfall variations at the studied level. Range annual rainfall during the study period varied from 1537.095mm for UK method to 1764.98 mm for IDW method (OK=1537.95 and EBK=1753.144) for the Iran using interpolation methods. These values were different from those observed on the dataset. So, range monthly rainfall during the study period varied from 200.467 mm for IDW method in January to 208.93 mm for OK method (UK=208.41mm and EBK=207.617 mm) for the Iran using interpolation methods. Range monthly rainfall during the study period varied from 224.44 mm for EBK method in February to 225.541 mm for IDW method (UK and OK=225.209 mm) for the Iran using interpolation methods. Range monthly rainfall during the study period varied from 263.27 mm for OK method in March to 264.71 mm for IDW method (UK=263. 276 mm and EBK=263. 63 mm) for the Iran using interpolation methods. Range monthly rainfall during the study period varied from 147.075 mm for OK and UK methods in April to 161.14 mm for IDW method (EBK=160 mm) for the Iran using interpolation methods. So, range monthly rainfall during the study period varied from 65.649 mm for UK method in May to 71.17 mm for IDW method (OK=65. 65 mm and EBK=70. 6 mm) for the Iran using interpolation methods. Range monthly rainfall during the study period varied from 52.42 mm for UK method in June to 57.489 mm for IDW method (OK=52. 44 mm and EBK=57. 01 mm) for the Iran using interpolation methods. Range monthly rainfall during the study period varied from 46.24 mm for IDW method in July to 46.75 mm for EBK method

(OK=46. 49 mm and UK=46. 48 mm) for the Iran using interpolation methods. Range monthly rainfall during the study period varied from 108.7 mm for UK method in August to 109.93 mm for EBK method (OK=108. 71 mm and IDW=108. 86 mm) for the Iran using interpolation methods. So, range monthly rainfall during the study period varied from 261.39 mm for OK and UK methods in September to 266.5 mm EBK method (IDW=263. 6 mm) for the Iran using interpolation methods. Range monthly rainfall during the study period varied from 315.6 mm for OK and UK methods in October to 320.46 mm for EBK method (IDW=317. 63 mm) for the Iran using interpolation methods. Range monthly rainfall during the study period varied from 244.7 mm for OK and UK methods in November to 295.28 mm for IDW method (EBK=293. 64 mm) for the Iran using interpolation methods and range monthly rainfall during the study period varied from 230.14 mm for IDW method in December to 231.26 mm for EBK method (OK and UK=231. 17 mm) for the Iran using interpolation methods. These values were different from those observed on the dataset. The results show in terms temporal-spatial a maximum variation in the months of November, April and January and minimum variability in the months of July and December. Therefore, for the all stations, the precipitation data under two scenarios are higher compared and similarity to the forecasted data in spatialtemporal variations format in July and December and lower compared and similarity to the forecasted data in November, April and January. For the all stations, the results determine that the rainfall variations forecasted patterns in Iran match well with the observed data except for November, April and January. For the all stations, the results show that the rainfall variations forecasted patterns are higher than the observed data in November, April and January. As for the all stations and rainfall points, the results indicate that the spatial variation trend of the forecasted rainfall data are variety to those of simulation patterns by selective interpolation methods. The highest precipitation occurs in October, which was the extract the condition by selective interpolation methods. As for the all stations, the results indicate that the spatial variation trend ranges of the forecasted rainfall data are variety to those of simulation patterns by interpolation methods. The highest range of precipitation spatial variation trend occurs in April (44.295 mm), November (35.06) and October (33.528 mm), which was the extract the condition by interpolation methods and range lowest of precipitation spatial variation trend occurs in December (0.67 mm), July (5.587 mm) and February (6.035 mm), which was the extract the condition by selective interpolation methods. Therefore, for the all stations and rainfall points, the results determine that the rainfall variations forecasted trend patterns in Iran match well with the increasing observed south to north except for January and December (decreasing observed south to north). As, the simulated precipitation patterns by selective interpolation methods are higher than the observed ones during the autumn (818.992 mm) and winter (686.792 mm) period. Therefore, for the all stations and rainfall points, the results determine that the rainfall variations forecasted trend patterns in Iran match well with the increasing forecasted trend in Caspian sea and western mountainous regions to south and east, south for autumn season and in the west and western south for the winter season and in north and western north for spring season (204.7 mm) and in Caspian sea for summer season (417.079 mm). Therefore, for the all stations and rainfall points, the results determine that rainfall seasons are autumn and winter over Iran and is spring rainfall season

for western north and is the summer rainfall season for the Caspian Sea beach. Nevertheless, the overall trends of simulation and forecast patterns are a very good match. Thus, the precipitation trend variation in Iran is well simulated and forecasted by selective interpolation methods. After the selective interpolation methods outputs were validated, the future precipitation trends of 140 stations and rainfall points could be forecasted for the period of 2014-2064 over Iran. On the basis of the future precipitation trends of 140 stations and 37261 rainfall points, four different interpolation methods, including IDW, OK, UK and EBK, were used for producing the monthly and seasonal precipitation trends over Iran. The results reveal that the precipitation spatial trends generated by UK, OK and EBK methods are similar but different from those produced by IDW. This is because interpolation methods may be exactly interpolators. On the other hand, the interpolation results were compared on the basis of cross-validated RMSE. As shown Fig2. the RMSE for different methods are in the order EBK<OK<UK<IDW<PK<IK<DK<SK<RBF<GPI<LPI, indicating that the minimum RMSE is obtained by EBK,OK,UK and IDW, which is the method for interpolating future precipitation trends over Iran.



Figure 2. RMSE of Interpolation Methods (mm/month⁻¹)

The monthly, seasonal and annual precipitation patterns created by the best interpolation method (EBK, OK, UK and IDW) were used to forecast spatial variations of future precipitation variations patterns over Iran. The results show that the monthly precipitation would be increasing gradually from south to north Iran in February, March, April, May, June, July, August, September, October and November and would be decreasing from north to south Iran for January and December. The range of precipitation trend would be for winter of 48.16 to 180.053 mm season-1 (Fig.3).



Figure 3. Trend Predication of Winter Rainfall

Thus, the Western North and West Iran would receive the highest seasonal precipitation (approximately 180.053 mm season-1), whereas the Eastern South and East Iran would receive the lowest one (about 48.16 mm season-1) over the period of 2014–2064 and range would be increased from Eastern South to Western North approximately 131.893 mm season-1. The range of precipitation trend would be for spring from 0.111 to 116.88 mm season-1 (Fig.4).



Figure 4. Trend Predication of Spring Rainfall

Thus, the Western North Iran would receive the highest seasonal precipitation (approximately 116.88 mm season-1), whereas the Eastern South Iran would receive the lowest one (about 0.111 mm season-1) over the period of

2014–2064 and range would be increased from Eastern South to Western North approximately 116.769 mm season–1. The range of precipitation trend would be for the summer from 0.0011 to 27.773 mm season–1 (Fig.5).



Figure 5. Trend Predication of Summer Rainfall

Thus, the Western North Iran would receive the highest seasonal precipitation (approximately 27.773 mm season-1), whereas the Eastern South Iran would receive the lowest one (about 0.0011 mm season-1) over the period of 2014–2064 and range would be increased from Eastern South to Western North approximately 27.77 mm season-1. The range of precipitation trend would be for autumn from 1.32 to 152.079 mm season-1 (Fig.6).



Figure 6. Trend Predication of Autumn Rainfall

Thus, the Western North Iran would receive the highest seasonal precipitation (approximately 152.079 mm season-1), whereas the Eastern South

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Iran would receive the lowest one (about 1.32 mm season-1) over the period of 2014–2064 and range would be increased from Eastern South to Western North approximately 150.759 mm season-1. The range of precipitation trend would be for Annual from 55.791 to 477.222 mm year-1 (Fig.7).



Figure 7. Trend Predication of Annual Rainfall

Thus, the Western North Iran would receive the highest annual precipitation (approximately 477.222 mm year-1), whereas the Eastern South Iran would receive the lowest one (about 55.791 mm year-1) over the period of 2014–2064 and range would be increased from Eastern South to Western North approximately 421.43 mm year-1. All stations showed precipitation over Iran varies spatially at an annual, seasonal and monthly level with statistically significant results concentrated mostly in the North and Western parts of the country. A regionalization analysis in monthly precipitation was to estimate the temporal-spatial patterns variations in precipitation. The stronger spatial variations, the lower precipitation in general in Iran, while weaker spatial variations mean larger precipitation in the country. The density of winter precipitation spatial distribution is in the South of Caspian Sea and some parts of the highlands in West to Eastern South of Iran the severe reduced distribution. Precipitation spatial patterns over Iran varies and the spring precipitation range forecast using Inverse Distance Weighting for the whole country is 195.98 mm over the investigated period that decreased from Northern and Western North to South and Eastern South in Iran. The density of spring precipitation spatial distribution is in the North and Western North. On the summer scale, using Inverse Distance Weighting, all of the stations showed range about 380.183 mm that decreased from North to South in Iran. The density of summer precipitation spatial distribution is in the Caspian Sea. The spatial distribution of precipitation in autumn using Inverse Distance Weighting showed the range about 688.73 mm that decreased toward center and south into Iran. The density of autumn precipitation spatial distribution is in the North of Iran (Caspian Sea) and some parts of the highlands. In terms, spatial variations are very similar to the winter and autumn precipitation distribution. In our

study, the highest percentage of precipitation variations spatially was observed in autumn and lowest in spring.

Conclusions

Using a Geostatistical interpolation method, especially one with a graphical - quantitative editor that allows the user to specify the model by drawing it on a curtain -it is quite easy to add precipitation for a geostatistical spatial model. A primary purpose of our study was zoning temporal-spatial patterns variations in precipitation. Our other aim was to examine the variety of various geostatistical - spatial patterns. In this study, eleven geostatistical interpolation methods, were studied using monthly, seasonal and annual precipitation in Iran. 140 stations' and 37216 rainfall point precipitation was investigated using a geostatistical spatial model. Results indicated that there are various temporal-spatial variation patterns that affect precipitation in Iran. The findings also indicated that among the rainfall data which were influential on precipitation, seasonal then monthly and annual precipitation had the highest spatial variations in the rate of precipitation. The hypothesis for the spatial variability of the rainfall in Iran is also accepted. After all, the temporalspatial patterns affects the precipitation rate in Iran and the geostatistical interpolation methods, can show the magnitude of these variations on the precipitation rate changes and can well examine the variation patterns.

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Disclosure statement

The Authors reported that no competing financial interest.

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