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Evaluation of Different Cokriging Methods for Rainfall Estimation in Arid Regions (Central Kavir Basin in Iran)

M.A. Zare Chahouki[a], A. Zare Chahouki[b*], A. Malekian[a], R. Bagheri[c], S.A. Vesali[c]

[a] *Department of Rehabilitation of Arid and Mountainous Regions, University of Tehran, Karaj, Iran*
[b] *Faculty of Natural Resource Management, Yazd University, Yazd, Iran*
[c] *MENARID provincial project manager of Yazd Province, Yazd, Iran*

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Abstract

Rainfall is considered a highly valuable climatologic resource, particularly in arid regions. As one of the primary inputs that drive watershed dynamics, rainfall has been shown to be crucial for accurate distributed hydrologic modeling. Precipitation is known only at certain locations; interpolation procedures are needed to predict this variable in other regions. In this study, the ordinary cokriging (OCK) and collocated cokriging (CCK) methods of interpolation were applied for rainfall depths as the primary variate associated with elevation and surface elevation values as the secondary variate. The different techniques were applied to monthly and annual precipitation data measured at 37 meteorological stations in the Central Kavir basin. These sequential steps were repeated for the mean monthly rainfall of all twelve months and annual data to generate rainfall prediction maps over the study region. After carrying out cross-validation, the smallest prediction errors were obtained for the two multivariate geostatistical algorithms. The cross-validation error statistics of OCK and CCK presented in terms of root mean square error (RMSE) and average error (AE) were within the acceptable limits for most months. Then the two approaches were compared to select of the most accurate method (AE close to zero and RMSE from 0.53 to 1.46 for 37 rain gauge locations for all months). The exploratory data analysis, variogram model fitting, and generation precipitation prediction map were accomplished through use of ArcGIS software.

Keywords: Altitude; Central Kavir basin; Cokriging; geographical information system; Precipitation

1. Introduction

Most of the water received by a river basin occurs as rainfall events over the basin. As one of the primary inputs that drive watershed dynamics, the estimation of spatial variability of precipitation has been shown to be crucial for accurate distributed hydrologic modeling. The estimation of precipitation, accordingly, is very important for assessing water resources. The estimation of precipitation is also important for predicting natural hazards caused by heavy rain.

To estimate precipitation properly, it is necessary to have optimally distributed rain gauges and to apply an appropriate technique for the estimation. In this study, we used a geostatistical approach. To calculate average spatial statistics in climatology, there is a wide choice of interpolation techniques for rainfall mapping. The most important methods in this case are kriging. Kriging has seen many applications, especially in the mining industry and, more recently, in hydrology and meteorology. Early applications of kriging in rainfall estimation were described by Delhomme and Delfiner (1973) (from: PardoIgu´ zquiza (1998)). Many papers have tried to apply geostatistics to these themes.

Tabios and Salas (1985) found kriging to be superior to other commonly-used interpolation techniques such as Thiessen polygons, polynomial trend surfaces, inverse distance, and inverse square distance methods for

* Corresponding author. Tel.: +98 351 8123245,
Fax: +98 351 8123245.
E-mail address: zare.chahouki@gmail.com

precipitation estimation in a 52 000 km^2 region in Nebraska and Kansas.

According to Ahmed and De Marsily (1987), kriging with external drift (KED) is more adapted than ordinary kriging for coarse sampling data. It lies in the adoption of an external variable which is observed with a spatial density exceeding that of the original variable. Grimes *et al*. (1999) adopted kriging with external drift using both satellite data and ground rain gauges to improve the estimation of decadal rainfall and their spatial distribution while Goovaerts (2000) adopted a digital elevation model for monthly and annual rainfall totals in south Portugal.

Hevesi *et al*. (1992a, b) analyzed annual precipitation estimates with geostatistical techniques. Then they used cokriging to estimate the precipitation distribution as a function of elevation. Compared with other techniques, they found that cokriging gave the best estimate. Creutin *et al*. (1988) introduced a simplified cokriging system to optimize merging radar rainfall and rain gauge data and found it very effective in reducing system size.

Phillips *et al*. (1992) compared three geostatistical procedures for spatial analysis of precipitation in mountainous terrain in western Oregon (Willamette River basin). Detrended kriging and cokriging compared with kriging offer improved spatially distributed precipitation estimates in mountainous terrain on the scale of a few million hectares.

PardoIgu´zquiza (1998) compared the areal average climatological rainfall mean estimated by the classical Thiessen method, ordinary kriging, cokriging, and kriging with an external drift (the first two methods used only rainfall information, while the latter two used both precipitation data and orographic information) in the Guadalhorce river basin in southern Spain, and concluded that kriging with an external drift seemed to give the most coherent results in accordance with cross-validation statistics and had the advantage of requiring a less demanding variogram analysis than cokriging.

Goovaerts (2000) compared TP, WMA, ordinary kriging with varying local means, kriging with external drift and collocated co-kriging for spatial interpolation of monthly and annual rainfalls. The results showed large prediction errors of the TP and WMA, while ordinary kriging was more accurate.

Diodato and Ceccarelli (2005) compared the inverse squared distance method with linear regression and ordinary cokriging (OCK) for the Sannio Mountains (southern Italy), obtaining the best results with cokriging that included elevation as secondary information.

Diodato (2005) studied the influence of topographic co-variables on the spatial variability of precipitation over small regions of complex terrain. The results showed that ordinary cokriging is a very flexible and robust interpolation method, because it may take into account several properties (soft and hard data) of the landscape.

Li *et al*., (2006) estimated daily suspended sediment loads (S) using cokriging (CK) of S with daily river discharge based on weekly, biweekly, or monthly sampled sediment data. The results showed that the estimated daily sediment loads with CK using the weekly measured data best matched the measured daily values.

Hengl *et al.* (2007) discussed the characteristics of regression-kriging (RK) or Universal Kriging, its strengths and limitations, and illustrated these with a simple example and three case studies.

Portal´es *et al*. (2009) performed a comparative study of different univariate and multivariate interpolation in eastern Spanish Mediterranean coast. Models were achieved for seasonal scales, considering a total of 179 rain gauges; data from another 45 rain gauges were also used to predict errors. Results proved that there is no ideal method for all cases; the method to be used will depend on (a) the number of geographical factors that influence rainfall, and (b) the major or minor spatial correlation within the rainfall.

Zhang and Srinivasan (2009) developed nearest-neighbor (NN), inverse distance weighted (IDW), simple kriging (SK), ordinary kriging (OK), simple kriging with local means (SKlm), and kriging with external drift (KED) to facilitate the estimation of automatic spatial precipitation while incorporating the geographic information system program in the Luohe watershed, located downstream of the Yellow River basin. The evaluation results showed that the SKlm_EL_X and KED_EL_X methods, which incorporate elevation and spatial coordinates into SKlm and KED, respectively, produced significantly better results than Thiessen polygon and IDW in terms of the coefficient of correlation.

The present study's goal was to use multivariate geostatistical methods to predict rainfall from elevation information and map the spatial variability. The specific objectives were: 1. to extract elevation points from the DEM for analysis and rainfall data for use in CK methods as a primary variate and elevation values as a secondary variate, 2. to attempt different CK methods and select the best one through analyzing the cross-validation error statistics through cross-semivariogram models, and 3. to use the selected CK method to predict rainfall values at unmeasured locations.

The benefits of a geographical information system (GIS) and a geostatistics approach to accurately model the spatial distribution pattern of precipitation are known.

2. Materials and Methods

The study area is located in the center of Iran (latitude between 34º 15´and 36º 56´N, longitude between 52º 15´and 56º 53´ E) on the southern border of the Alborz mountain range. Central Kavir basin is one of the largest regions in Iran's central zone. The study area is part of this basin with a surface area of approximately 57784 km^2. To the north lie districts within the Alborz mountain range. The maximum and minimum altitudes in the region are 3884 and 648 m a.s.l., respectively. The mean altitude is about 1238 m a.s.l. Figure 1 shows the DEM, with a spatial resolution of 50 m, used in this research.

Mean annual precipitation reaches approximately 180 mm in the majority of the areas of the region, ranging from <70 mm in the south of the study region to as much as >300 mm in the northern mountainous areas. One of the most important characteristics of the precipitation is its interannual variability. The region has a dry season from June to November and a wet season from December to May (>80% of the precipitation falls between these months). Kavir basin is an arid region where the water balance is negative.

The delineated base map (i.e. polygon feature class) of the study area and the location of rainfall gauging stations within the Kavir basin (i.e. point feature class) were generated using ArcGIS as two different coverage feature classes. The point feature class coverage map, representing the rainfall locations, also contained the mean monthly rainfall depths for twelve months as attribute values. The base map and the rainfall point coverage map were overlaid to represent the rain gauge locations. The DEM of study area was used to extract approximately 160 elevation points ranging from of 670 to 3600 m a.s.l. covering the entire study area for use in co-kriging analysis. The geostatistical analysis extension module of ArcGIS 9.3 was used to analyze and develop kriged surfaces. Several interpolation approaches are available in geographical information systems (GISs) to meet the general requirements of interpolation. Figure 1 shows the spatial distribution of the rain gauge stations and the locations of 160 extracted elevation points from DEM with elevations used in this study. Many stations are situated in mountainous areas.

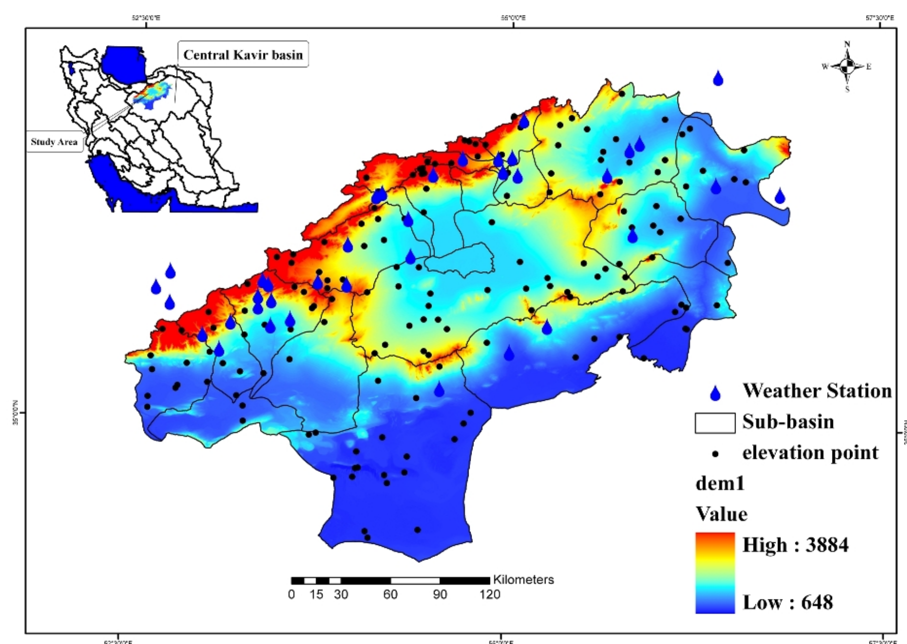

Fig. 1. Location and topography of the study area and locations of extracted elevation points from DEM and rain and meteorological station locations

Daily precipitation data for 30 years (1971-2004) were obtained from 37 meteorological stations. Rainfall measurements are collected daily and compiled to generate monthly totals. Estimating rainfall depth at unsampled locations can be i mproved by interpolating between the nearest gauges. The daily observations made at all stations pass through a rigoro us quality control procedure. Consistency checks were applied to the data. After assuring the quality of the raw data, monthly precipitation averages were calculated. Some basic sample statistics were also determined (Table 1). Data used in the analysis were derived from Iran's Ministry of Energy. The analysis of the primary variate (mean monthly rainfall depth) and secondary variate (elevation) resulted in good correlation values, ranging from 0.50 (January) to 0.77 (September).

Table 1. Descriptive statistics of the monthly and annual precipitation (mm) data for 37 meteorological stations

month	Mean	Median	Standard deviation	Maximum value	Minimum value	Coefficient of skewness	Kurtosis	Co*
January	20.26	19.10	7.63	41.90	8.20	0.86	0.69	0.50
February	22.81	20.20	8.75	39.90	9.40	0.52	-0.80	0.73
March	28.97	28.60	1.60	50.40	9.10	0.30	-0.16	0.70
April	27.10	25.30	9.57	48.20	9.70	0.51	-0.61	0.69
May	22.49	18.70	11.04	44.70	5.90	0.53	-0.87	0.75
June	7.37	5.10	5.76	24.40	0.20	1.21	0.89	0.73
July	4.84	3.80	4.16	15.40	0.30	1.11	0.46	0.74
August	3.54	2.20	3.25	11.80	0.10	1.24	0.59	0.75
September	3.57	2.60	2.93	10.80	0.00	0.85	-0.17	0.77
October	6.99	5.40	4.98	18.90	1.50	0.99	-0.36	0.69
November	12.35	9.50	8.09	33.30	3.10	1.35	0.81	0.62
December	20.94	18.40	9.73	57.00	7.50	1.61	3.95	0.72
Annual	181.41	154.92	76.24	348.54	73.54	0.80	-0.43	0.78

*: Cor = Linear correlation coefficient between precipitation and altitude.

2.1. Geostatistical interpolation techniques

In this section, the estimators used in the case study are briefly introduced. More information about them can be found in Goovaerts (1997).

All geostatistical estimators are variants of the linear regression estimator $Z^*(x)$:

$$Z^*(x) - m(x) = \sum_{i=1}^{n} w_i(x).\left[Z(x_i)m(x_i)\right] \qquad (1)$$

where each datum, $Z(x_i)$, has an associated weight, $w_i(x)$, and $m(x)$ and $m(x_i)$ are the expected values of $Z^*(x)$ and $Z(x_i)$, respectively. The kriging weights must be determined to minimize the estimation variance, Var $[Z^*(x)-Z^*(x)]$, while ensuring the unbiasedness of the estimator, $E[Z^*(x)- Z^*(x)] = 0$. All different types of kriging are distinguished depending on the chosen model for the trend, $m(x)$, of the random function $Z(x)$ (Goovaerts, 1997).

In this study, three phases were completed to conduct any geostatistical work (Moral, 2009):

1. *Exploratory analysis of data*. Data were studied without considering their geographical distribution. Statistics were applied to check data consistency, remove outliers, and identify the statistical distribution from where the data came.
2. *Structural analysis of data*. Spatial distribution of the variable was analyzed. Spatial correlation or dependence can be quantified with semivariograms.

A variogram shows the degradation of spatial correlation between two points of space when the separation distance increases. Function has two components: i) the nugget effect, which characterizes the discontinuity jump observed at the origin of distances and quantifies the short-term, erratic variations of the studied phenomenon plus measurements and data errors; ii) the increasing part of the variogram, which may reach the sill (theoretical sample variance), level off the curve, for a distance called range, or increase continuously with distance. The non-nugget part of the variogram measures the non-random part of the phenomenon and models its average medium-scale behavior in space.

The variogram is a function of both distance and direction, and so direction-dependent variability can be accounted for.

Cokriging is a branch of kriging which uses additional covariates, usually more intensely sampled, to assist in predicting. Cokriging is most effective when the covariates are highly correlated. Both kriging and cokriging assume the homogeneity of first differences. Cokriging uses one or more secondary features which are usually spatially correlated with the primary feature (e.g., heights secondary, rain primary). Cokriging means kriging with more than one variable. The cokriging approach is another possible way to incorporate secondary data. Although it is indicated when the secondary information is not exhaustive, i.e. auxiliary data are not available at all grid-nodes, if this information is known everywhere and changes smoothly across the study area, the cokriging system can retain only the secondary datum collocated with the location which is estimated (Goovaerts, 1997). In the current study we performed two cokriging methods. Ordinary co-kriging is the estimation of one variable based on the measured values of two or more variables. It is a generalization of kriging in the sense that at every location there is a vector of many variables instead of one variable. OCK is the multivariate extension of kriging (Goovaerts, 1997). OCK analysis was performed for the 37 primary data points and the secondary variate (elevation points extracted from the DEM). Collocated ordinary co-kriging is a conditional estimator of CK where the neighborhood uses the secondary variable as a subset of locations where primary data are available along with the estimated locations (Wackernagel, 2003). The primary variate of the 37 measured values of precipitation and the corresponding altitude values were used in the analysis. CCK analysis was performed for 41 primary data points (precipitation) and the secondary variate was the elevation of the point locations included in the primary variate [See Goovaerts (1997) for a detailed presentation of cokriging algorithms].

All geostatistical analyses were conducted using the extension Geostatistical Analyst of the GIS software ArcGISd (version 9.3, ESRI Inc). After modeling annual and monthly precipitation with the selected algorithms, a set of map layers in raster format was generated.

2.2. Error statistics

The performances of the OCK and CCK algorithms were assessed and compared using cross-validation results. This was achieved by temporarily removing one datum at a time from the data set and re-estimating the deleted value from the remaining data using kriging algorithms. In the present study, the reduced mean square error (RMSE) and the average error (AE) were the error statistics used (Campling *et al*., 2001) to compare the model-predicted results with the observed values. RMSE was used to check the consistency between the estimation errors and the standard deviation of the observed values:

$$RMSE = \left(\frac{1}{n} \sum_{i=1}^{n} \left[\frac{Z(o_i) - Z(p_i)}{s} \right]^2 \right)^{1/2} \quad (2)$$

AE was used to test the predictability of the developed models:

$$AE = \frac{1}{n} \sum_{i=1}^{n} \frac{Z(o_i) - Z(p_i)}{s} \quad (3)$$

where:
zoi = observed value at location i
zpi = predicted value at i
N = number of pairs of observed and predicted values
S = standard deviation of the observed values.

This RMSE value should be within the range of 1 ±[2(2/N)$^{1/2}$] for the model to be acceptable (Ella *et al*., 2001). The AE value should be close to zero for the model to be acceptable.

3. Results

The exploratory data analysis performed on the primary variate and the secondary variate of elevation revealed that the data are normally distributed and free of outliers. In cokriging, the primary and secondary variates were fitted using different models available in the ArcGIS geostatistical extension module, and the optimal cross-semivariogram was selected. Figures 2 and 3 show annual and monthly semivariograms.

After calculating OCK and CCK, the cross-validation error statistics were compared to select the best method to perform the CK, Then, the best CK algorithm (either OCK or CCK) was used to predict the primary variate values for more locations within the study region. The database of these predicted variables corresponding to elevation locations provided the rainfall depths at predicted unmeasured locations. The cross-validation statistics in terms of RMSE and AE were estimated to ascertain the model algorithms, and finally the interpolated surface reflecting the variation of rainfall depth over the study area was generated using ArcGIS. These procedures were followed to generate the spatial variability map of long-term mean monthly rainfall for one month and replicated for all twelve months to generate twelve such maps. The interpolated surface was generated for the study region for the twelve months, and the map of annual rainfall, driest (august) and wettest (March) months of the year are presented in Figures 4 and 5, respectively.

The predicted mean monthly rainfall values from the CK algorithm and the observed data of rain gauge locations for all twelve months were subjected to ordinary kriging analysis.

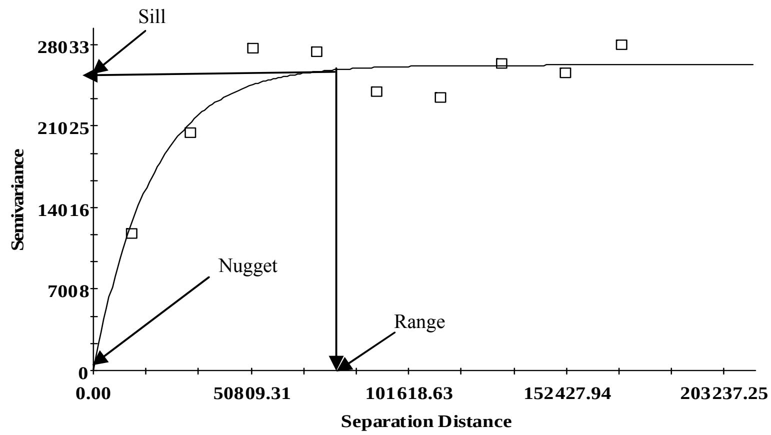

Fig. 2. Annual Rainfall Semivariogram

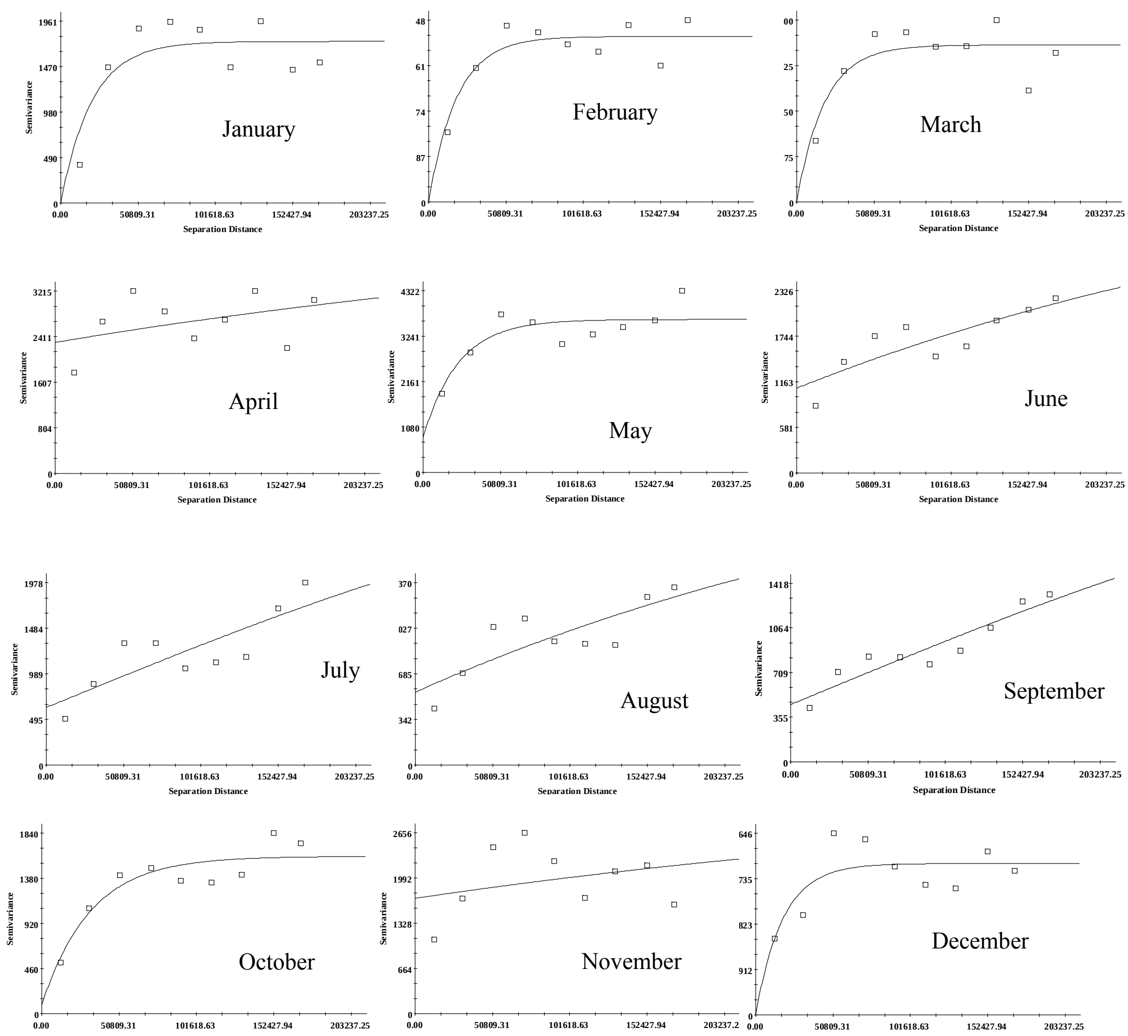

Fig. 3. Monthly Rainfall Semivariogram

This was performed to select the best method for predicting rainfall at unmeasured locations and to predict spatial variability. The cross-validation error statistics were estimated using Equations 2 and 3 to select the best model.

The calculated RMSE of cross-validation results for a ll months were well within the acceptable range for the model obtained through the OCK and CCK method. Moreover, the AE values calculated from the cross-validation results of the CCK and OCK algorithm methods for all months were close to zero. The cross-validation statistics performed for both the OCK and CCK methods of CK (Table 2) revealed that the OCK method performed better than the CCK method. Hence, the OCK algorithm was used to predict the rainfall prediction map.

Table 2. Comparison of OCK and CCK methods in terms of model fitting cross-validation statistics

month	Variogram model	ordinary cokriging Cross-validation statistics		collocated ordinary cokriging Cross-validation statistics	
		AE[a]	RMSE[b]	AE[a]	RMSE[b]
January	Exponential	0.032	1.02	0.036	1.03
February	Exponential	0.016	0.73	0.009	0.82
March	Exponential	0.013	0.76	0.040	0.95
April	Exponential	0.005	0.93	0.014	0.98
May	Exponential	-0.016	0.74	0.005	0.90
June	Exponential	0.004	0.81	0.018	0.89
July	Spherical	-0.003	0.74	-0.002	0.78
August	Spherical	0.016	0.77	0.018	0.81
September	Spherical	-0.006	0.73	0.005	0.81
October	Exponential	0.005	0.87	0.009	0.91
November	Exponential	0.026	0.91	0.026	0.92
December	Exponential	0.008	0.77	0.005	0.80
Annual	Exponential	0.006	0.93	0.013	0.86

[a] The acceptable value of KAE is close to zero.
[b] The acceptable value of KRMSE ($1 \pm [2(2/N)^{1/2}]$ is 0.53 to 1.46 ($N = 37$).

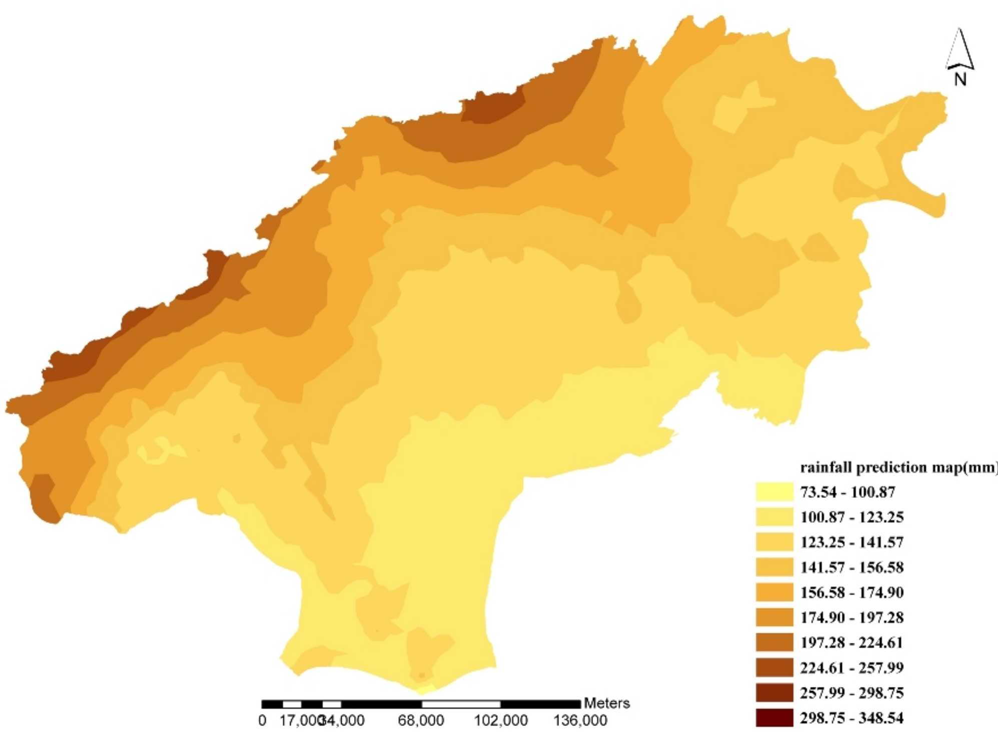

Fig. 4. Annual Rainfall Prediction Map

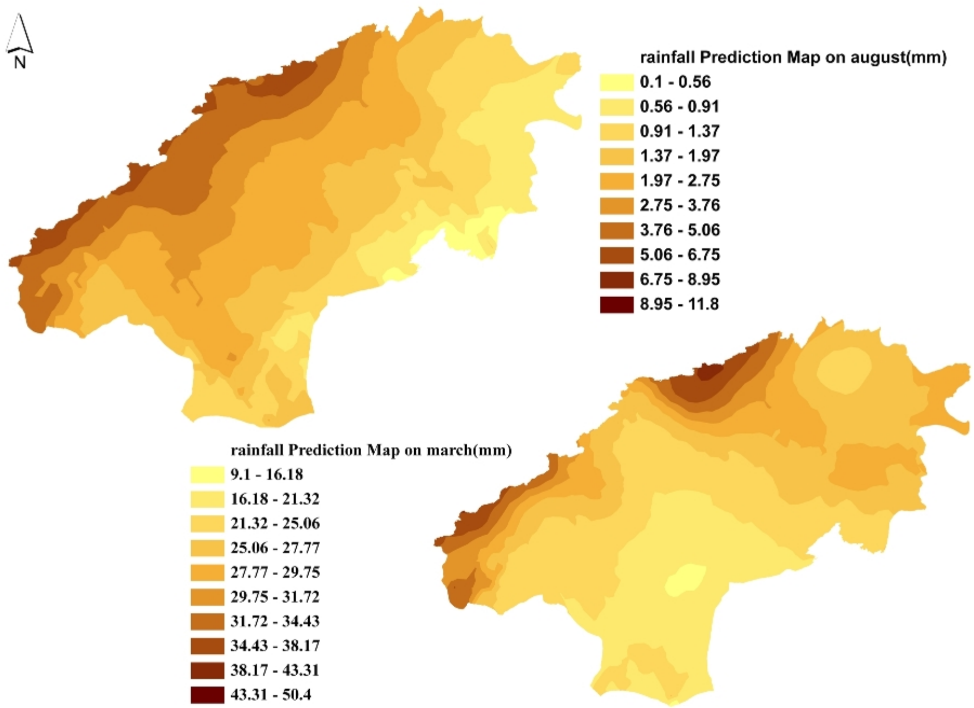

Fig. 5. Rainfall prediction map for the driest (August) and wettest (March) months

4. Discussion and Conclusion

Many studies, particularly those performed in Iran such as Zabihi *et al*., (2011), Mirmousavi et al., (2010), Shaabani (2010), Saghafian *et al*., (2011), and Mahdavi *et al*., (2004) solely compared IDW interpolation and kriging family approaches, and all of the above-mentioned studies concluded that the kriging approach is best.

The mentioned researchers attempted to compare a deterministic method (IDW) with the univariate kriging family and concluded that the ordinary kriging method was the most appropriate technique. Some noted researchers the declared co-kriging to be the best among IDW and univariate kriging family techniques. The results of these comparisons are obvious. In many studies, concluded that the kriging method is most suitable, without regard to the origin of data and the point distribution. Comparison of interpolation approach while is worthwhile that the different methods from one family were compared.

In the current research, different geostatistical approaches were classified into deterministic, univariate kriging, and multivariate kriging categories. Then each method was compared within each family. For example, ordinary co-kriging (OCK) and collocated co-kriging (CCK) were compared with each other and not compared with the deterministic approach.

It is understood that modeling rainfall spatial variability of an arid region with a sparse rain gauge network poses a challenging task in terms of prediction accuracy. Furthermore, the short observation record of some stations and inconsistency in data recording also influence the rainfall predictability over the arid region. This necessitates the use of exploratory data analysis techniques as a pre requisite before using the data for geostatistical modeling. It also revealed the necessity of using some secondary variables such as altitude, proximity to large bodies of water, and land cover and the support of remote sensing.

Different multivariate kriging approaches used in this study to predict the spatial rainfall variability for arid regions with orographic effects are simple and reasonable approaches which can be applied to similar locations having sparse rain gauge locations and undulating topography.

OCK analysis was performed for the 37 primary data points (elevation and rainfall values) and the secondary variate (elevation points extracted from the DEM). CCK analysis was performed for 37 primary data points (elevation and rainfall values) and the secondary variate which was the elevation of the point locations included in the primary variate. Both the OCK and CCK methods were compared based on cross-validation error statistics.

The developed methodology of geostatistical analysis and mathematical association of rainfall and elevation values to estimate a standardized value for use in the CK method and the combination of OCK and CCK approaches to generate rainfall prediction maps can be applied to account for the spatial variability of rainfall.

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