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Applying Geostatistical Methods for Analyzing Regional Flood Frequency in North of Iran (Case Study: Mazandaran Catchments)

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ABSTRACT

In Iran, applying geostatistics to regional analysis is said to be in its early stages. The fundamental principle of this technique emphasizes the interpolation of hydrological variables in physiographical, instead of geographical, spaces. This paper deals with the adaptation, application, and comparison of two regional analysis methods based on geostatistics. In this study, data from 38 gauging stations located in the north of Iran were used to investigate the performance of geostatistical methods in two physiographical spaces. Two multivariate analysis methods, namely, Canonical Correlation Analysis (CCA) and Principal Components Analysis (PCA), were used to identify physiographical spaces. Gaussian and exponential models were selected as the best theoretical variogram models in CCA and PCA spaces, respectively. Ordinary and simple kriging geostatistical estimators were also used for regional estimations in both physiographical spaces. Using the interpolation methods in CCA and PCA spaces, regional flood estimations were made for different return periods (10, 20, 50, and 100 years). Finally, performance of both models was studied using five statistical indices. The results showed that both methods had similar and satisfactory performance; however, regional estimations in CCA had higher accuracy and less uncertainty than those in PCA-space. Furthermore, the results indicated that the ordinary kriging method had better performance than the simple kriging method in both spaces and the best interpolation efficiency was observed in the CCA space.

Keywords: Interpolation, Kriging, Physiographical space, Principle Component Analysis (PCA).

INTRODUCTION

Lack of data at sites of interest is one of the problems that hydrologists often face during estimation in many river basins. To solve this problem, regional analyses have been proposed (Stedinger and Tasker, 1985; Burn, 1990; Rosbjerg and Madsen, 1994; Alila, 2000). Several techniques, which seek similarity between sites by attributes of catchment and at-site flow statistics, have been developed for regionalization. Such application of regionalization can be observed in several recently published papers, including those by Malekinezhad *et al*. (2011), Yan and Moradkhani (2015), and Mosaffaie (2015).

According to recent research, geostatistical interpolations, apart from their primary role in interpolation of point data (De Marsily and Ahmed, 1987), are effective means to solve the issue of regionalization of hydrometric data (Skøien*et al*., 2006; Chokmani and Ouarda, 2004). Geostatistical methods were developed firstly for the mining industry (Journel and Huijbregts, 1978).However, the catchment hydrology is applied quite differently (Skøien*et al*., 2006). In other words, hydrological variables are discontinuous variables in the geographical space. Since flood generation mechanisms are

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specific to each catchment, they may change dramatically from a catchment to an adjacent catchment. Consequently, the direct application of interpolation methods in the geographical space does not seem practical (Sauquet, 2000). In order to resolve this problem, Chokmani and Ouarda (2004) proposed a new approach to regionalize hydrological data using geostatistical methods. In this method, based on the concept of hydrological neighborhood (Burn, 1990; Castellarin *et al*., 2001) and using geostatistical methods, hydrological variables are interpolated in physiographical space, instead of conventional geographical space. In classical statistics, there is no relationship between the measured values of a quantity in a specific sample and values of the same quantity in another sample with specific distance. On the other hand, in geostatistics, it is assumed that there is a relationship between various values of a quantity in the population of samples and their distance and placement direction at some specific distance. This spatial relationship is called spatial structure in mathematical definitions. In a geographical space, flood is a quantity with the feature of discontinuity which lacks any spatial structure. Responses to these hydrological events also vary even in the neighboring basins, because the flood generation mechanism and its effective parameters are unique in each specific basin. The occurrence of flood at a specific site indicates a hydrological response to the dominating climate of the area and reflects the effect of physical and geomorphological properties of basins. Thus, although flood does not have a continuous nature in geographical spaces, it will have a continuous nature within the physiographic space, which can be considered a hydrological reaction to the regional climatic and physiographical variables and its interpolation will be possible (Chokmani and Ouarda, 2004). Physiographical Space-Based Interpolation (PSBI) methods hold much promise for many aspects of hydrology. This is a topical issue in hydrology, which is increasingly gaining attention from the scientific community.

After successful application of a PSBI method, this method has attracted the attention of other researchers for instance Skøien*et al*. (2006), Joseph *et al*. (2006), Shu and Ouarda (2007), Skøien and Bloschl (2007), Ouarda *et al*. (2008), Hundecha *et al*. (2008), Castiglioni *et al*. (2009), Kamali Nezhad *et al*. (2010, 2011), Castiglioni *et al*. (2011), Vormoor *et al*. (2011); Laaha *et al*. (2013); Archfield *et al*. (2013), Pugliese *et al*. (2013), Laaha *et al*. (2014), and Castellarin (2014).

Although geostatistical methods are getting increasing attention in the field of regional frequency analysis, they are not regarded as popular among Iranian researchers, and virtually there are nostudies done on the application of such methods in Iran. The current study was undertaken to shed light on the knowledge gap here in this region, and it aimed to apply geostatistical methods (ordinary and simple kriging) in CCA and PCA physiographical spaces to regionalize the catchments located east of the Caspian Sea. Additionally, we aimed to determine the best approach to estimate the regional flood and investigate the efficiency of the interpolation methods in two physiographical spaces.

MATERIALS AND METHODS

Study Region

The study area consisted of the catchments of Mazandaran, located in the north of Iran (see Figure 1). The study area covers a wide

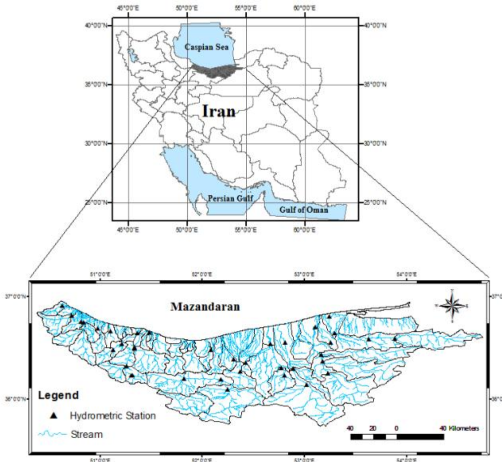

Figure 1. Location of the study area and distribution of hydrometric stations.

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geographical region (over 23,756.4 km^2) which includes 1.46% of the whole territory of Iran. The Mean Annual Rainfall (MAR) in the region ranges from more than 1,500 mm in the west to 180 mm in the east of Mazandaran.

Data and Statistical Analyses

The study area included 78 gauging stations (7.1 to 4,028 km^2) for which daily stream flows were available. The annual maximum daily discharge series from 38 gauging stations with greater than 15 years of records were used to estimate flood frequency quantiles corresponding to 10, 20, 50, and 100 year return periods. Table 1 contains a summary of catchment properties for selected stations in this region. Moment Ratio Diagrams (MRDs) (Hosking and Wallis, 2005) for all stations are shown in Figure 2, based on which, a high degree of heterogeneity can be identified from the L-moment ratio diagrams. The distributions presented in Figure 2 include GEV (Generalized Extreme Value distribution), GLOG (Generalized Logistic distribution), LOGN (Three-parameter Log Normal distribution), and PIII (Pearson type III distribution).

Local flood quantiles for each gauging station were calculated by fitting the best appropriate statistical distribution to the historical flood record (Kouider *et al*., 2002; KamaliNezhad *et al*., 2011).The following distributions were considered at each site: Normal (N), Weibull (WE), Exponential (EXP), Gamma (GA), Logistic (LOG), Generalized Logistic (GLOG), Two-Parameter Log-Normal (LN2), Log Pearson type III (LP3), and GEV. These distributions were fitted with the Maximum Likelihood method and the method of L-Moments. The distributions that were selected most frequently wereN, LOG, GEV and LN2. Probability distributions for flood frequency analysis were defined through applying chi-square and Kolmogorov-Smirnoff tests. Finally, considering the best distributions, at-site flood Quantiles (Q_{loc}) corresponding to the return periods of 10, 20, 50 and 100 years were obtained. In Figure 3, at-site quantiles plots of two stations are shown, using the following plotting position formula (Rao and Hamed, 1997):

$$P_{i:n}= (1-0.35)/n \quad (1)$$

Where, $P_{i:n}$ is the plotting position estimator of observation i in the sample of size n.

In addition to hydrological data, in each river basin, a number of physiographic and climatic descriptors were collated for each site. The set of physiographic and climatic descriptors included: MAR (mm $year^{-1}$), Mean Monthly Rainfall (MMR in mm $month^{-1}$), latitude and longitude (La, Lo in UTM), Maximum, Mean and Minimum Elevations (MaE, MeE, MiE in m), Catchment Mean Slope (CMS in %), Catchment Area (CA in km^2), Catchment Perimeter (CP in km), Main Channel Length (MCL in km),Slope of Main Channel (SMC in %), Height of Station (HS in m), and Percentage of the basin occupied by Lakes and Forest (PL, PF in %).

PSBI Method

The regionalization steps based on PSBI are illustrated in Figure 4. In particular, the regional analysis method using geostatistical methods is composed of two major steps of constructing physiographical space and employing interpolation methods within that physiographical space.

Physiographical space is a multi-dimensional space defined by the effective climatic and physiographical parameters for the considered quantity and its coordinate is obtained by geomorphological descriptors of each basin and multivariate statistical methods. As a result, basins with similar climatic and physiographical properties would have equal coordinates in this space. There are numerous methods for constructing physiographical space, which include PCA and CCA.

Accordingly, in the physiographical space, each basin can be positioned as one point and the empirical values for the considered quantity (at-site flood Quantiles (Q_{loc}) with different return periods) are regarded as the third axis (Z). Hence, interpolation can be carried out using a standard interpolation algorithm, such as simple or ordinary kriging methods (Castiglioni *et al*., 2009).Coordinates of physiographic space are obtained as the

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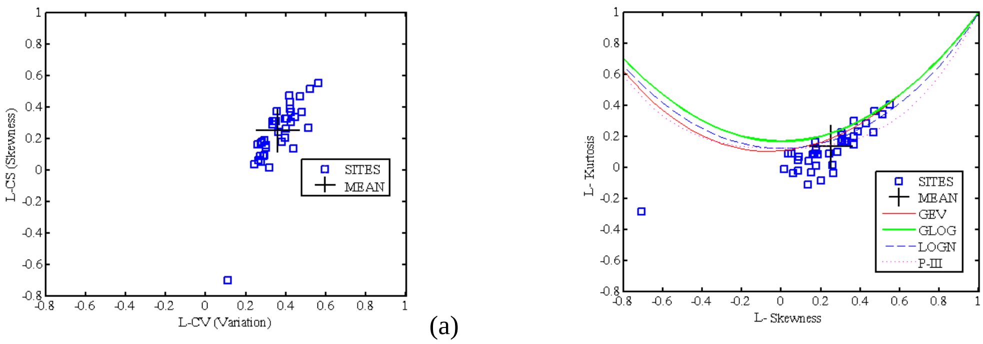
Table 1. The characteristics of the 38 study catchments.

Number	Code	Station	Record Length (Years)	Drainage Area (km^2)	Elevation (m)	latitude	Longitude
1	13-005	Sefidchah	34	1036.918	1030	36° 35' 55"	53° 52' 58"
2	13-009	Gelevard	27	1427.736	600	36° 35' 19"	53° 37' 29"
3	13-013	Abeloo	30	1905.605	50	36° 38' 54"	53° 17' 41"
4	13-006	Nozarabad	34	2017.318	-15	36° 48' 38"	53° 14' 31"
5	13-019	Soleiman-Tangeh	46	1248.253	400	36° 15' 12"	53° 13' 41"
6	13-025	Rig-Cheshmeh	48	2715.254	270	36° 22' 31"	53° 10' 31"
7	13-027	Garmrood	26	876.788	175	36° 26' 17"	53° 09' 54"
8	13-029	Kordkheil	35	4026.573	-5	36° 42' 36"	53° 06' 17"
9	13-017	Darbkola	28	27.573	110	36° 33' 32"	53° 15' 07"
10	14-021	Kerikela	22	566.639	570	36° 08' 29"	53° 01' 13"
11	14-007	Kiakola	54	2386.789	-5	36° 33' 34"	52° 48' 41"
12	14-005	Kasilyan-Shirgah	54	342.896	220	36° 18' 05"	52° 53' 14"
13	14-001	Talar-Shirgah	50	1776.156	220	36° 17' 57"	52° 53' 10"
14	14-071	Pashakola	15	211.338	130	36° 14' 14"	52° 48' 04"
15	14-011	Ghoran-Talar	53	406.617	102	36° 18' 18"	52° 46' 23"
16	14-017	Koshtargah	54	1625.154	1	36° 32' 43"	52° 39' 49"
17	14-013	Baladeh	28	752.74	1360	36° 12' 18"	51° 49' 14"
18	15-015	Razan	36	1182.311	1240	36° 11' 47"	52° 10' 49"
19	15-011	Panjab	29	235.523	860	36° 05' 46"	52° 14' 41"
20	15-017	Karesang	55	3986.658	375	36° 16' 25"	52° 22' 05"
21	15-041	Boliran	15	82.061	175	36° 21' 32"	52° 25' 32"
22	16-003	Aghozkoti	46	140.623	200	36° 29' 00"	52° 05' 00"
23	16-011	Noshahr	34	75.495	-10	36° 39' 27"	51° 28' 41"
24	16-017	Harijan	21	84.839	1900	36° 13' 57"	51° 18' 56"
25	16-081	Valiabad	21	181.099	1750	36° 14' 00"	51° 18' 10"
26	16-083	Abshar	22	586.186	980	36° 19' 50"	51° 15' 21"
27	16-019	Dooab	28	627.434	375	36° 29' 41"	51° 20' 14"
28	16-021	Polezoghal	56	1583.362	350	36° 30' 38"	51° 20' 13"
29	16-023	Kelardasht	48	190.465	1380	36° 28' 57"	51° 07' 21"
30	16-085	Valet	27	330.512	975	36° 32' 31"	51° 12' 45"
31	16-025	Zavat	30	419.008	-23	36° 38' 43"	51° 21' 54"
32	16-033	Mashallh-Abad	20	151.349	70	36° 40' 11"	51° 06' 03"
33	16-041	Haratbar	38	776.2	140	36° 45' 53"	50° 50' 13"
34	16-049	Ganegsar	32	409.227	80	36° 49' 07"	50° 43' 05"
35	16-051	Ramsar	35	135.818	100	36° 54' 49"	50° 37' 43"
36	16-089	Dinarsara	25	224.689	160	36° 41' 47"	50° 58' 36"
37	16-200	Oskomahaleh	18	81.302	215	36° 23' 26"	52° 18' 27"
38	16-203	Rezapat	15	108.192	120	36° 45' 28"	50° 48' 52"



(a) (b)

Figure 2. (a) LC_v–LC_s moment ratio diagram, and (b) L-skewness versus L-kurtosis moment ratio diagram for 38 stations in the north of Iran.

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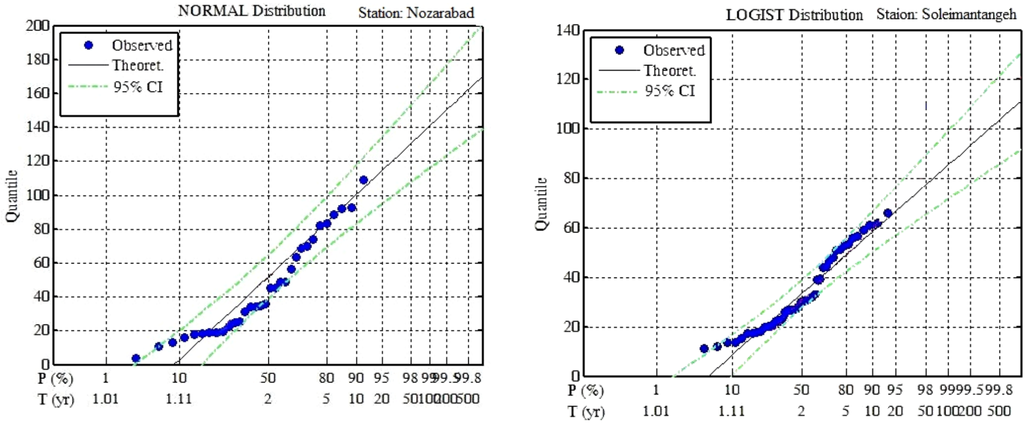

Figure 3. At-site plotting positions and quantile estimations of twostations.

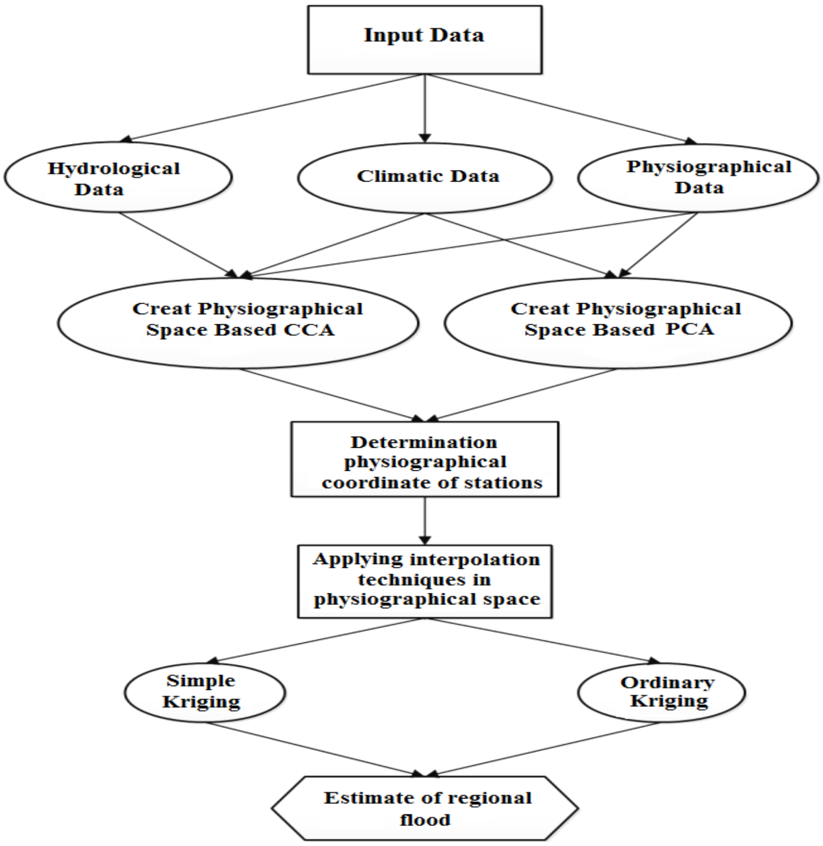

Figure 4. Flowchart of regional analysis based on geostatistical methods.

function of geomorpho-climatic catchment descriptors. Therefore, basins with similar characteristics have similar coordinates in physiographic space (Chokmani and Ouarda, 2004).Finally, by employing interpolation methods (e.g. kriging) within CCA and PCA physiographical spaces, regional flood analysis is obtained according to different return periods.

Analysis and Evaluation of Results

The jack-knife cross-validation procedure, which is also referred to as delete-one cross-

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validation in the literature, is extremely versatile and capable of providing adequate evaluation of the performance of interpolation techniques (Castiglioni *et al*., 2009). Five indexes were adopted to study the relative performances of the various regionalization approaches. These include the mean Bias (BIAS), the relative mean Bias (BIASr), the Root Mean Square Error (RMSE), the relative Root Mean Square Error (RMSEr) as well as the Nash criterion, which can be written as follows:

$$BIAS = \frac{1}{ns}\sum_{i=1}^{ns}(Q_{reg}(i) - Q_{loc}(i)) \tag{2}$$

$$BIASr = \frac{1}{ns}\sum_{i=1}^{ns}\left[\frac{(Q_{reg}(i) - Q_{loc}(i))}{Q_{loc}(i)}\right] \tag{3}$$

$$RMSE = \sqrt{\frac{1}{ns}\sum_{i=1}^{ns}\left[Q_{reg}(i) - Q_{loc}(i)\right]^2} \tag{4}$$

$$RMSEr = \sqrt{\frac{1}{ns}\sum_{i=1}^{ns}\left[\frac{(Q_{reeg}(i) - Q_{loc}(i))}{Q_{loc}(i)}\right]^2} \tag{5}$$

$$NASH = 1 - \frac{\sum_{i=1}^{ns}(Q_{reg} - Q_{loc})^2}{\sum_{i=1}^{ns}(Q_{loc} - \overline{Q}_{loc})^2} \tag{6}$$

Where, $Q_{loc}(i)$, $Q_{reg}(i)$ correspond, respectively, to the local and regional estimates of the discharge Q (corresponding to a given return period T) at station i, and ns is the number of stations (Ouarda *et al*., 2008).

RESULTS AND DISCUSSION

Designing physiographical space is the most important step in the PSBI process. In this study, multivariate statistical methods (CCA and PCA) and geomorpho-climatic variables were used to design physiographical spaces.

Based on the correlations between the hydrologic and physiographic/climatic variables, the variables for designing the physiographical spaces were identified. Results showed that the catchment area was strongly correlated to flood quantiles. The addition of CA, CP, MCL, SMC, MiE, CMS, Lo and HS showed to be highly correlated to flood quantiles. The correlation coefficient between the hydrologic and geomorpho-climatic variables presented in Table 2 and Figure 5 denotes the interrelations between the chosen geomorpho-climatic variables and the hydrological variables.

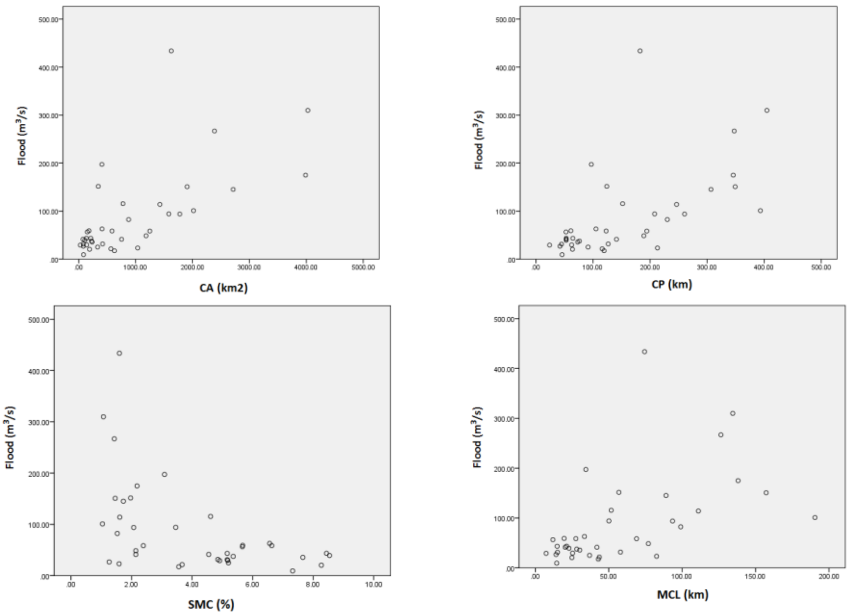

Figure 5. Scatter plot of site characteristics and flood quantiles.

Table 2. The correlation coefficients between the selected variable and flood quantiles.

Variable	CP	CA	MiE	CMS	SMC	MCL	HS	Lo
R^2	0.588	0.657	-0.365	-0.329	-0.513	0.533	0.371	0.350
Sig	0.000	0.000	0.012	0.022	0.000	0.000	0.011	0.016

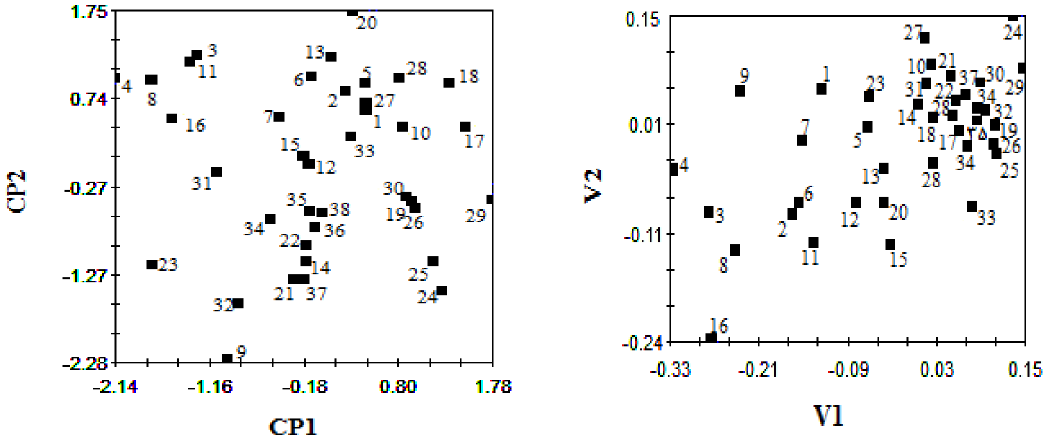

Figure 6. The distribution of stations in the PCA and CCA physiographical space, respectively.

PCA-space was constructed considering 6 physiographical variables of CA, BMS, MCL, SMC, MiE, and HS. In this method, PCA-space was a two-dimensional space constructed based on the first and second principle components. These two components accounted for 73.74% of the total variance (41.73 and 32%, respectively).

Additionally, CCA was used to construct the physiographical space. This method defines the relationship and correlation between two sets of dependent and independent variables. The independent variables considered included CA, CP, MCL, MiE, CMS, and HS. The dependent variables were two hydrological variables of the Q_{20} and Q_{10}. The two-dimensional space formed by the first (V_1) and second (V_2) canonical variables was made through CCA-space, where V_1 and V_2 are the linear combination of two sets of physiographical variables with maximum correlation with the selected hydrological variables. Figures 6-a and -b indicate the position of the hydrometric stations in PCA and CCA spaces, respectively. The identification number specified for each hydrometric station is presented in Table 1.

After designing the physiographical space, physiographical coordinate of each station was obtained according to its position in the physiographical space. Then, the spatial structure of hydrological quantity was examined using GS+ software (GS+TM) based on empirical variograms. The variograms fitted to the quantity of local flood for different return periods in PCA and CCA spaces are shown in Figures 7 and 8, respectively.

After calculating the empirical variograms, the theoretical model must be fitted to them. Spherical, linear, exponential, and Gaussian theoretical models were tested for fitting by empirical variograms. The most common variogram model is said to be the spherical variogram. This variogram, which begins from the origin of the coordinate system, has linear behavior close to the origin. The exponential model is mostly analogous to the spherical model. Although exponential variogram has a linear behavior, the rising rate in variograms is slower than that of the spherical model. While the linear variogram is a sill-less model, the Gaussian model is considered as a transitional model which reaches its sill asymptotically and exhibits a parabolic behavior near the origin. More details are available in Isaaks and Srivistava (1989)

The results of fitting the variogram models are presented in Table 3. Considering the

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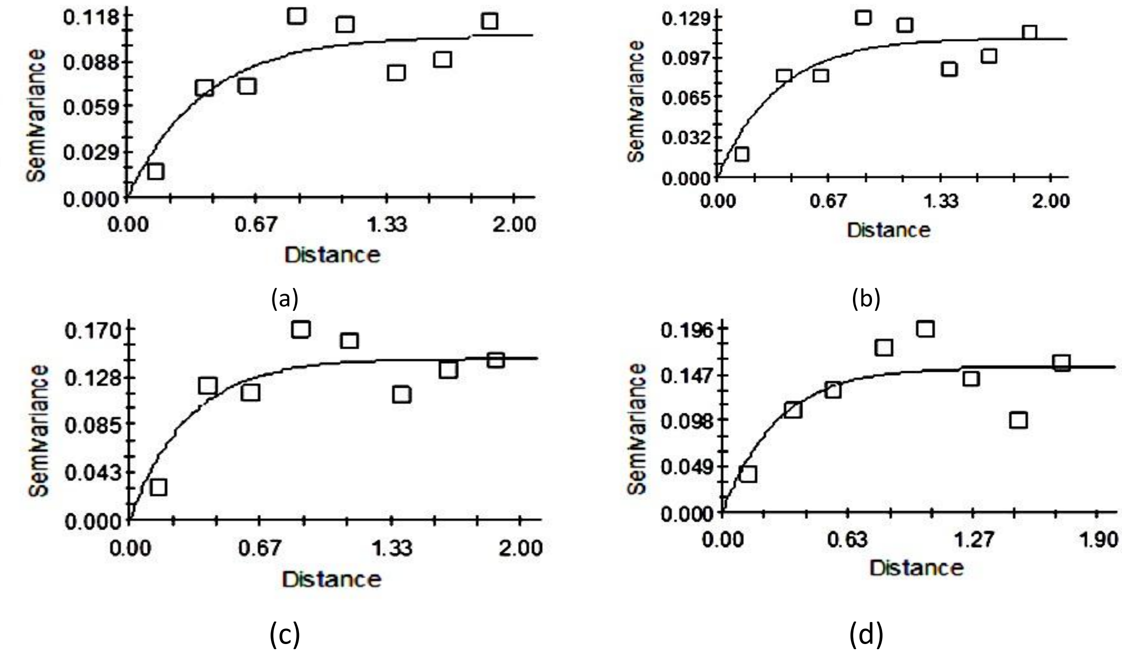

Figure 7. Variograms fitted to the quantity of local flood in PCA-physiographical space (with return periods a= 10, b= 20, c= 50, d= 100 years).

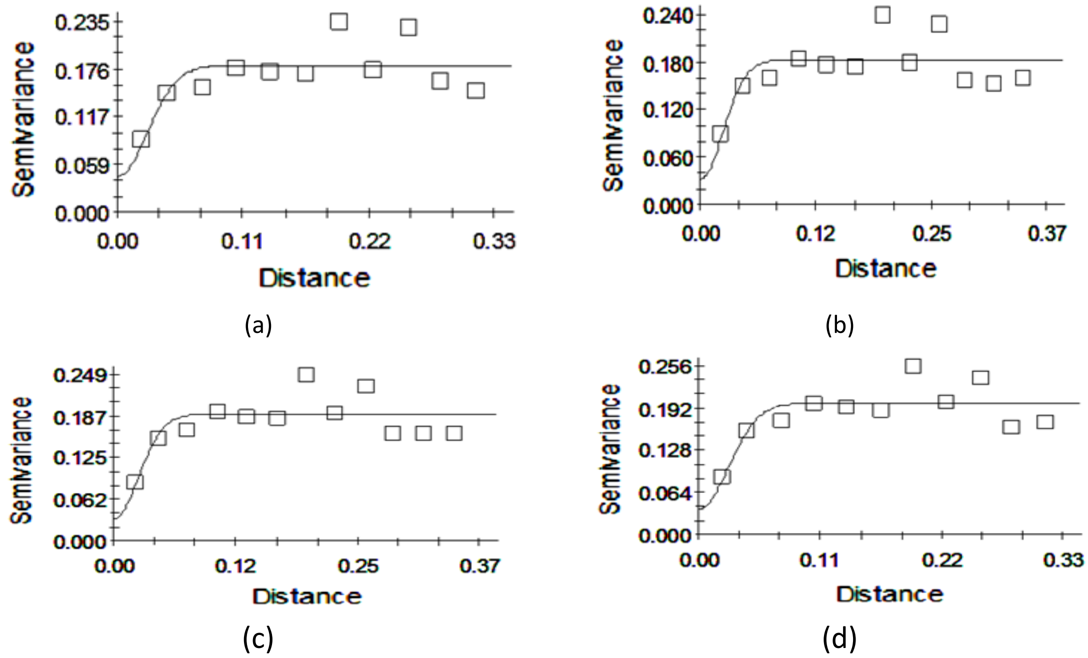

Figure 8. Variograms fitted to the quantity of local flood in CCA physiographical space (with return periods a= 10, b= 20, c= 50, d= 100 years).

spatial pattern demonstrated by empirical variograms and correlation coefficient indices (r^2), sum of the Residual Squares (RSS), spatial structure (C/C_0+C), and the exponential and Gaussian models were evaluated to be appropriate in the PCA and CCA spaces. According to Table 3, in order to select the best variogram model, maximum r^2, lowest value of RSS, and spatial structure of close to one were taken into account. Fitting of the

Table 3.Results of fitting variogram models based on physiographical space.

Physiographical Space	Variable	Model	Nugget effect (C_0)	Sill (C)	C/C_0+C (Spatial structure)	r^2 (Correlation coefficient)	RSS (sum of residual squares)
CCA	Q_{10}	Spherical	0.13380	0.26860	0.502	0.230	0.0118
		exponential	0.15310	0.30720	0.502	0.112	0.0137
		Linear	0.13772	0.19745	0.302	0.226	0.0101
		Gaussian	0.04370	0.18040	0.757	0.514	7.531×10^{-3}
	Q_{20}	Spherical	0.13570	0.27240	0.502	0.392	0.0118
		exponential	0.06900	0.19300	0.642	0.497	8.081×10^{-3}
		Linear	0.13934	0.20601	0.324	0.283	0.0105
		Gaussian	0.03260	0.1822	0.821	0.508	8.029×10^{-3}
	Q_{50}	Spherical	0.14090	0.28280	0.502	0.269	0.0137
		exponential	0.05260	0.19920	0.736	0.532	8.791×10^{-3}
		Linear	0.14560	0.21274	0.318	0.259	0.0118
		Gaussian	0.03350	0.18900	0.822	0.540	8.226×10^{-3}
	Q_{100}	Spherical	0.14610	0.29320	0.502	0.259	0.0151
		exponential	0.06190	0.20580	0.699	0.534	9.535×10^{-3}
		Linear	0.15001	0.21926	0.316	0.250	0.0127
		Gaussian	0.0392	0.19940	0.803	0.609	7.574×10^{-3}
PCA	Q_{10}	Spherical	0.00010	0.10120	0.902	0.702	1.985×10^{-3}
		exponential	0.00010	0.10520	0.999	0.769	1.882×10^{-3}
		Linear	0.04685	0.11675	0.599	0.470	0.0165
		Gaussian	0.00990	0.10080	0.902	0.716	3.561×10^{-3}
	Q_{20}	Spherical	0.00010	0.1120	0.999	0.712	3.485×10^{-3}
		exponential	0.00010	0.11320	0.999	0.765	2.176×10^{-3}
		Linear	0.05526	0.1244	0.556	0.409	0.0171
		Gaussian	0.00880	0.10860	0.919	0.699	3.724×10^{-3}
	Q_{50}	Spherical	0.00010	0.14220	0.999	0.716	4.055×10^{-3}
		exponential	0.00010	0.14420	0.999	0.748	3.583×10^{-3}
		Linear	0.08279	0.15759	0.475	0.317	0.0219
		Gaussian	0.00120	0.14040	0.991	0.709	4.740×10^{-3}
	Q_{100}	Spherical	0.00010	0.14920	0.999	0.657	4.481×10^{-3}
		exponential	0.00010	0.15320	0.999	0.728	4.019×10^{-3}
		Linear	0.09539	0.16548	0.424	0.265	0.0212
		Gaussian	0.10990	0.2208	0.502	0.157	0.0115

theoretical Gaussian model as the best variogram in CCA-space indicated maximum spatial structure for the hydrological variables in this space. After fitting the theoretical models, regional flood analysis estimates were made using Ordinary (OK) and Simple (SK) Kriging techniques in the physiographical spaces. Cross analysis of the flow values estimated based on ordinary kriging method in PCA and CCA spaces along with the observed flow values is shown in Figures 9 and 10, respectively.

Results of cross validation based on jack-knife and five statistical indices are presented in Table 4. Among *BIASr*, *BIAS*, *RMSE*, and *RMSEr* indices, the least value indicates the best performance. The negative values obtained by *BIAS* and *BIASr* indices show overestimates. It must be noted that, when evaluating the performance of regional flood quantity, performance of relative indices

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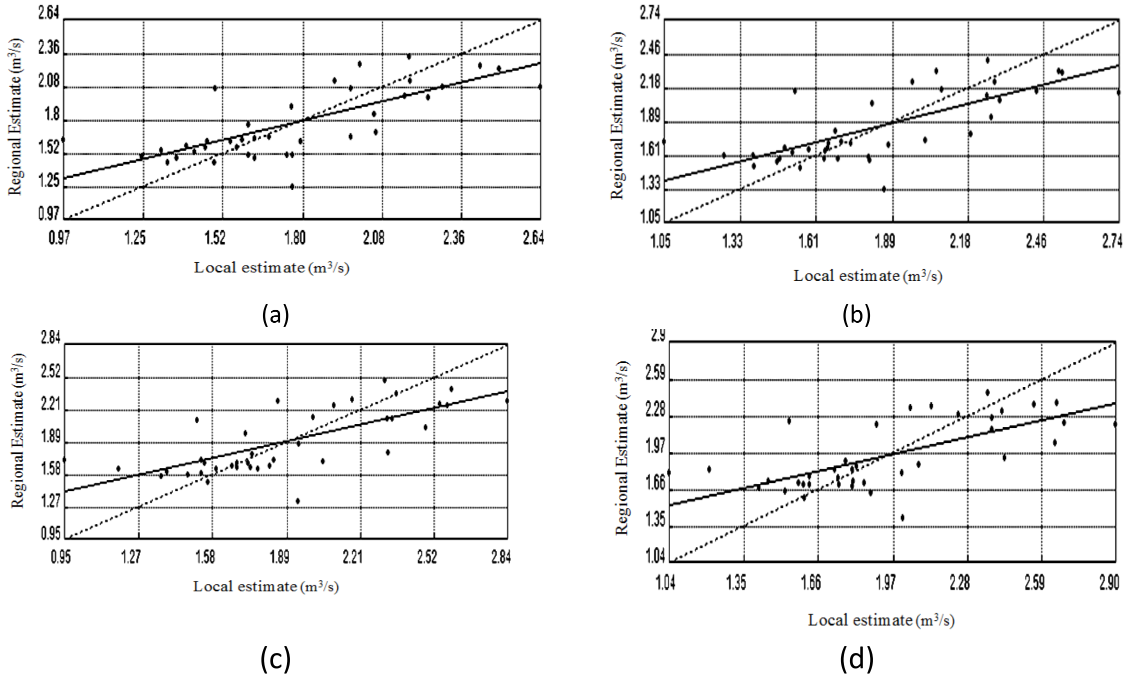

Figure 9. Cross validation results of ordinary kriging in PCA-physiographical space (with return periods a= 10, b= 20, c= 50, d= 100 years).

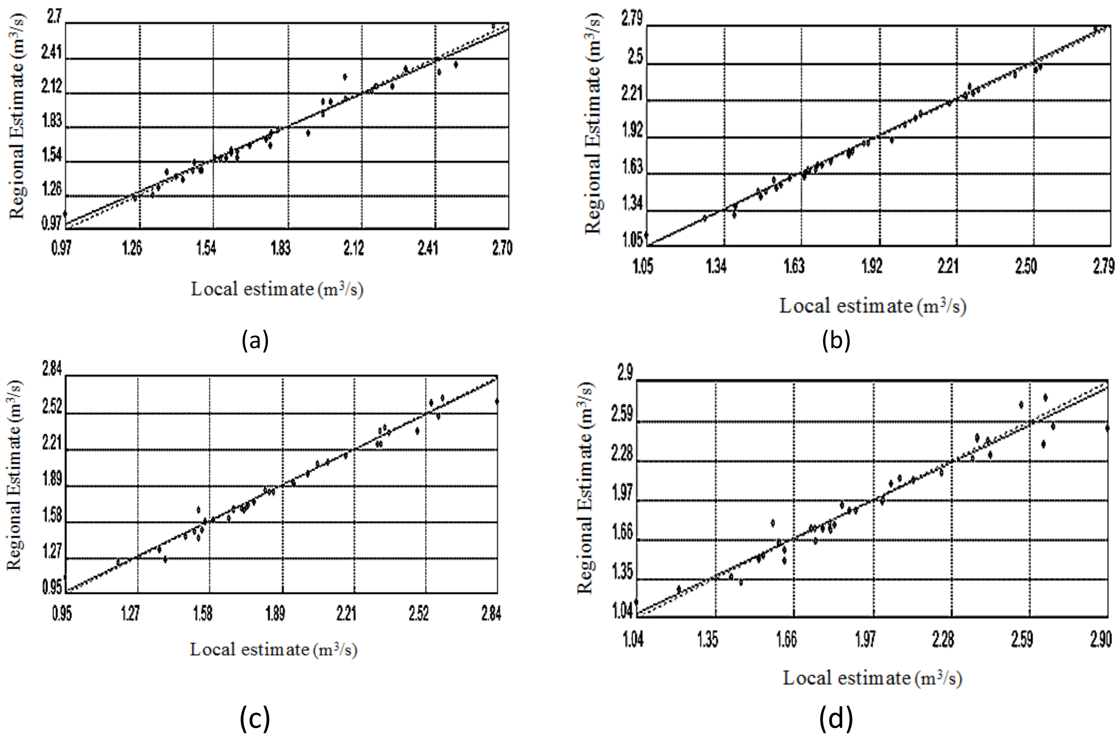

Figure 10. Cross validation results of ordinary kriging in CCA-physiographical space (with return periods a= 10, b= 20, c= 50, d= 100 years).

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Table 4. The results of the cross validation of regional flood estimation based on geostatistical methods [Ordinary (OK) and Simple Kriging (SK)] in the physiographical spaces.

Physiographical space	Method	Variable	*BIAS*	*BIASr*	*RMSE*	*RMSEr*	*NASH*
PCA	OK	Q_{10}	0.0029	2.46	0.25	17.38	0.53
		Q_{20}	0.0043	2.46	0.26	16.85	0.51
		Q_{50}	0.0057	3.29	0.29	19.88	0.51
		Q_{100}	0.0073	3.57	0.32	20.22	0.44
PCA	SK	Q_{10}	0.0011	2.71	0.25	18.15	0.52
		Q_{20}	00031	2.69	0.26	17.29	0.51
		Q_{50}	0.0070	3.87	0.30	21.39	0.48
		Q_{100}	0.0089	3.84	0.31	20.31	0.47
CCA	OK	Q_{10}	0.0052	0.54	0.06	3.95	0.97
		Q_{20}	0.0038	0.31	0.03	2.29	0.99
		Q_{50}	-0.0030	0.15	0.06	4.27	0.97
		Q_{100}	-0.0052	0.10	0.10	5.24	0.94
CCA	SK	Q_{10}	0.0042	0.47	0.06	4.06	0.97
		Q_{20}	-0.0060	-0.11	0.04	2.95	0.98
		Q_{50}	-0.0095	0.54	0.09	5.43	0.95
		Q_{100}	-0.0108	-0.95	0.12	6.11	0.91

(BIASr and RMSEr) have particular importance, since employing relative, instead of deterministic, indices (RMSE and BIAS) eliminates any potential scale effect of the results (Ouarda *et al*., 2008).

Results shown in Table 4 indicate that increasing the return period caused the values of *BIAS* and *RMSE* indices to have an increasing trend in both physiographical spaces. This issue indicated that uncertainty of regional estimates was increasing with the increase in return period. However, results of the relative indices (BIASr and RMSEr) showed the improved performance of PSBI methods had a direct relationship with the increase in return period. These results were in good agreement with the results reported by Ouarda *et al*. (2008) and Martel *et al*. (2011). The findings stated by Ouarda *et al*. (2008) demonstrated that, although values for *RMSE* and *BIAS* indices increased with an increase in return period, the performance of geostatistical techniques improved according to *BIASr* and *RMSE*r relative indices. Moreover, results presented by Martel *et al*. (2011) showed that, based on *BIASr* and *RMSEr* indices, the relative efficiency of geostatistical technique was improved by increasing the return period; however, *BIAS* and *RMSE* values were increasing anyway.

The performance of the interpolation techniques in two physiographical spaces was evaluated based on five statistical indices. The performance of the *NASH* index in CCA and PCA spaces was more than 0.9 and 0.4-0.5, respectively. According to the results of the *NASH* index, the performance of interpolation methods in the PCA-space was relatively satisfactory; while in the CCA-space, it provided accurate and acceptable flood prediction.

According to the results of the statistical indices, it can be concluded that the regional analysis based on CCA-space had better performance than the ones in the PCA-space. The main reason for this can be attributed to the different nature of multivariate statistical methods. Moreover, one can relate the weaker performance of kriging in PCA-space to the uncomfortableness with the stationary assumption. Thus, the PCA method used in designing physiographical space sought to maximize variance along the axes of the space, while the main objective of CCA method was

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to maximize the correlation between climatic, physiographical, and hydrological variables, which could be also the reason for better performance of interpolation techniques in the CCA physiographical space. The better performance of regional estimations in the CCA-space, compared to the PCA-space, is in complete agreement with the results by Chokmani and Ouarda (2004) and Guillemette *et al*. (2009). In addition, the comparison of performance between the two interpolation techniques (ordinary and simple kriging) showed that ordinary kriging had better performance than the simple kriging in both of the physiographical spaces.

In the current study, identified problematic gauging stations had high observed relative mean square error in both spaces. Seven stations (Identification numbers: 13009, 13017, 14017, 16017, 16081, 16019, and 16025) were found to have very high relative errors. Further research showed that three stations (13017, 16017 and 16081) had basin areas of less than 200 km^2. It seems that the 200 km^2 threshold is not adequate and the area limit under which the basin can be considered as small should be redefined. Another possible reason of the underestimation of quantiles from small basins lies in the fact that the surfaces of these basins are themselves underestimated (Chokmani and Ouarda, 2004). The elimination of these seven stations improved the results significantly. For instance, the *NASH* calculated 0.4-0.5 estimated within the PCA-space drops from 0.5 to 0.7 and the relative mean bias from 2-3 to 1-2%.Additionally, the range of *RMSE* values decreased from 0.25-0.32 to 0.18-0.26. This means that the method presented in this study is rather sensitive to the quality of physiographical and meteorological data.

CONCLUSIONS

The present study was conducted to apply and develop physiographical space based geostatistical methods for regional flood frequency analysis in ungauged basins. Continuity of hydrological variables throughout the physiographical space is considered as one of the most important characteristics of physiographical spaces. In this regard, physiographical coordinates of each basin are obtained based on the characteristics of the basins that had the most similar properties to the target basin; therefore, in this case, regional estimations will have more accuracy and less uncertainty. Designing physiographical space is one of the most important and influential stages of implementing physiographical space based interpolation method, since the type of physiographical space directly affects the accuracy and validity of the results. This issue can be confirmed by different performances of interpolation methods in CCA-space from those in PCA-space. In addition to the nature of multivariate statistical methods, the geomorpho-climatic variables used for designing physiographical space also affect the efficiency of geostatistical methods. Investigating the type and number of geomorpho-climatic variables for designing physiographical space requires a comprehensive study. Fitting the exponential theoretical model to empirical variograms in PCA-space and fitting the Gaussian model in CCA-space show that the physiographical space influences not only the accuracy and validity of regional estimations, but also the spatial structure of hydrological variables. Thus, hydrological variables in CCA-space have higher spatial continuity than PCA-space. The results of this study demonstrated that the application of geostatistical methods can be an effective and efficient approach for the regional flood frequency analysis. In this approach, for any ungauged site, the flood quantiles can be estimated through interpolation of local quantile estimates with physiographical neighborhood. To achieve this, physiographical and meteorological characteristics of ungauged sites were used to estimate the coordinates of the sites in the physiographical space. It can be claimed that this method has the required potential for the regional estimation of hydrological data and provides more accurate and reliable estimates than other conventional methods in this regard.

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کاربرد روش‌های زمین‌آمار در تحلیل فراوانی منطقه‌ای سیلاب در شمال ایران (مطالعه موردی: آبخیزهای مازندران)

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چکیده

کاربرد زمین‌آمار برایتحلیل‌های منطقه‌ای در ایران بسیار نوپاست. پایه واساس این تکنیک بر درونیابی متغیرهای هیدرولوژیکی در فضای فیزیوگرافی بجایفضای جغرافیایی استوار است. هدف این مطالعه انطباق، کاربرد و مقایسه دو روشتحلیل منطقه‌ای بر پایه زمین آمار است. در مطالعه حاضر، مجموعه اطلاعات ۳۸ایستگاه دارای آمار واقع در شمال ایران به منظور بررسی عملکرد روش‌هایزمین‌آماری در دو فضای فیزیوگرافی مورد استفاده قرار گرفت. دو روش تحلیلچندمتغیره تحلیل همبستگی کانونی (CCA)و تجزیه مولفه‌های اصلی (PCA) بهمنظور تبیین فضای فیزیوگرافی مورد استفاده قرار

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گرفت. مدل‌های گوسی و نمایییعنوان بهترین مدلهای تئوری واریوگرام به ترتیب در فضای فیزیوگرافی CCAو PCA انتخاب گردیدند. برآوردگرهای زمین-آماری کریجینگ معمولی و کریجینگ سادهبه منظور تخمین‌های منطقه‌ای در هر دو فضای فیزیوگرافی مورد استفاده قرارگرفت. با استفاده از روش‌های درون‌یابی در فضاهای فیزیوگرافی CCA وPCA ،برآوردهای منطقه‌ای سیلاب برای دوره بازگشت‌های مختلف (۱۰، ۲۰، ۵۰ و ۱۰۰سال) بدست آمد. در نهایت عملکرد هر دو مدل با استفاده از پنج شاخص آماریمورد بررسی قرار گرفت. نتایج نشان داد که هر دو روش عملکرد مشابه و قابلقبولی ارائه می‌کنند؛ با این حال برآوردهای منطقه‌ای در فضای فیزیوگرافی CCA از دقت بالاتر و عدم قطعیت کمتری نسبت به فضای فیزیوگرافی PCA برخوردارمی‌باشد. علاوه براین نتایج نشان داد که روش کریجینگ معمولی عملکرد بهترینسبت به روش کریجینگ ساده در هر دو فضا ارائه می‌کند و بهترین عملکرددرونیابی در فضای فیزیوگرافی CCA مشاهده شد.