Analysis of interpolation methods to map the long-term annual precipitation spatial variability for the Republic of Bashkortostan, Russian Federation

IVAN AFANASEV, TCVETANA VOLKOVA, ALEXEY ELIZARYEV
Department of Production Safety and Industrial Ecology
Ufa State Aviation Technical University
K. Marx Street 12, Ufa, The Republic of Bashkortostan, 450000
RUSSIAN FEDERATION
ivan-afanasiev91@yandex.ru

ANTONIA LONGOBARDI
Department of Civil Engineering
University of Salerno
Via Giovanni Paolo II, 132 - 84084 - Fisciano (SA)
ITALY
alongobardi@unisa.it

Abstract: - In meteorological modeling it is very important to have accurate data about the amount of precipitation over particular territory. This data can be obtained by the interpolation of the point sources. In this case several interpolation methods (inverse distance weighting, ordinary kriging, geo-regression and co-kriging) are used to map average long-term precipitation over Republic of Bashkortostan, a region of the Russian Federation. Data of more than 30 years of observations from 41 stations have been processed. Several variogram models for ordinary kriging and co-kriging methods have also been fitted. It was found out that no variogram in ordinary kriging method fits best to the observed amounts, the closest one is linear model. In order to make the geo-regression method, elevation of each station was taken. The correlation between elevation and precipitation of all points was not good enough, so cluster analysis was carried out to find out points with good correlation. Results of cluster analysis show small correlation between elevation and precipitation, despite that fact, results of geo-regression (when divided on 4 clusters) show better results, than IDW or kriging. Among all methods co-kriging with linear modeled variogram and which previously was divided by 4 clusters shows the closest result to observed amounts.

Key-words: - Spatial analisys, interpolation methods, precipitation distribution, kriging, variogram, inverse distance weighting, geo-regression, co-kriging, cluster analysis, The Republic of Bashkortostan.

1. Introduction

At different temporal scales, maps of precipitation are the primary input to many hydrological models such as those used for crop growth simulation, water resources management, drought risk assessment flood forecasting and so on [1,2]. To earn the full benefits from these models, models themselves must be then based on accurate estimates of precipitation. Since precipitation measurements are usually provided at a finite number of rain gauges, producing a precipitation map from these point values requires an estimation procedure [3]. Precipitation mapping would help accounting for the spatial variability of the rainfall process but would also be useful, in regional scale application, to predict precipitation amount in point or catchments where no data are available [4].

Therefore it is really important to have necessary amount of data points, located close enough to each other. For example the study [10] of water potential interpolation (fig 1) shows inappropriate results in places with no data points.

Lack of wide system of water objects monitoring gives inappropriate results of ecological flow estimation, especially closer to the estuary. It is also necessary to have data points that are close enough to each other and have data, which was collected and calculated in the same way. Such data as amounts of environmental flow or precipitation does not have administrative borders, so sometimes it is useful to take information from data points located over the studied area.

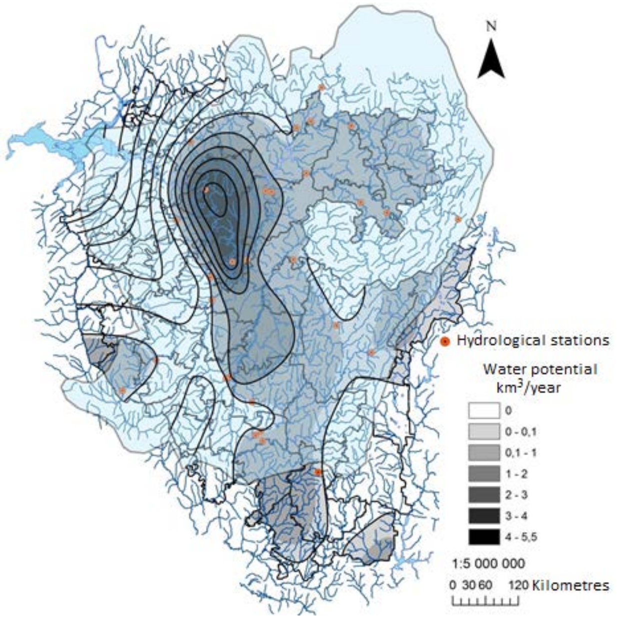


Fig. 1 Map of the distribution of water potential over the territory of the Republic of Bashkortostan

As shown, spatial interpolation can be used for different purposes and a wide range of interpolation methods is available, ranging from simple techniques such as Thiessen polygons or inverse distance weighting schemes to more complex and computationally intensive approaches such as geostatistical kriging [5,6,7,8,9,10]. The more complex approaches often use additional information from static (e.g., elevation) or dynamic (e.g., rainfall radar) covariates that are available as spatially distributed data sets [11].

The inverse distance weighting (IDW) is a simple technique which has been used for spatial prediction of rainfall in the southern region of the USA [12]. Precipitation, however, shows a significant spatial variation suggesting that interpolation techniques which explicitly incorporate this spatial variability into the estimation process should be employed [13,14]. A well-known geostatistical method, i.e., kriging provides unbiased estimates with minimum variance taking into account the spatial relationship between the data points [3]. The benefit of using the geostatistical interpolation approaches over conventional techniques for spatial estimation of rainfall has been reported by several authors [13,15,16,17,18]. A major advantage of kriging over simpler techniques, such as IDW, besides providing a measure of estimation uncertainty (kriging variance), is that it can make use of correlated dense secondary variables to improve the prediction of sparsely sampled primary variable [3]. It was suggested that topographic information, digital elevation model (DEM) can be used as a valuable and cheap source of secondary data to guide and supplement the mapping of rainfall [13]. In fact over monthly and annual periods, precipitation and elevation tend to be related due to the orographic effect of mountainous terrain [13].

Considering topography as secondary variable, rainfall prediction can be improved using other multivariate extensions of kriging such as ordinary cokriging (OCK) and collocated cokriging (COCK), when compared with ordinary kriging (OK)[13,19,20,21,22].

The main objective of this paper is to obtain the best interpolation method, which provide the most accurate and physically plausible estimates of precipitation over the territory of the Republic of Bashkortostan.

2. Material and methods

2.1 Study area and data sets

The Republic of Bashkortostan is a region of the Russian Federation, located in the south of the Ural mountains, covering an area of about 143000 km^2 [23]. It is located between latitudes 56°33' N 51°35' S and longitudes 53°9' W 59°59' E.

The Bashkortostan territory is bounded by the Perm Territory and the Sverdlovsk Region on the north, by the Chelyabinsk Region on the east, by the Orenburg Region on the south-west, south and south-east, by the Republic of Tatarstan on the west and by the Udmurtian Republic on the north-west (Fig. 2).

The Bashkortostan climate is typically continental, with long winter and warm, sometimes hot summer.

Duration of period with average day temperature below 0°C is 165 days to the west and 175 days to the east of Ural Mountains. Duration of period with average day temperature below -5°C is in accordance 135 and 145 days. Duration of period with stable snow cover is 140-160 days. The coldest month is January with mean month temperature from -14,5°C to -17,5°C, minimum temperature in winter can get below -51°C. Precipitation in cold period (from November to March) appears mostly in the form of snow in amount of 150 mm to the east and 200 mm to the west of the Urals.

The period with mean daily temperature over 15°C begins in May or in the beginning of June and lasts for 60-90 days. The warmest month is July with mean monthly temperature from 17,5°C to 20,5°C. Maximum temperature can get over 39°C.

Duration of frostless period is about 90-145 days.

About 350 mm of precipitation occurs to the west and 200 mm to the east from the Urals during warm period of the year [24].

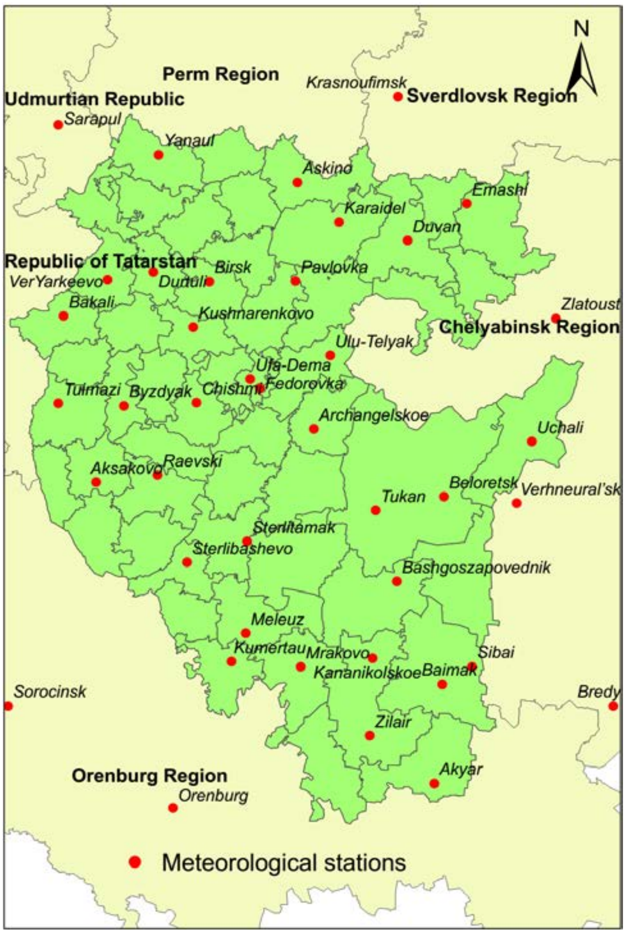


Fig. 2 Map of the Republic of Bashkortostan and its neighborhood with meteorological stations

The analysis of long term precipitation data on the 34 meteorological stations of the Bashkortostan Republic and 7 stations beyond the territory of Republic has been performed. Station name, elevation and mean annual precipitation for the 41 meteorological stations are shown in the Table 2.

Data was collected from the Bashkir Territory Management on Hydrometeorology and Environmental Monitoring and from the Carbon Dioxide Information Analysis Center (CDIAC) [25].

2.2 Spatial interpolation methods

2.2.1 Inverse distance (IDW)

The inverse distance method uses a "simple" distance weighted averaging method to calculate grid node values. It does not extrapolate values beyond those found in the data file, but it tends to draw circles or bulls-eyes around each data point [26].

The IDW estimate is a linear weighted average of several neighboring observations. The IDW estimator is given as:

$$\hat{z}(u) = \frac{\sum_{i=1}^{n(u)} \frac{z(u_i)}{d_i^{\alpha}}}{\sum_{i=1}^{n(u)} \frac{1}{d_i^{\alpha}}} \qquad (1)$$

Where $n(u)$ is the number of neighboring observations, $z(u_i)$ is used to estimate the value of rainfall at an unsampled location u, d is the separation distance between the location u and each sampled location and a is the distance weighting power, i is a step (1…n). The basic assumption is that the values at nearby locations have to be more closely related than those at distant locations to the value at the interpolation location [27]. However, as the value of power *a"* is increased, the effect of the farthest observations on the estimated value is decreased. As is the case in this study, the power "*a"* is commonly set to 2 meaning that the weights are inversely proportional to the square distance between location u and observations [3,13,14].

2.2.2 Ordinary kriging (OK)

The kriging method uses trends in the map to extrapolate into areas of no data, sometimes resulting in minimum and maximum Z values in the grid that are beyond the values in the data file. This could be acceptable in a structure map or topography map, but not in an isolines map where the extrapolation produces negative thickness values [26].

As for IDW, the OK estimate at any unsampled location is obtained by a linear combination of the available sample data. The two approaches differ in the way that nearby locations are weighted. For OK, the weights are assigned based on the distances between the data and the location being estimated as well as the spatial structure of the variable. A semivariogram is commonly used to characterize the spatial structure of the variable under study. The semivariogram quantifies the dissimilarity between sampled points as the distance between the samples increases [3].

2.2.3 Geo-regression

Linear regression is a simple and straightforward approach, in which rainfall is estimated as a linear function of the elevation [3]:

$$\hat{z}(u) = \hat{b}_0 + \hat{b}_1 h(u) \quad (2)$$

Where *h(u)* represents the elevation data available at all grid nodes being estimated, and b_0 (the intercept) and b_1 (the slope) are the parameters estimated from the set of collocated rainfall and elevation. This approach however assumes that the residual values are not spatially correlated [13].

2.2.4 Co-kriging

A method to improve the interpolation of the data would be to extract as much information as possible from variables (covariates) related to the average annual precipitation. This procedure, called co-kriging, has been shown to be of particular interest in the estimation of the average annual precipitation [13,15,28,29]. It consists in the identification of a regression model to estimate the value of the variable of interest as a function of the values of a set of covariates. The estimation is then improved by combining this result with the residual, interpolated to give a spatial distribution , using ordinary kriging. For the study area, given the rather obvious link found between the average annual precipitation and the proportion topographical, as previously indicated for the geo-regression method, we have chosen a model with a single covariate, represented by the elevation. The field of mean annual precipitation, h (x), with x the position of the station in the space, is described as:

$$h(x) = \mu[Z(x)] + W(x) + \varepsilon(x) \quad (3)$$

where μ[Z (x)] is precisely the deterministic trend, estimated in correlation to the elevation as the equation (2), W(x) is a random field with small scale structure and zero mean, and ε(x) is a purely random error term.

3 Results

To calculate and visualize the results of the different applied interpolation methods the Surfer (ver. 8.0) software was used.

3.1 Inverse distance weighting

Results of interpolation, using Inverse distance weighting (IDW) are presented in the following Fig. 3.

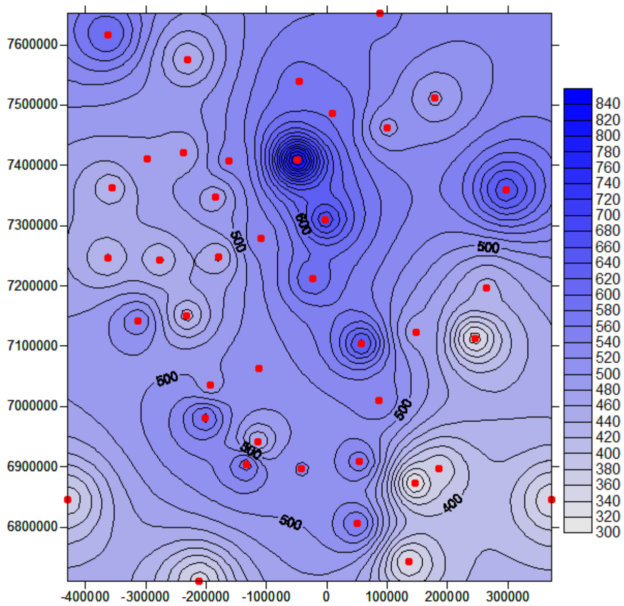
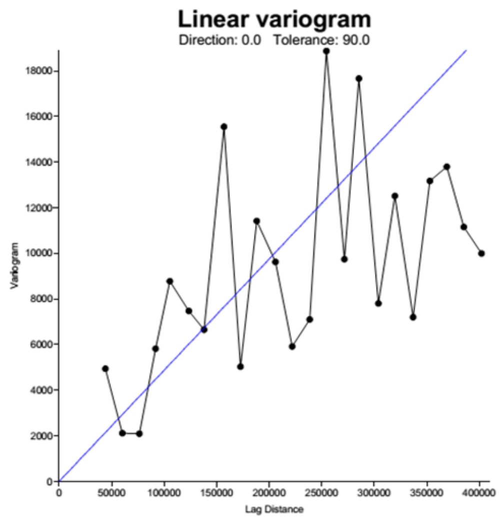
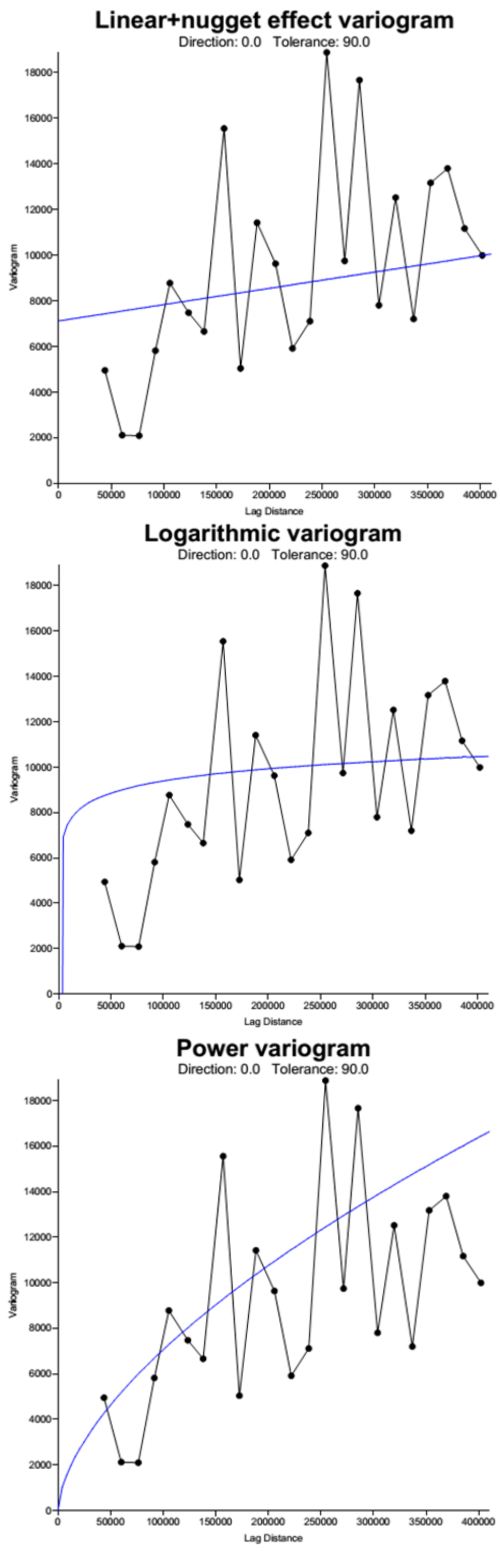


Fig. 3 Map of mean annual precipitation distribution over the territory of the Republic of Bashkortostan interpolated using IDW method.

3.2 Kriging method

To perform the interpolation by the kriging method, an experimental variogram needs to be estimated and modelled by a theoretical one. Different types or models for variograms can be considered and the impact on the interpolation results can be assessed [3]. Different variogram models have been used to represent the spatial variability. Empirical and fitted models are presented in the following fig. 4, for the case study.





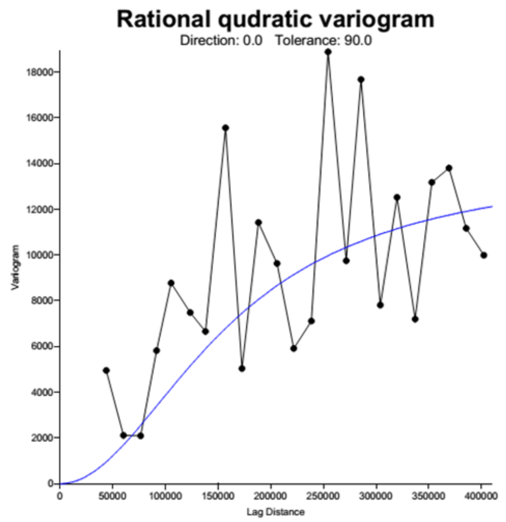
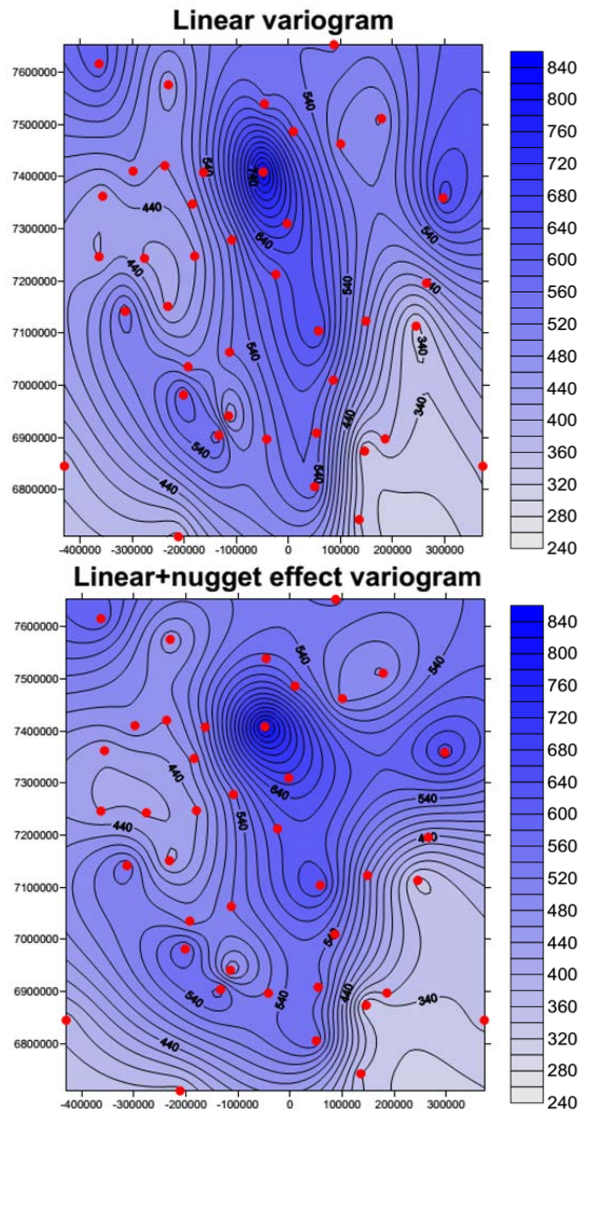


Fig. 4 Variogram models.

In the following figure 5, maps of mean annual precipitation spatial distribution, built by different models are given.



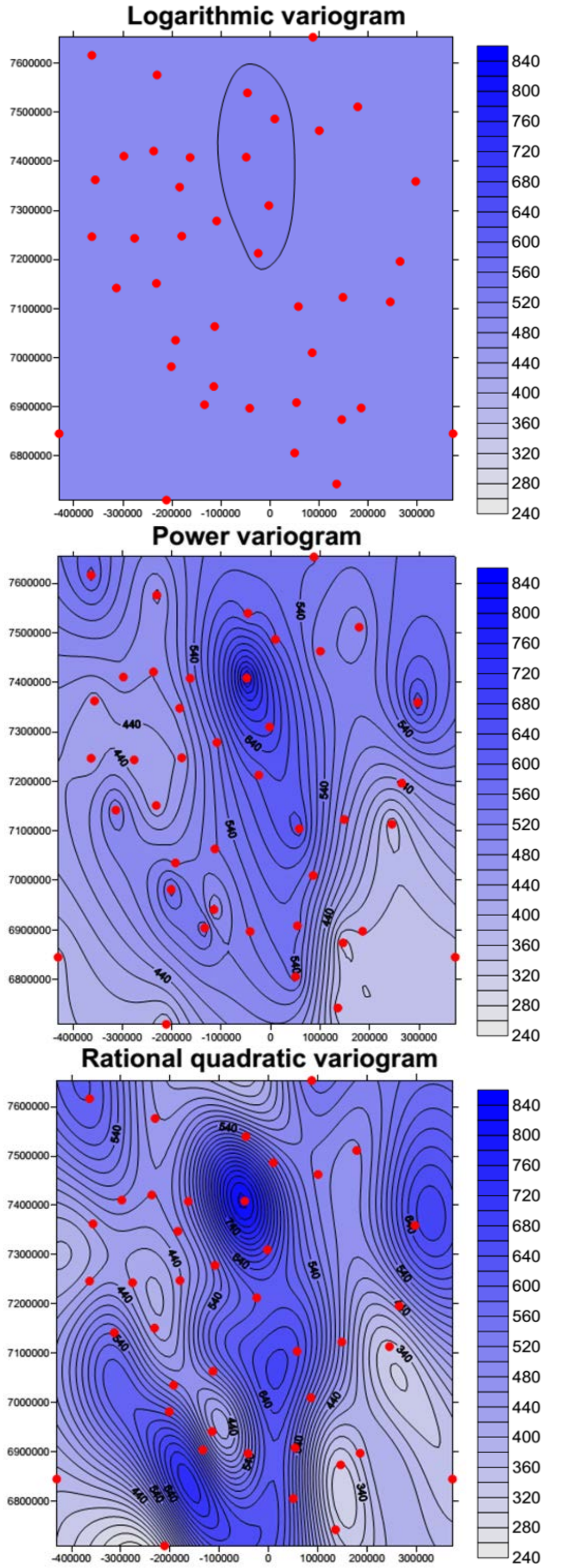


Fig. 5 Map of mean annual precipitation interpolated by the kriging method.

However, different variograms models would correspond to different interpolation maps and thus performances. In this study linear, linear+nugget, logarithmic, power and rational quadratic models variograms were used.

To show the accuracy of the different interpolated maps, a cross-validation procedure was performed.

Results of cross validation are presented in table 1. To compare the results, the following statistics were used:

- mean;
- variance;
- root mean square error (RMSE);
- coefficient of variation – a normalized measure of dispersion .

Table 1: Performance comparison of different modelled Kriging variograms.

	Observed	Variogram models				
		Linear	Linear + nugget	Logarithmic	Power	Rational quadratic
Mean (mm)	495	495	492	495	496	498
Variance (mm^2)	11224	5971	5263	6	4437	12843
RMSE (mm)	-	82,39	85,88	106,06	82,22	110,92
Coeff of Variation	-	0,17	0,17	0,21	0,17	0,22

Results show that the average annual precipitation values for each variogram are close to each other and to the observed one. The variances are not comparable to each other and are not close to the observed one, the closest is amount, excepted for the "Rational quadratic" model variogram. The RMSE and the coefficient of variation of such method are however larger than in the remaining cases.

According to the results, the "linear" variogram model has the best estimation in term of mean value. The amount of variance should be higher, but of the RMSE and the coefficient of variation have the smallest estimation. Given this explanation, the "linear" variogram model can be considered as the most suitable to be used for the case study.

3.3 Geo-regression

The interpolation method is based on the database of elevation for the territory under consideration and for each of the meteorological station (table 2).

Table 2: Gauged stations Elevation.

№	Station name	Mean annual Precipitation (mm)	Elevation (m.a.s.l.)
1	Aksakovo	535,9	348
2	Akyar	340,5	341
3	Archangelskoe	601,6	142
4	Askino	566,5	207
5	Baimak	317,7	488
6	Bakali	424,7	125
7	Bashgoszapovednik	539,2	494
8	Beloretsk	468,4	568
9	Birsk	527,0	186
10	Byzdyak	417,5	190
11	Chishmi	437,3	118
12	Durtuli	459,6	101
13	Duvan	493,9	338
14	Emashi	476,9	233
15	Fedorovka	584,2	341
16	Kananikolskoe	553,2	532
17	Karaidel	579,9	156
18	Kumertau	570,0	349
19	Kushnarenkovo	467,7	99
20	Meleuz	437,4	180
21	Mrakovo	522,0	238
22	Pavlovka	823,1	282
23	Raevski	413,2	120
24	Sibai	364,6	360
25	Sterlibashevo	490,1	277
26	Sterlitamak	520,2	191
27	Tuimazi	418,7	135
28	Tukan	643,8	550
29	Uchali	434,8	525
30	Ufa-Dema	533,5	118
31	Ulu-Telyak	672,2	119
32	VerYarkeevo	477,1	108
33	Yanaul	443,9	102
34	Zilair	559,8	521
35	Sarapul	598,95	135
36	Krasnoufimsk	544,54	205
37	Zlatoust	653,43	532
38	Verhneural'sk	332,24	401
39	Sorocinsk	369,33	122
40	Bredy	345,64	309
41	Orenburg	352	115

The relation between elevation and mean annual precipitation is represented in the following fig.6 , for the case study. The linear interpolation regression equation has been fitted (using the least square method) and indicated in the same figure.

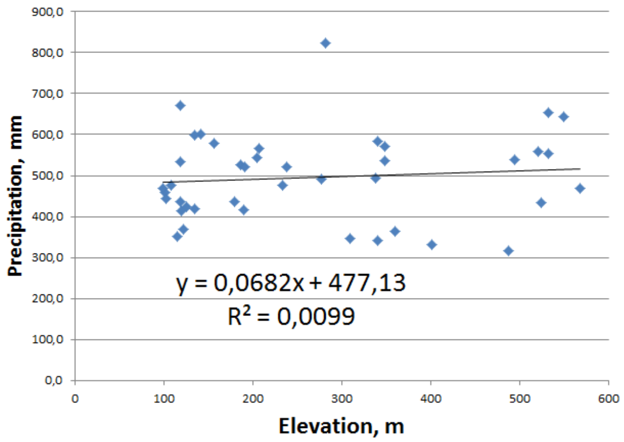


Fig. 6 Linear regression relation between mean annual precipitation and elevation for the case study.

According to the Fig 6, the correlation between the mean annual precipitation and the elevation is really poor for the case study, which can be probably caused by a climate non homogeneity due to the broad extension of the region under interest. In order to search for improved relation between elevation and precipitation, a preliminary cluster analysis has been performed.

Precipitation and elevation data have been used to cluster the data themselves. A number of 2 to 4 clusters have been considered (fig. 7 - 9).

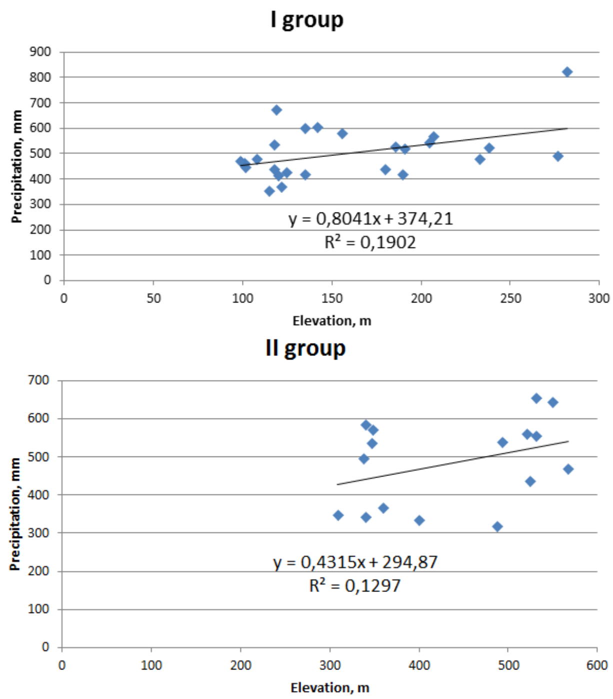


Figure 7 – Linear regression relation between mean annual precipitation and elevation divided by 2 groups

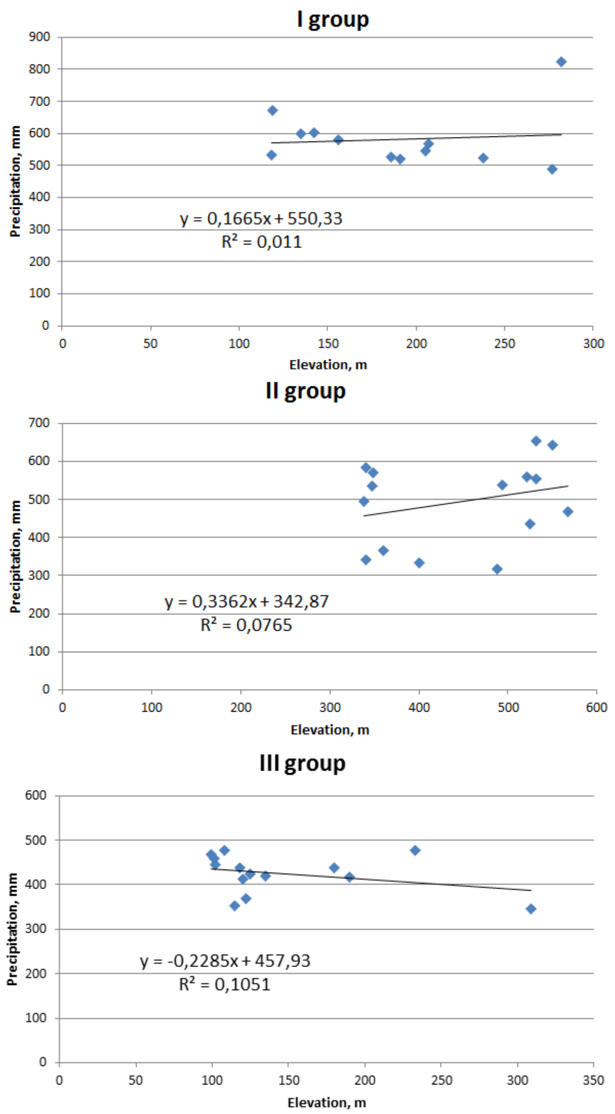
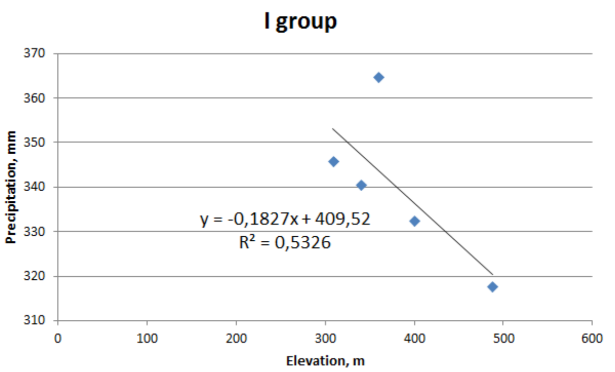


Figure 8 - Linear regress ion relation between mean annual precipitation and elevation divided by 3 groups



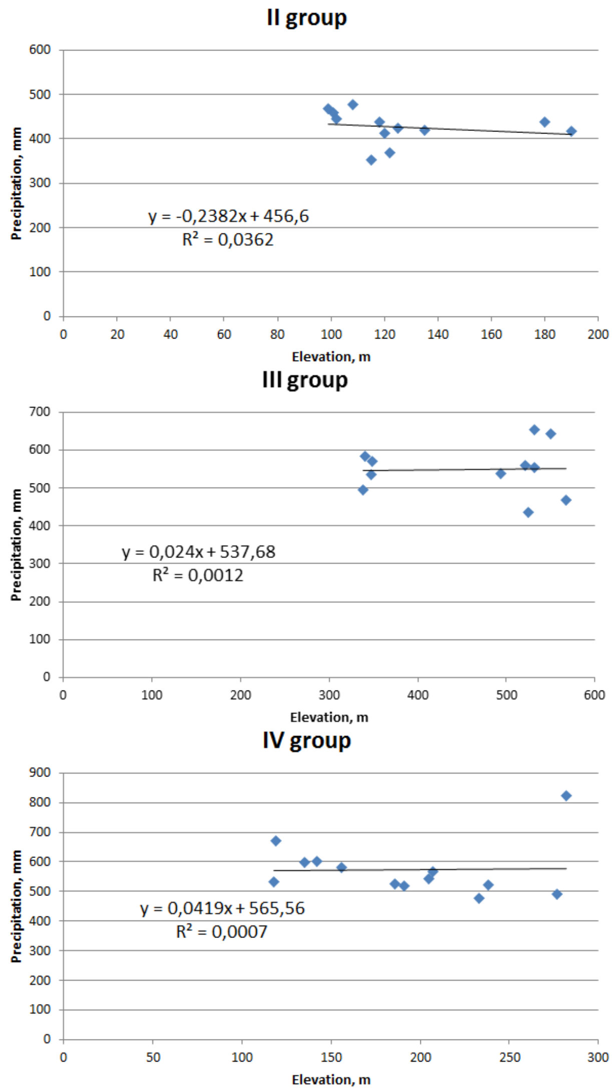


Figure 9 - Linear regression relation between mean annual precipitation and elevation divided by 4 groups

Results of the estimation of mean annual precipitation, divided by cluster analysis, are presented in table 3.

Table 3 - Estimated mean annual precipitation

Station	Observed	Regression	Regress. 2 clusters	Regress. 3 clusters	Regress. 4 clusters
1	2	3	4	5	6
Aksakovo	535,90	500,86	445,03	459,87	546,03
Akyar	340,50	500,39	442,01	457,51	347,22
Archangelskoe	601,60	486,81	461,39	573,97	571,51
Askino	566,50	491,25	513,66	584,80	574,23
Baimak	317,70	510,41	505,44	506,94	320,36
Bakali	424,70	485,66	447,72	429,37	426,83
Bashgoszapovednik	539,20	510,82	508,03	508,95	549,54
Beloretsk	468,40	515,87	539,96	533,83	551,31
Birsk	527,00	489,82	496,77	581,30	573,35
Bredi	345,64	490,09	428,20	387,32	353,07
Byzdyak	417,50	485,18	499,99	414,52	411,34
Chishmi	437,30	484,02	442,09	430,97	428,49

Durtuli	459,60	500,18	428,42	434,85	432,54
Duvan	493,90	493,02	440,72	456,51	545,79
Emashi	476,90	500,39	534,57	404,69	575,32
Fedorovka	584,20	513,41	442,01	457,51	545,86
Kananikolskoe	553,20	487,77	524,43	521,73	550,45
Karaidel	579,90	500,93	472,65	576,30	572,10
Krasnoufimsk	544,54	483,88	512,05	584,46	574,15
Kumertau	570,00	489,41	445,46	460,20	546,06
Kushnarenkovo	467,70	493,36	426,82	435,31	433,02
Meleuz	437,40	496,36	491,95	416,80	413,72
Mrakovo	522,00	485,31	538,59	589,96	575,53
Orenburg	352,00	501,68	439,68	431,65	429,21
Pavlovka	823,10	496,02	573,97	597,28	577,38
Raevski	413,20	490,16	443,70	430,51	428,02
Sarapul	598,95	486,34	455,76	572,81	571,22
Sibai	364,60	514,64	450,21	463,90	343,75
Sorocinsk	369,33	512,94	445,31	430,05	427,54
Sterlibashevo	490,10	485,18	569,95	596,45	577,17
Sterlitamak	520,20	485,25	500,79	582,13	573,56
Tuimazi	418,70	484,50	455,76	427,08	424,44
Tukan	643,80	484,09	532,20	527,78	550,88
Uchali	434,80	512,66	521,41	519,38	550,28
Ufa-Dema	533,50	486,34	442,09	569,98	570,50
Ulu-Telyak	672,20	491,11	442,90	570,14	570,55
Verhneuralsk	332,24	513,41	467,90	477,69	336,26
Ver. Yarkeevo	477,10	504,48	434,05	433,25	430,87
Yanaul	443,90	485,45	429,23	434,62	432,30
Zilair	559,80	498,20	519,68	518,03	550,18
Zlatoust	653,43	484,97	524,43	521,73	550,45

As an example, the four groups clustering is illustrated in Fig. 10.

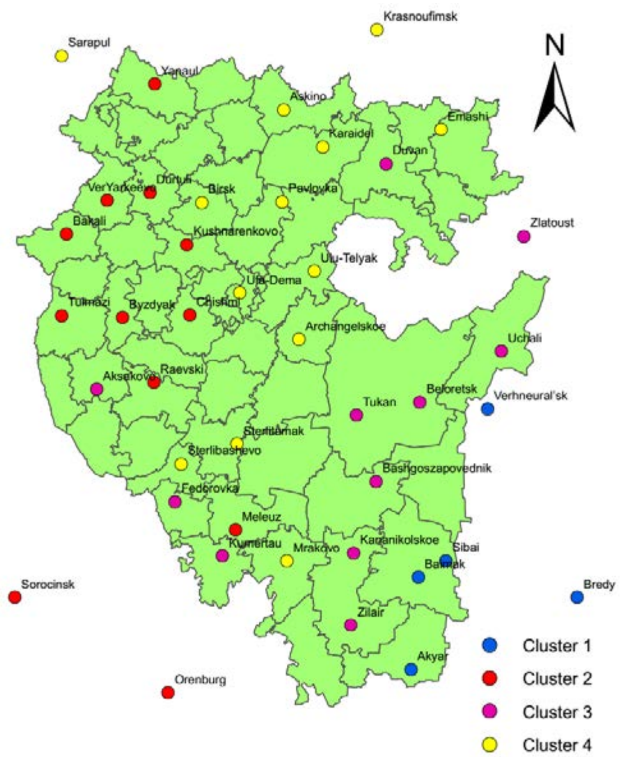


Fig. 10 Meteorological stations divided by cluster analysis

For each of the identified cluster, the linear regression between mean annual precipitation and elevation has been estimated and comparison, in terms of relevant statistics, is given in table 4.

Table 4: Results of geo regression by different groups of clusters

	Observed	Types of cluster analysis			
		Regression (1 cluster)	Regression (2 clusters)	Regression (3 clusters)	Regression (4 clusters)
Mean	495	495	479	495	495
Variance	11224	112	1836	4423	7240
RMSE	-	108,50	97,61	81,46	62,36
Coeff of Variation	-	0,22	0,20	0,16	0,13

Despite the fact (fig. 9), that the correlation between the amount of mean annual precipitation and elevation is not good enough and according to the findings presented in table 4, the use of a preliminary cluster analysis results in an interesting increase in the variance of the interpolated field, from 112 mm^2 to 7240 mm^2 (with a particular reference to the 4 clusters case), obviously closed to the observed. Errors measures are also smaller in this particular case (fig 11).

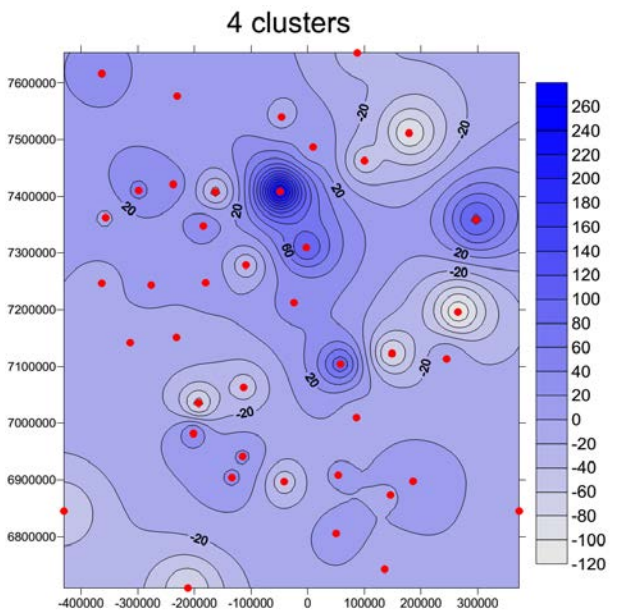
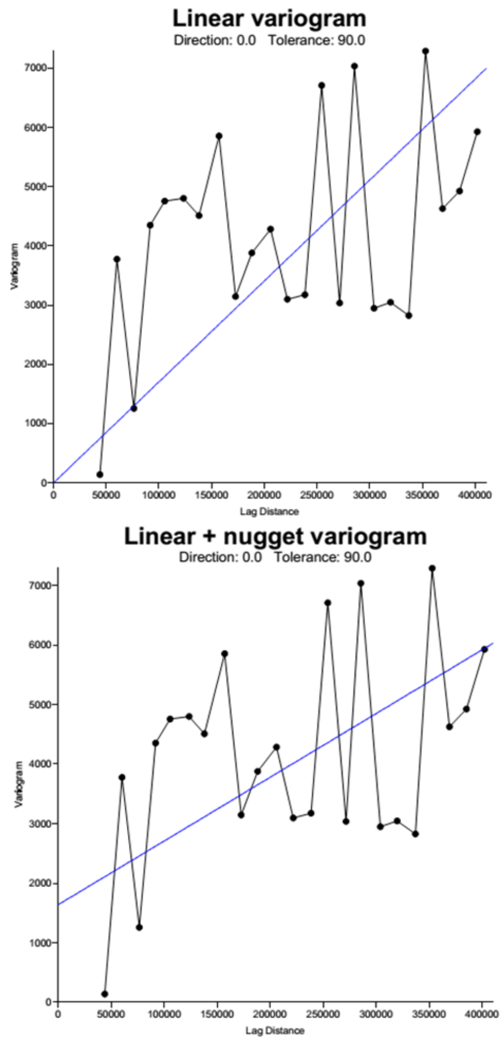


Fig. 11 Interpolation of errors for 4 clusters analysis.

3.4 Co-kriging

To use this method it is needed to start from the results of the georegression method. The 4 clusters georegression has been here applied to estimate the mean annual precipitation at each site, based on the station elevation.

As a second step, the residuals of the georegression model have been estimated, as the difference between observed and estimated, and an interpolation of them has been performed using the kriging method. In the end the georegression estimation value has been added (site by site) to the kriging interpolated errors, to provide the results of the co-kriging application. As in the case of simple kriging, also for this application, different model variogram have been used to describe the interpolated field variability. Results are reported in table 4. With reference to the four assumed error statistics, different types of variograms were used (fig. 12)



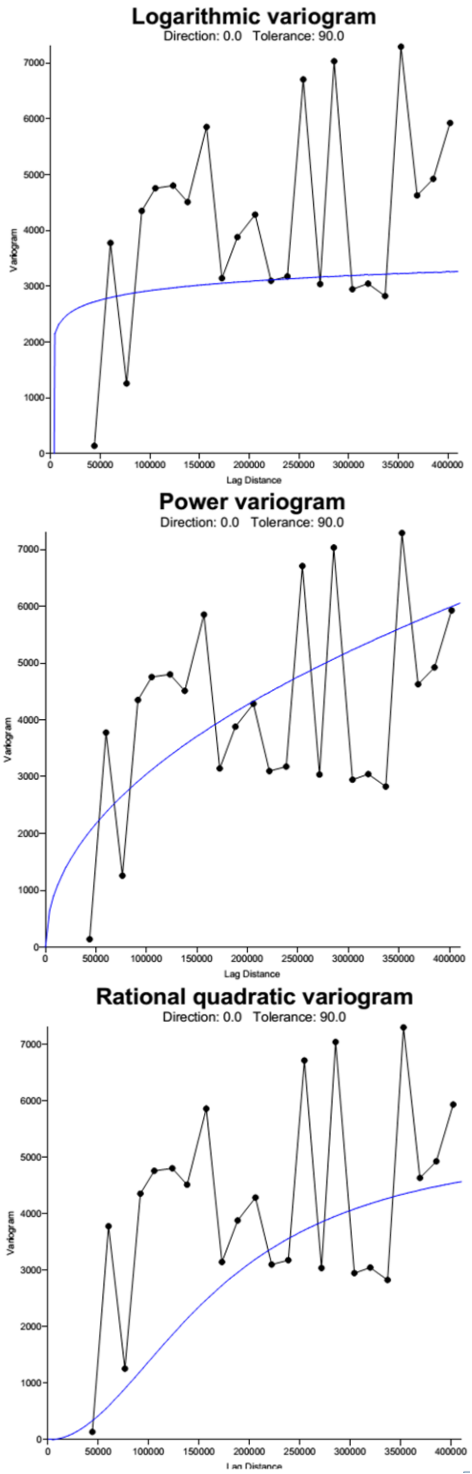


Fig. 12 Variogram models

Table 5: Co-kriging results comparison.

	Observed	Types of Variograms				
		Linear + nugget	Linear	Power	Rational quadratic	Logarithmic
Mean	495	494	495	496	501	495
Variance	11224	9704	10249	9322	17132	7288
RMSE	-	73,67	72,62	66,27	108,90	63,85
Coeff of Variation	-	0,15	0,15	0,13	0,22	0,13

4 Conclusion

In this study four different methods of interpolation have been used to provide the mean long-term annual precipitation spatial variability over the territory of the Republic of Bashkortostan, Russian Federation. The results of the applications are summarized in the following Table 6.

Table 6: Comparison of four different methods of interpolation

	Observed	Interpolation			
		IDW (linear)	Kriging (linear variogram)	Geo-regression (4 clusters)	Co-kriging (linear variogram)
Mean	495	501	494	495	495
Variance	11224	1370	6272	7240	10249
RMSE	-	92,10	80,31	62,36	72,62
Coeff. of Variation	-	0,19	0,16	0,13	0,15

The Inverse distance weighting method is the worst performing approach, as it yields the largest errors and the estimated precipitation mean value and variance are significantly different from the observed one. It is not then a suitable to be used for the region under investigation.

The ordinary kriging method has not a good performance as well. It provides the second largest errors and the estimated precipitation mean value and variance are still significantly different from the observed one.

An improvement in the mean annual precipitation field estimation has been instead achieved including the information about the orography in the interpolation methods.

The Geo-regression method performance has been showed to be affected by a large climate non homogeneity, perhaps due to the broad extension of the studied region, and a previous cluster analysis, based on elevation and precipitation data, has identified 4 clusters. Despite the fact, that the correlation was not really good, the georegression application has appeared to be rather satisfactorily, except for the variance estimation, still too different from the observed one.

A further improvement has been then approached when the co-kriging method has been applied, as also the estimated field variability of this particular interpolation method seems to well capture the observed one.

According to this comments and comparing all four methods, the Co-kriging, using a linear modeled variogram, has appeared to be the most suitable technique to be used for spatial analysis purposes of the investigated area.

References

[1] Rosenthal WD, Hammer GL, Butler D (1998) Predicting regional grain sorghum production in Australia using spatial data and crop simulation modeling. *Agricultural and Forest Meteorology Journal* 91:263–274

[2] Haberlandt U (2007) Geostatistical interpolation of hourly precipitation from rain gauges and radar for a large-scale extreme rainfall event. *Journal of Hydrology* 332:144–157

[3] Delbari M, Afrasiab P, Jahani S (2013) Spatial interpolation of monthly and annual rainfall in northeast of Iran. *Meteorology and Atmospheric Physics Journal* (2013) 122:103–113

[4] Volkova T, Longobardi A, Krasnocorskaya N (2014) Gamma distribution function as a tool for monthly precipitation generation in the Bashkortostan Republic, Russian Federation. *Proceeding of the 7th International Conference on ENVIRONMENTAL and GEOLOGICAL SCIENCE and ENGINEERING (EG '14) Salerno,* Italy June 3-5, 2014

[5] Thiessen, A.H., 1911. Precipitation averages for large areas. *Monthly Weather Review* 39 (7), 1082–1084.

[6] Di Piazza, A., Lo Conti, F., Noto, L.V., Viola, F., La Loggia, G., 2011. Comparative analysis of different techniques for spatial interpolation of rainfall data to create a serially complete monthly time series of precipitation for Sicily, Italy. *International Journal of Applied Earth Observation and Geoinformation* 13, 396–408.

[7] Teegavarapu, R.S.V., Tufail, M., Ormsbee, L., 2009. Optimal functional forms for estimation of missing precipitation data. *Journal of Hydrology* 374, 106–115.

[8] Buytaert, W., Celleri, R., Willems, P., De Bièvre, B., Wyseure, G., 2006. Spatial and temporal rainfall variability in mountainous areas: a case study from the south Ecuadorian Andes. *Journal of Hydrology* 329, 413–421.

[9] Zhang, X., Srinivasan, R., 2009. GIS-based spatial precipitation estimation: a comparison of geostatistical approaches. *Journal of The American Water Resources Association* 45 (4), 894–906.

[10] Elizaryev A. N., Fashchevskaya T. B., Afanasiev I. A., Kiyashko I. Yu., Estimation of Bashkortostan Republic water potential via GIS-technologies, *Digital scientific journal ‘Modern problems of science and education’ ISSN 2070-7428*, No.2, 2013

[11] Paul D. Wagner, Peter Fiener, Florian Wilken, Shamita Kumar, Karl Schneider (2012) Comparison and evaluation of spatial interpolation schemes for daily rainfall in data scarce regions. *Journal of Hydrology* 464–465 (2012) 388–400.

[12] Bosch DD, Davis FM (1998) Rainfall variability and spatial patterns for the southeast. In: *Proceedings of the 4th international conference on precision agriculture*, 19–22 July, St Paul, MN.

[13] Goovaerts P (2000) Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. *Journal of Hydrology* 228:113–129

[14] Lloyd CD (2005) Assessing the effect of integrating elevation data into the estimation of monthly precipitation in Great Britain. *Journal of Hydrology* 308:128–150.

[15] Phillips DL, Dolph J, Marks D (1992) A comparison of geostatistical procedures for spatial analysis of precipitation in mountainous terrain. *Agricultural and Forest Meteorology Journal* 58:119–141

[16] Tabios GQ, Salas JD (1985) A comparative analysis of techniques for spatial interpolation of precipitation. *Water Resour Bulletin* 21(3):365–380

[17] Ali A, Woosenu A, Van Horn S, Khanal N (2000) Temporal and spatial characterization of rainfall over central and south Florida. *Journal of The American Water Resources Association* 36(4):833–848

[18] Tsintikidis D, Georgakakos KP, Sperfslage JA, Smith DE, Carpenter TM (2002) Precipitation uncertainty, raingauge network design within Folsom Lake watershed. *ASCE Journal of Hydrologic Engineering* 7(2):175–184

[19] Hevesi JA, Flint AL, Istok JD (1992a) Precipitation estimation in mountainous terrain using multivariate geostatistics. Part II: isohyetal maps. *Journal of Applied Meteorology* 31:677–688

[20] Hevesi JA, Istok JD, Flint AL (1992b) Precipitation estimation in mountainous terrain using multivariate geostatistics. Part I: structural analysis. *Journal of Applied Meteorology* 31:661–676

[21] Diodato N (2005) The influence of topographic co-variables on the spatial variability of precipitation over small regions of complex terrain. *International Journal of Climatology* 25:351–363

[22] Moral FJ (2010) Comparison of different geostatistical approaches to map climate variables: application to precipitation. *International Journal of Climatology* 30:620–631

[23] The Republic of Bashkortostan, about the Rpublic, http://www.bashkortostan.ru/republic/

[24] Gareev AM, Galimova RG, *The Republic of Bashkortostan climatology guide (part 1)*, Bashkir State University, 2010

[25] http://cdiac.ornl.gov/ftp/russia_daily/

[26] Bresnahan T, Dickenson K, *Surfer Training Guide*, Golden Software, Inc., 2011

[27] Delbari M (2013) Accounting for exhaustive secondary data into the mapping of water table elevation. *Arabian Journal of Geosciences*. doi:10.1007/s12517-013-0986-2

[28] Faulkner, D. S. and Prudhomme, C.: Mapping an index of extreme rainfall across the UK, Hydrol. Earth Syst. Sc., 2, 183–194, 1998

[29] Diodato N, Ceccarelli M. 2005. Processes using multivariate geostatistics for mapping interpolation of climatological precipitation mean in the Sannio Mountains (Southern Italy). Earth Surface Processes and Landforms 30: 259–268