Article info

Article history:
Received 6 April 2018
Received in revised form
3 June 2018
Accepted 12 June 2018
Available online 19 June 2018

Keywords:
Point data
Daily rainfall
Variability patterns and nearest neighbor’s patterns

Abstract

In this data study, assessment of daily rainfall nearest neighbor’s patterns (DRBBP) was described in Iran. This article presents some spatial patterns of daily rainfall nearest neighbor’s patterns for Iran from 170 stations and 31195 rainfall points by comparing ordinary kriging techniques based on the forecast models. For the nearest neighbor’s patterns of the daily rainfall, rainfall data series of 1975–2014 was employed to estimate the point data of daily rainfall. The statistical properties were analyzed to indicate an increase in dispersed variability patterns of daily rainfall in Iran. Dispersed patterns were selected as the best nearest neighbor’s models to model daily rainfall variability. The data results will help climatologists and hydrologists in model assessment and planning of natural environment in Iran.

© 2018 The Authors. Published by Elsevier Inc. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
Experimental features | GIS-based and spatial statistical Analysis
---|---
Data source location | Data collected from Meteorological Organization of Iran (IRIMO) and GIS-based extracted data
Data availability | All data included in this article

### Value of the data

- The data could be suitable for climatic analysis in predicting of rainfall variability for climate classification in Iran.
- The data base could provide viewpoints of variability patterns of the daily rainfall using nearest neighbor’s techniques in Iran.
- The dataset will help climatologists and hydrologists in model fitting and planning of natural environment in Iran.
- The data will be helpful in predicting of the variability patterns of the daily rainfall through which the environmental planning.

### 1. Data

The rainfall data series for this study was extracted from the Meteorological Organization of Iran (IRIMO) from 1975 through 2014 from 170 synoptic and climatology stations in Iran. The point dataset to estimate the daily rainfall nearest neighbor’s patterns (DRBBP) for all stations is extracted from a rainfall dataset of the stations. Rainfall data series obtained from the IRIMO differs from rainfall datasets predicted by the ordinary kriging in the data distributions are estimated on models of the ordinary kriging. In addition, rainfall validation datasets (RVD) were extracted from ordinary kriging models based on its spatial coordinates calculated by [1,2]:

$$Y_{(5)} = \beta_0 + \beta_1 x + \beta_2 y + \beta_3 x^2 + \beta_4 y^2 + \beta_5 xy$$

where $Y_{(5)}$ this is a second-order polynomial trend surface on the spatial x- and y-coordinates. The point dataset collected are used based on observed mean distance, expected mean distance, nearest neighbor index, z-score, and p-value to assess the nearest neighbor’s patterns. However, the point daily rainfall dataset across the rainfall points 31195 is a suitable tool to analyze the nearest neighbor’s patterns. DRBBP depends on dataset extracted methods such as the ordinary kriging, and the

### Table 1

| Method         | Circular | Spherical | Tetraspherical | Pentaspherical | Exponential | Gaussian | Rational | Quadratic | Hole Effect | K-Bessel | J-Bessel | Stable Bessel |
|----------------|----------|-----------|----------------|----------------|-------------|----------|----------|-----------|-------------|----------|----------|---------------|
| Mean           | 0.906    | 0.9048    | 0.9052         | 0.9054         | 0.9058      | 0.9016   | 0.9038   | 0.9097    | 0.9035      | 0.9038   | 0.9049   |

### Table 2

| Method         | Circular | Spherical | Tetraspherical | Pentaspherical | Exponential | Gaussian | Rational | Quadratic | Hole Effect | K-Bessel | J-Bessel | Stable Bessel |
|----------------|----------|-----------|----------------|----------------|-------------|----------|----------|-----------|-------------|----------|----------|---------------|
| Mean           | 0.665    | 0.666     | 0.667           | 0.667          | 0.671       | 0.665    | 0.6696   | 0.667     | 0.668       | 0.668    | 0.669    |
Table 3
The statistical properties of the data extracted from ordinary kriging models.

| Model         | N  | Mean  | SE of mean | Interquartile range | Standard deviation | Variance | Coefficient Variations | Minimum | Maximum | Median | Skewness | Kurtosis |
|---------------|----|-------|------------|---------------------|--------------------|----------|------------------------|---------|---------|-------|----------|----------|
| Circular      | 170| 0.9056| 0.0414     | 0.6525              | 0.5353             | 0.2866   | 59.11                  | 0.2148  | 3.1019  | 0.8111| 1.31     | 2.34     |
| Exponential   | 170| 0.9058| 0.0401     | 0.6742              | 0.5185             | 0.2688   | 57.24                  | 0.2141  | 3.1843  | 0.8305| 1.42     | 3.24     |
| Gaussian      | 170| 0.9016| 0.0426     | 0.6774              | 0.5511             | 0.3037   | 61.12                  | 0.2125  | 3.2318  | 0.7866| 1.41     | 2.62     |
| Hole Effect   | 170| 0.9098| 0.0387     | 0.6683              | 0.5003             | 0.2503   | 54.99                  | 0.2128  | 2.6599  | 0.8587| 0.96     | 0.95     |
| J-Bessel      | 170| 0.9039| 0.042     | 0.6724              | 0.5431             | 0.295    | 60.09                  | 0.2151  | 3.1515  | 0.8005| 1.39     | 2.51     |
| K-Bessel      | 170| 0.9035| 0.0413     | 0.6391              | 0.5331             | 0.2842   | 59                     | 0.2123  | 3.2021  | 0.8051| 1.42     | 2.94     |
| Pentaspherical| 170| 0.9058| 0.0412     | 0.6409              | 0.532              | 0.283    | 58.73                  | 0.2141  | 3.165   | 0.8199| 1.37     | 2.76     |
| Rational      | 170| 0.9038| 0.0413     | 0.6378              | 0.5338             | 0.2849   | 59.06                  | 0.1963  | 3.2821  | 0.827 | 1.51     | 3.45     |
| Quadratic     |    |       |            |                     |                    |          |                        |         |         |       |          |          |
| Spherical     | 170| 0.9048| 0.0412     | 0.6446              | 0.5327             | 0.2838   | 58.88                  | 0.2155  | 3.1357  | 0.8114| 1.34     | 2.55     |
| Stable        | 170| 0.9049| 0.0409     | 0.6437              | 0.5284             | 0.2793   | 58.4                   | 0.2118  | 3.221   | 0.8246| 1.43     | 3.16     |
| Tetraspherical| 170| 0.9052| 0.0412     | 0.6414              | 0.5326             | 0.2837   | 58.84                  | 0.2154  | 3.1594  | 0.8202| 1.36     | 2.68     |
## Table 4
The statistical properties of the data extracted from point models of the ordinary kriging.

| Model         | N   | Mean    | SE of mean | Interquartile range | Standard deviation | Variance | Coefficient Variations | Minimum     | Maximum    | Median     | Skewness | Kurtosis |
|---------------|-----|---------|------------|--------------------|--------------------|----------|------------------------|-------------|------------|------------|----------|----------|
| Point_Circular| 3195| 0.66504 | 0.00251    | 0.53112            | 0.44382            | 0.19698  | 66.74                  | 0.17738     | 3.73058    | 0.52028    | 1.79     | 4.63     |
| Point Exponential | 3195| 0.6711  | 0.00247    | 0.54293            | 0.43635            | 0.1904   | 65.02                  | 0.17291     | 4.01968    | 0.51859    | 1.89     | 5.43     |
| Point Gaussian | 3195| 0.665  | 0.0026     | 0.5232             | 0.45863            | 0.21034  | 68.97                  | 0.16669     | 3.89062    | 0.50801    | 1.95     | 5.51     |
| Point Hole Effect | 3195| 0.66737 | 0.00244    | 0.5662             | 0.43065            | 0.18546  | 64.53                  | 0.15987     | 3.22307    | 0.52491    | 1.49     | 2.94     |
| Point J-Bessel | 3195| 0.66815 | 0.00257    | 0.51501            | 0.45395            | 0.20607  | 67.94                  | 0.13191     | 3.86073    | 0.51208    | 1.94     | 5.42     |
| Point K-Bessel | 3195| 0.66819 | 0.00253    | 0.53295            | 0.44678            | 0.19961  | 66.86                  | 0.17617     | 3.78929    | 0.51579    | 1.91     | 5.33     |
| Point Pentaspherical | 3195| 0.66915 | 0.00252    | 0.5366             | 0.44424            | 0.19735  | 66.59                  | 0.17822     | 3.85764    | 0.51827    | 1.87     | 5.14     |
| Point Rational Quadratic | 3195| 0.66964 | 0.00253    | 0.52503            | 0.44754            | 0.20029  | 66.83                  | 0.17525     | 3.87946    | 0.51322    | 1.99     | 5.85     |
| Point Spherical | 3195| 0.66585 | 0.00251    | 0.53565            | 0.44409            | 0.19722  | 66.69                  | 0.17608     | 3.78894    | 0.51935    | 1.82     | 4.87     |
| Point Stable | 3195| 0.66937 | 0.00251    | 0.53713            | 0.4425             | 0.19581  | 66.11                  | 0.17481     | 3.9058     | 0.51768    | 1.9      | 5.41     |
| Point | 3195| 0.66665 | 0.00251    | 0.53741            | 0.44419            | 0.19731  | 66.63                  | 0.17631     | 3.82861    | 0.51882    | 1.85     | 5.02     |
Table 5
DRBBP based on the Ordinary kriging models.

| Method          | Circular | Tetraspherical | Pentaspherical | Exponential | Gaussian | Rational | Hole Effect | K-Bessel | J-Bessel | Stable |
|-----------------|----------|----------------|----------------|-------------|----------|----------|-------------|----------|----------|--------|
| Mean            | 1.41633  | 1.41633        | 1.41633        | 1.82566     | 1.20635  | 1.82566  | 1.82566     | 1.82566  | 1.82566  |

Fig. 1. Spatial variability of the daily rainfall using spherical model in Iran.

Fig. 2. Variability of the point daily rainfall using ordinary kriging models in Iran.
Fig. 3. Variability of the daily rainfall using ordinary kriging models in Iran.

Fig. 4. Variability of the point daily rainfall distribution using ordinary kriging models in Iran.
The point average nearest neighbor (PANN) is defined as [3]:

\[
PANN = \frac{OMD}{EMD} = \frac{\sum_{i=1}^{n} d_i/n}{0.5/\sqrt{n/A}}
\]

OMD is the observed mean distance between each rainfall point and its nearest neighbor, EMD is the expected mean distance in a random distribution, \( d_i \) is the distance between rainfall point and its nearest neighboring, \( n \) is the total number of rainfall points, and \( A \) is the area of a minimum enclosing rectangle around all rainfall points. For the average nearest neighbor ratio (Moran’s I index), a Moran’s I index value less than 1 shows a pattern clustering (less spatial variability), while a Moran’s I index value greater than 1 indicates a dispersion pattern (more spatial variability). In this analysis, Moran’s I index value equal to 1, shows a random pattern the statistically significant the random of daily rainfall series. The quality and characteristics of the point dataset can be studied using spatial statistical methods tools such as calculating areas (for each rainfall point in a polygon rainfall points dataset), estimating distance band from neighbor count (the minimum, maximum, and average distance to the specific Nth nearest neighbor), switching rainfall points data (transfers rainfall points to weighted rainfall point data), and converting spatial weights matrix to table (transforms a binary spatial weights matrix file to a table) for a dataset of rainfall points. The rainfall point dataset is a climatic time series affecting the climatic variability in the climate classification. Rainfall point data sets were extracted from the GIS-based layers using the ordinary kriging based on the Circular, Spherical, Tetraspherical, Pentaspherical, Exponential, Gaussian, Rational Quadratic, Hole Effect, K-Bessel, J-Bessel, and Stable models. Therefore, the estimated daily rainfall dataset over the forty years is a suitable typical data series of the spatial variability of RVD as revealed in Tables 1–5. The nature and characteristics of the daily rainfall dataset can be studied using spatial statistical methods tools such as daily rainfall nearest neighbor’s patterns (DRBBP).
1.1. The mean estimation of the data from ordinary kriging

Table 1 presents the mean estimation of the data extracted from ordinary kriging. Fig. 1 also presents the data. Fig. 1 describes the statistical variability properties revealing the spatial variability of the daily rainfall in Iran.

1.2. The mean estimation of the point data from ordinary kriging

Table 2 presents the mean estimation of the data extracted from ordinary kriging. Fig. 2 also presents the data. Fig. 2 depicts the statistical variability properties revealing the point daily rainfall in Iran.

1.3. The statistical properties of the data from ordinary kriging

Table 3 presents the statistical properties of the data extracted from ordinary. Fig. 3 also presents the data. Fig. 3 describes the statistical variability properties revealing the spatial variability of the daily rainfall in Iran.

1.4. The statistical properties of the data from point model of the ordinary kriging

Table 4 presents the statistical properties of the data extracted from point ordinary kriging. Fig. 4 also presents the data. Fig. 4 depicts the statistical distribution variability properties revealing the spatial variability of the abnormal distribution of the daily rainfall in Iran.

1.5. The statistical properties of the data from DRBBP

Table 5 presents the statistical estimation of the data extracted from DRBBP in Iran. Fig. 5 also presents the data. Fig. 5 depicts the nearest neighbor’s patterns properties revealing the dispersed variability pattern of the daily rainfall in Iran.

2. Materials and methods

Several studies have been presented on nearest neighbor’s patterns properties of rainfall [4–10]. The rainfall data for this analysis were collected from the IRIMO from 1975 through 2014 from 170 synoptic and climatology stations in Iran. The rainfall dataset extracted and compared in the climatology primary data such as daily rainfall point series was employed as recorded variables for the present article result.

Acknowledgments

We thank PayameNoor University for their funding attempts supporting the competing of this article process. We thank the also thank PayameNoor research management of PayameNoor University.

Transparency document. Supporting information

Transparency data associated with this article can be found in the online version at https://doi.org/10.1016/j.dib.2018.06.021.
References

[1] M. Javari, Geostatistical modeling to simulate daily rainfall variability in Iran, Cogent Geosci. 3 (1) (2017) 1416877.
[2] K. Johnston, et al., Using ArcGIS geostatistical analyst, Esri Redlands, 2001.
[3] ESRI, Using ArcGIS geostatistical analyst: Esri Redlands, 2017.
[4] M. Chattopadhyay, S.K. Mitra, Comparative decision models for anticipating shortage of food grain production in India, Theor. Appl. Climatol. 131 (1) (2018) 523–530.
[5] J. George, L. Janaki, J. Parameswaran Gomathy, Statistical downscaling using local polynomial regression for rainfall predictions – a case study, Water Resour. Manag. 30 (1) (2016) 183–193.
[6] M. Javari, Spatial variability of rainfall trends in Iran, Arab. J. Geosci. 10 (4) (2017) 78.
[7] G.-F. Lin, M.-J. Chang, J.-T. Wu, A hybrid statistical downscaling method based on the classification of rainfall patterns, Water Resour. Manag. 31 (1) (2017) 377–401.
[8] G.B. Lyra, et al., Evaluation of methods of spatial interpolation for monthly rainfall data over the state of Rio de Janeiro, Brazil, Theor. Appl. Climatol. (2017).
[9] C.K. Unnikrishnan, M. Rajeevan, Atmospheric water budget over the South Asian summer monsoon region, Meteorol. Atmos. Phys. 130 (2) (2018) 175–190.
[10] S. Yakowitz, M. Karlsson, Nearest neighbor methods for time series, with application to rainfall/runoff prediction, in: I.B. MacNeill, G.J. Umphrey, A.I. McLeod (Eds.), Advances in the Statistical Sciences: Stochastic Hydrology: Volume IV Festschrift in Honor of Professor V. M. Joshi’s 70th Birthday, Springer, Netherlands: Dordrecht, 1987, pp. 149–160.