Spatial Monitoring and Variability of Daily Rainfall in Iran

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Abstract
The most important aim of this study was on the monitoring spatial variability in rainfall through the study of daily data in Iran. The analysis shows a pattern based on daily rainfall data, for 1951 to 2014 periods, in 170 stations. The results indicate that during the period 1951-2014, show the change of spatial autocorrelation in the eastern parts of Iran in daily rainfall data distributed in different years. Results reveals that the daily rainfall data occurred a change of squared difference in different years, in the western south part, whereas in the eastern part it was indicated in different years. For daily rainfall data in Iran, the change point of 0.5 is a good starting point where, typically, the values vary between small parts (0.2 to 0.4) and large parts (0.6 to 1). Change point in spatial variability distribution of daily rainfall series during 1951-2014 was observed at variability boundary (0.5) in Iran between the western north region (effective region) and central and eastern south region (inoperative region) in Iran. Results reveals that the spatial clusters of daily rainfall data for most of the stations with low values.

Hot Spot analysis shows that dissimilar is the daily rainfall data distribution patterns in Iran. In OLS analysis, significant spatial relationships ($R^2=0.72$) were observed between the stations elevation distribution and daily rainfall data distribution in Iran. Statistically significant clustering of high and low residuals in daily rainfall data analysis with series period suggested that the GWR model is specified. The result of variance inflation factor (VIF) indicated {large variance inflation factor (VIF) values ($>7.5$)} revealed redundancy among stations elevation distribution. In general, result of Ripley's K-function analysis was observed the observed K value is larger than the upper confidence envelope value, spatial clustering (western and southwestern of Caspian Sea) for daily rainfall data values that are
statistically significant. However, in rainfall variability is important the spatial distribution in Iran.

**Keywords:** spatial autocorrelation, cluster analysis, Ripley's K-function and Rainfall.

**INTRODUCTION:**
Rainfall spatial distribution and variability is an essential rainfall variability aspect, for the reason that it is the most effectiveness component in the regionalization of climate and rainfall formation conditions. Analysis of rainfall spatial distribution and variability is important in calculating the distance between each station cell centroid and its nearest neighbor's centroid station cell location on the regional climatic conditions (Roy & Rouault, 2013). Therefore, the estimation of rainfall averages all station cells nearest neighbor distances on a regional scale is necessity (ESRI, 2014). If the rainfall cells average distance is less than the average for a hypothetical distribution, the distribution and variability of the rainfall cells being calculated are revealed clustered (Johnston, Ver Hoef, Krivoruchko, & Lucas, 2001). If the station cells average distance is greater than a hypothetical distribution, the rainfall cells are reflected dispersed (Shen, Li, & Si, 2016). The rainfall cells average spatial distribution ratio (RCASP) is calculated as the rainfall cells detected average distance (RCDAD) divided by the rainfall cells predictable average distance (RCPAD). If the RCASP is less than 1, the rainfall cells average pattern distribution and variability displays clustering pattern (javari 2016; Zhou, Minnick, Mattson, Geza, & Murray, 2015). If the RCASP is greater than 1, the rainfall cells average pattern distribution and variability displays dispersion pattern (Cattaneo, Rillo, & Mercogliano, 2014). In addition, when the p-value is very small, it means it is very unlikely that the rainfall cells spatial distribution and variability is the result of random spatial distribution and variability. Very high or very low (negative) z-scores, associated with very small p-values, are discovered in the tails of the normal distribution and variability (Bede-Fazekas, Horváth, Trájer, & Gregorics, 2015). The rainfall cells local spatial pattern analysis tools including hot spot analysis and cluster and outlier analysis, The local Moran's I present a rainfall cells spatial distribution and variability (Bede-Fazekas et al., 2015; Cattaneo et al., 2014; Cheng, Zhang, & Peng, 2013; Dummer et al., 2015; Zhang, Su, Wu, & Liang, 2015). Local spatial distribution and variability analysis work by considering each rainfall cell within the area of neighboring rainfall cells and determining if the local pattern (a target rainfall cell and its neighbors) is statistically different from the global pattern (all rainfall cells in the dataset). Rainfall cells near to each other tend to be similar; more often than not spatial rainfall series displays this type of dependency. However, many statistical tests want rainfall cells to be independent. For rainfall local spatial distribution and variability analysis methods this is because the spatial dependency can theatrically increase statistical significance. Spatial dependency is intensified with rainfall local pattern analysis methods because
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Each cell is evaluated within the area of its neighbors, and rainfall cells that are near each other will likely share many of the same neighbors. This overlap emphasizes rainfall spatial dependency. Several statistics in the rainfall spatial distribution and variability are inferential spatial pattern analysis methods, including spatial autocorrelation (Global Moran's I), cluster and outlier analysis (Local Moran's I), and hot spot analysis (Getis-Ord Gi*). Measures the degree of rainfall cells spatial distribution and variability clustering for either high values or low values using the Getis-Ord General G statistic (ESRI, 2014; Johnston et al., 2001). The High/Low Clustering (Getis-Ord General G) technique is an inferential statistic, which means that the results of the method are interpreted within the context of the rainfall spatial clustering. The null hypothesis for the High/Low Clustering (General G) statistic states that there is no spatial clustering of rainfall cells values. If the null hypothesis is rejected, then the sign of the z-score becomes important (ESRI, 2014). If the z-score value is positive, the rainfall cells General G index is larger than the rainfall cells expected General G index, indicating high values for the rainfall cells are clustered in the study area. Measures spatial autocorrelation based on rainfall cells locations and rainfall cells values using the Global Moran's I statistic. Given a set of rainfall cells and a related quality, it evaluates whether the rainfall spatial pattern expressed is clustered, dispersed, or random. Given a set of rainfall cells and an analysis rainfall cells area, the cluster and outlier analysis method identifies spatial clusters of rainfall cells with high or low values. In this study, the cluster and outlier analysis method calculates a local Moran's I value, a z-score, a p-value, and a procedure representing the rainfall spatial distribution and variability cluster type for each statistically significant rainfall cells. The local Moran's I value represent the statistical significance of the computed rainfall spatial distribution and variability values. A positive value for local Moran's I indicates that a rainfall cell series has neighboring rainfall cells series with similar high or low quality values; this rainfall cell is part of a cluster. A negative value for local Moran's I indicates that a rainfall cell series has neighboring rainfall cells series with dissimilar values; this rainfall series is an outlier. The hot spot analysis method identifies statistically significant rainfall cells spatial clusters of high values (hot spots) and low values (cold spots). A rainfall cell series with a high value is interesting but may not be a statistically significant hot spot (ESRI, 2014). To be a statistically significant hot spot, a rainfall cell series will have a high value and be surrounded by other rainfall cells series with high values as well. The local sum of a rainfall cells series and its neighbors is compared proportionally to the sum of all rainfall cells series; when the local sum is very different from the expected local sum, and when that difference is too large to be the result of random chance in the rainfall spatial distribution and variability (Becketti, 2013). For statistically significant positive z-scores, the larger the z-score is, the more intense the rainfall spatial clustering of high values (hot spot). For statistically significant negative z-scores, the smaller the z-score is, the more intense the rainfall spatial clustering of low values (cold spot). Presents global ordinary least squares (OLS) linear regression to create predictions or to model a rainfall cell series in terms of its relationships with a set of explanatory rainfall cells series (Pawar, Mukherjee, & Shankar, 2015; Pohlmann, 1993). Regression is used to evaluate relationships
between two or more rainfall cells series (Araghi, Adamowski, & Jaghargh, 2016). Ordinary Least Squares (OLS) is the best known of all regression techniques. It is also the suitable starting point for all rainfall cells spatial regression analyses (ESRI, 2014; Moran, P, 1950). It provides a global model of the rainfall cell series or rainfall cells spatial distribution and variability to predict; it creates a single or multi regression model to represent that rainfall cells spatial distribution and variability. Presents Geographically Weighted Regression (GWR), a local form of linear regression (Javari, 2016) used to model rainfall cells spatially varying relationships (Liu, Guo, Jiang, Zhang, & Chen, 2015; Pasculli, Palermi, Sarra, Piacentini, & Miccadei, 2014). Geographically Weighted Regression (GWR) is one of several spatial regression methods increasingly used in climate and rainfall cells spatial distribution and variability (Caloiero, Buttafuoco, Coscarelli, & Ferrari, 2015; Haberlandt, 2007; Ly, Charles, & Degré, 2013; Shiau & Huang, 2015; Taxak, Murumkar, & Arya, 2014). GWR provides a local model of the rainfall cells series to predict by fitting a regression model to every rainfall cell series in the dataset. In this study, were used the mentioned methods for daily rainfall series in Iran.

**ANALYSIS OF LOCAL STATISTICS:**

We define a local variability in single rainfall series is simply to calculate local statistics in a moving frame in the same way as is done with the focal machinists. A more complex method is to weight series as a function of their distance from the center of the frame. Such methods are the subject of the following sections:

**Geographically weighted statistics:**

Many weighting patterns, both binary and continuous, have been advanced in analysis of rainfall variability. A weighting pattern uses the Gaussian function. Gaussian function simulations operates by first creating a grid of randomly assigned rainfall series depicted from a standard normal distribution and variability. The covariance pattern is then applied to the raster rainfall layer. This confirms that the rainfall layer follow to the spatial distribution and variability found in the rainfall series. The results shown that the rainfall raster layer represents one categorical recognition, and many more can be created using a different raster of normally distributed rainfall each time. If conditional simulation has been selected, the unconditional (categorical) rainfall raster layer is conditioned via specific interpolation. In this study, is used the Gaussian geostatistical simulation (GGS), more specifically, is suitable for rainfall series and supposes that the rainfall series, or a transformation of the series, has a normal (Gaussian) distribution and variability. The main hypothesis following GGS is that the rainfall is stationary and spatial pattern (semivariogram) does not change over the spatial dominion of the series. Another important hypothesis of GGS is that the random function being patterned is a multivariate Gaussian random function. For the normal (Gaussian) distribution and variability, the Gaussian function is used (ESRI, 2014):
\[ f(x) = \frac{\exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right)}{\sigma\sqrt{2\pi}} \]

\( \sigma \) is continuous scale parameter and \( \mu \) is continuous location parameter. In this study, is employed the Gaussian tool to analyze the daily rainfall mean. The Gaussian Geostatistical Simulation tool accepts any simple kriging model. However, simulation results are only valid if the rainfall series is normally distributed. Rainfall series in some situations is non-normally distributed, was using a normal score transformation. Some interpolation and simulation methods require the rainfall series to be normally distributed. The normal score transformation (NST) is designed to transform rainfall series so that it closely be similar to a standard normal distribution and variability. We apply the semivariogram pattern for spatial distribution and variability. Semivariogram modeling is an important factor between spatial description and spatial monitoring. The main application of semivariogram is the monitoring of attribute rainfall series at un-sampled locations. The empirical semivariogram provide evidence on the spatial autocorrelation of rainfall series. However, semivariogram do not provide facts for all possible directions and distances in the rainfall series. For application of semivariogram, we is used the Geostatistical wizard tools in the ArcGIS10.3. The Geostatistical wizard tools provides three different viewpoints of the empirical semivariogram amounts. We can use one, two or all three of them (model, binned and averaged) to aid in fitting a pattern to the rainfall series. Model values are shown as blue line. Binned amounts are shown as red dots, and are created by grouping empirical semivariogram points together using square cells that are one lag wide. Average points are shown as blue crosses, and are created by binning empirical semivariogram points that fall within angular sectors. Binned points show local variability in the semivariogram amounts, whereas average amounts show smooth semivariogram amount variations. In rainfall analysis, it is easier to fit a model to the averaged amounts, as they offer a less cluttered view of the spatial autocorrelation in the rainfall series and present smoother changes in the semivariogram amounts than the binned points. In semivariogram, the sill, range, and nugget are the important characteristics of the model. The height that the semivariogram reaches when it levels off is called the sill. It is often composed of two parts: a discontinuity at the origin, called the nugget effect, and the partial sill; added together, these give the sill. The nugget effect can be further divided into measurement error and microscale variations. The semivariogram is shown as(ESRI, 2014; Johnston et al., 2001):

\[ Y_{(s_i,s_j)} = 0.5\sigma^2\left(Z_{(s_i)} - Z_{(s_j)}\right) \]

where \( \sigma^2 \) is the variance for two locations, \( s_i \) and \( s_j \). In addition, for transforms the original rainfall amounts into a normal distribution and variability, we is used the Fuzzy Gaussian function in the ArcGIS10.3. The Fuzzy Large transformation function is used when the larger rainfall series are more likely to be a member of the series. The defined midpoint identifies the crossover point (assigned a membership of 0.5)
with amounts greater than the midpoint having a higher possibility of being a member of the series and values below the midpoint having a decreasing membership. For study the geographically weighted variants of standard statistical indexes, we is used the geographically weighted mean. The geographically weighted mean can be computed with (ESRI, 2014):

$$\bar{Z}_i = \frac{\sum_{j=1}^{n} z_i w_{ij}}{\sum_{j=1}^{n} w_{ij}}$$

Spatial statistics incorporate distribution and variability and spatial relationships directly into their mathematics (mean, area, distance, length, or proximity). Typically, these spatial relationships are defined correctly through amounts called spatial weights. Spatial weights are organized into a spatial weights matrix. A spatial weights matrix calculates the spatial and temporal relationships that exist among the rainfall patterns in rainfall series. There is a variety of weighting likelihoods including inverse distance, fixed distance, space-time window, K nearest neighbors, contiguity, and spatial interaction that in this study, is used for the analysis of rainfall spatial distribution and variability. In this study, for the analysis of rainfall spatial distribution and variability is used the K nearest neighbors method. The K nearest neighbors method includes the Spatial Autocorrelation (Global Moran's I), Hot Spot Analysis (Getis-Ord Gi*), and Cluster and Outlier Analysis (Local Moran's I) methods. The Spatial Autocorrelation (Global Moran's I) index calculates spatial autocorrelation based on both rainfall patterns locations and rainfall patterns amounts at 1951 to 2014 periods.

The Spatial Autocorrelation (Global Moran's I) index can be computed with (ESRI, 2014; Johnston et al., 2001):

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{S_o}$$

$$S_o = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}$$

$$z_i = \frac{1 - E[I]}{\sqrt{V[I]}}, E[I] = -1/(n-1)$$

$$V[I] = E[I^2] - E[I]^2$$
Where $z_i$ is the deviation of a rainfall variable from mean and $w_{i,j}$ is the spatial weights between two rainfall points. For the Global Moran's I statistic, the null hypothesis states that the rainfall data being analyzed is randomly distributed among the series in the study area; said another way, the spatial processes promoting the observed pattern of values is random chance. When the p-value is very small, it means it is a very small probability that the observed spatial pattern is the result of random processes, so can reject the null hypothesis. The Local Moran's I index can be computed with (ESRI, 2014):

$$ I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1}^{n} \sum_{j \neq i} w_{i,j} (x_i - \bar{X}) $$

$$ S_i^2 = \frac{\sum_{j=1}^{n} \sum_{j \neq i} w_{i,j} (x_i - \bar{X})^2}{n - 1} - \bar{X}^2 $$

A check for spatial autocorrelation can be created where there is a necessarily large quantity of rainfall series. By accepting that the series are depicted independently from a normal distribution and variability that is approximately normal with predictable amount of I given by (Cheng et al., 2013; ESRI, 2014):

$$ ZI_i = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}}, E[I_i] = -\frac{\sum_{j=1, j \neq i}^{n} w_{ij}}{(n-1)} $$

$$ V[I_i] = E[I_i^2] - E[I_i]^2 $$

A positive value for $I_i$ indicates that a pattern has neighboring patterns with similarly high or low rainfall values; this pattern is part of a cluster. A negative value for $I_i$ indicates that a pattern has neighboring patterns with dissimilar amounts; this rainfall pattern is an outlier. In other hand, the p-value for the rainfall pattern must be small enough for the cluster or outlier to be considered statistically significant. Note that the local Moran's I index ($I_i$) is a relative measure and can only be interpreted within the situation of its calculated z-score or p-value. The z-scores and p-values reported in the output rainfall pattern class are uncorrected for multiple testing or spatial dependency. The cluster/outlier type field distinguishes between a statistically significant cluster of high values (HH), cluster of low values (LL), outlier in which a high value is surrounded primarily by low values (HL), and outlier in which a low value is surrounded primarily by high values (LH). Statistical significance is set at the 95 percent confidence level. When no false discovery rate correction (FDRC) is applied, rainfall patterns with p-values smaller than 0.05 are considered statistically
significant. The FDR correction reduces this p-value threshold from 0.05 to a value that better reflects the 95 percent confidence level given multiple testing. The Hot Spot Analysis tool computes the Getis-Ord Gi* statistic (pronounced G-i-star) for each pattern in a series. The resultant z-scores and p-values tell where patterns with either high or low amounts cluster spatially. The Gi* statistic returned for each pattern in the series is a z-score. For statistically significant positive z-scores, the larger the z-score is, the more intense the clustering of high values (hot spot). For statistically significant negative z-scores, the smaller the z-score is, the more intense the clustering of low values (cold spot). The Getis-Ord Gi local statistic can be computed with(Bede-Fazekas et al., 2015; Cheng et al., 2013; ESRI, 2014):

\[
G_{i}^{*} = \frac{\sum_{j=1}^{n} w_{i,j} x_{i} - \bar{X} \sum_{j=1}^{n} w_{i,j}}{\sqrt{\left(\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right)^{n-1}}} \\
S = \sqrt{\frac{\sum_{j=1}^{n} w_{i,j}^2}{n} - \left(\bar{X}\right)^2}
\]

Neighbor relationships in the rainfall spatial distribution and variability may also be constructed so that each pattern is assessed within the spatial situation of a specified number of its closest neighbors. K (the number of neighbors), closest neighbors to the focus pattern will be included in calculations for that pattern. In locations where rainfall pattern density is high, the spatial situation of the rainfall analysis will be smaller. Similarly, in locations where rainfall pattern density is sparse, the spatial situation for the rainfall analysis will be larger. For analysis the number of neighbors in the daily rainfall analysis, is used the Geographically Weighted Regression (GWR) and the exploratory regression method (OLS). Geographically Weighted Regression (GWR) is one of several spatial regression techniques increasingly used in climatology. GWR provides a local pattern of the rainfall predict by fitting a regression equation to every pattern in the series. The shape and size of the bandwidth are dependent on user rainfall for the Kernel type, Bandwidth method, Distance, and Number of neighbor’s parameters. The global OLS linear regression to create to model in terms of its relations to a series of explanatory variables. In analysis of daily rainfall by using the exploratory regression method, are studied the threshold criteria the Adjusted R², coefficient p-values, Variance Inflation Factor (VIF) values, Jarque-Bera p-values, and spatial autocorrelation p-values. For analysis the distance of daily rainfall series, is used geographically weighted standardized distance (GWSD) of the global and local for daily rainfall in Iran. The GWSD of the global and local methods
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provides a method of assessing locally noticeable deviations from the global mean (Bede-Fazekas et al., 2015; ESRI, 2014; Johnston et al., 2001):

\[
GWSD = \sqrt{\frac{\sum_{i=1}^{n} w_i (X_i - \bar{X})^2 + \sum_{i=1}^{n} (Y_i - \bar{Y})^2}{n}}
\]

Following the previous definitions, the geographically weighted Multi-Distance Spatial Cluster Analysis (Ripley's K Function) is given by (ESRI, 2014; Johnston et al., 2001):

\[
K = \sqrt{\frac{A \sum_{i=1}^{n} \sum_{j=1}^{n} K_{i,j}}{\pi n(n - 1)}}
\]

Where A is the total area and K is the weight. The Multi-Distance Spatial Cluster Analysis method, based on Ripley's K-function, is another method to study the spatial pattern of occurrence point rainfall series. When the daily rainfall series observed K amount is larger than the daily rainfall series expected K amount for a specific distance, the distribution and variability is more clustered than a random distribution and variability at that distance. When the daily rainfall series observed K value is smaller than the daily rainfall series expected K value, the distribution and variability is more dispersed than a random distribution and variability at that distance. When the daily rainfall series observed K value is larger than the upper confidence envelope (HiConfEnv) value, spatial clustering for that distance is statistically significant. When the daily rainfall series observed K amount is smaller than the lower confidence envelope (LwConfEnv) amount, spatial dispersion for that distance is statistically significant. In spatial distribution and variability of daily rainfall, we is analyzed the relation between precipitation and elevation. For analysis the relation between precipitation and elevation, is used the OLS for rainfall analysis as an independent variable is given by (Javari, 2010; Shen et al., 2016):

\[
Z_i = \beta_o + \beta_1 x_{i1} + \ldots + \beta_k x_{ik} + \epsilon
\]

where \( i \) refers to a location, \( x_{1i}, \ldots, x_{ki} \) are the independent series at location \( i \), \( \beta_o, \beta_1, \beta_k \) are the parameters and \( \epsilon \) is an error term. We in analysis of OLS was used to fit a line to the drawn amounts. For analysis of spatial distribution and variability is used the daily rainfall of Iran.
RESULTS AND DISCUSSION:

Distribution and variability of daily rainfall in different stations of a year was analyzed in this study (Fig. 1). The spatial autocorrelation of daily rainfall in 170 stations is shown in Fig. 2.

**Fig. 1:** Distribution of Stations

**Fig. 2:** The spatial autocorrelation of daily rainfall in 170 stations
The empirical semivariograms of daily rainfall in 170 stations provide information on the spatial autocorrelation of rainfall series in Iran (Fig. 2). Binned values of daily rainfall data are shown as red dots, and are created by category (binning) empirical semivariograms points collectively using square cells that are one lag wide. The daily rainfall data are displayed as blue crosses, and are created by binning empirical semivariograms points that fall within angular sectors. Binned points show daily rainfall data wide local variations in the semivariograms values, whereas average values show smooth semivariograms values variations. In many cases it isn’t easier to fit a model to the averaged values, as they offer a less cluttered view of the spatial autocorrelation in the daily rainfall data and show smoother changes in the semivariograms values than the binned points. In empirical semivariograms points of daily rainfall data, change in spatial autocorrelation ranges at many locations (The show daily rainfall data points control can be set to Binned and Averaged as shown in the figure above, Binned, or Averaged as shown in the figures below) in the eastern part was observed between 55° to 62° E with significant increasing spatial autocorrelation in the eastern and north eastern parts. Additionally, the lines are local polynomials fitted to the binned empirical semivariograms values of daily rainfall data. In Fig 2, change in the squared difference between the values of daily rainfall data points was observed against the distance separating the daily rainfall data points with significant increasing distance in the eastern parts. However, during period 1951-2014, the change of spatial autocorrelation in the eastern parts of Iran in daily rainfall data occurred in different years. At few daily rainfall data points in western south part, change in squared difference it was observed between the years 1951 to 2014. Similar results were reflected in the central parts for change in squared difference (Fig. 3).

Fig. 3: Change of squared difference of daily rainfall data
Daily rainfall data results revealed a change of squared difference in different years, in the western south part, whereas in the eastern part it was reflected in different years. In the eastern part, change of squared difference and spatial autocorrelation occurred in 1951 - 2014 at many stations. Increasing spatial squared difference in daily rainfall data was found from western to eastern and central and eastern parts, whereas decreasing spatial squared difference was observed in western-north, western and northwestern parts during 1951 - 2014 period. Fuzzy Gaussian function analysis at daily rainfall scale indicated increasing trends in probability of daily rainfall values in Fuzzy Gaussian values from western north to eastern south in Iran (Fig. 4).

![Fig.4: Fuzzy Gaussian function analysis at daily rainfall](image)

Fig.4 spread determines how rapidly the fuzzy membership daily rainfall values decrease from 1 to 0.2. The smaller the value (western south of the Caspian Sea and western parts), the fuzzy memberships approach 0.2 more slowly, the gentler the fuzzification around the midpoint (0.5) and the greater the value (eastern south and central parts), the steeper the fuzzification around the midpoint (0.5). In this study, 0.2 value (western south of the Caspian Sea) is a good starting point. For daily rainfall data in Iran, the change point of 0.5 is a good starting point where, typically, the values vary between small parts (0.2 to 0.4) and large parts (0.6 to 1). Change in fuzzification and occurrence probability of daily rainfall values during 1951-2014 was observed at change boundary (0.5) in the boundary region between the western north region (effective region) and central eastern south region (inoperative region) in Iran (Fig. 4). Change in occurrence probability of daily rainfall values during 1951-2014 in the effective region was observed the four sub-region (effective sub-regions) in Iran (Fig. 4). Effective sub-regions were observed significantly the diversity trend of occurrence probability of daily rainfall values (0.2, 0.3, 0.4 and 0.6 sub-regions) along
with a change point in the period 1951-2014 at western north in Iran. Effective sub-region was observed significantly the diversity trend of occurrence probability of daily rainfall values (0.2, sub-regions) along with Caspian Sea and western point in the period 1951-2014 in Iran (Fig. 4). The Spatial Autocorrelation (Global Moran's I) in the daily rainfall data average values is shown in Fig. 5. Global Moran's I analysis on rainfall series indicated the p-value is not statistically significant and the daily rainfall series has random patterns and the rainfall spatial processes supporting the observed pattern of values is random chance in daily rainfall data for most of the stations (Table.1).

**Table.1:** Incremental Spatial Autocorrelation by Global Moran's I Summary by Distance

<table>
<thead>
<tr>
<th>Distance</th>
<th>Moran’s Index</th>
<th>Expected Index</th>
<th>Variance</th>
<th>z-score</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>176435.00</td>
<td>0.3140</td>
<td>-0.006</td>
<td>0.002</td>
<td>7.84</td>
<td>0.000</td>
</tr>
<tr>
<td>234226.83</td>
<td>0.2806</td>
<td>-0.006</td>
<td>0.001</td>
<td>9.60</td>
<td>0.000</td>
</tr>
<tr>
<td>292018.66</td>
<td>0.2233</td>
<td>-0.006</td>
<td>0.001</td>
<td>9.55</td>
<td>0.000</td>
</tr>
<tr>
<td>349810.49</td>
<td>0.2057</td>
<td>-0.006</td>
<td>0.000</td>
<td>10.84</td>
<td>0.000</td>
</tr>
<tr>
<td>407602.32</td>
<td>0.2026</td>
<td>-0.006</td>
<td>0.000</td>
<td>12.51</td>
<td>0.000</td>
</tr>
<tr>
<td>465394.14</td>
<td>0.1832</td>
<td>-0.006</td>
<td>0.000</td>
<td>13.32</td>
<td>0.000</td>
</tr>
<tr>
<td>523185.97</td>
<td>0.1746</td>
<td>-0.006</td>
<td>0.000</td>
<td>14.65</td>
<td>0.000</td>
</tr>
<tr>
<td>580977.80</td>
<td>0.1692</td>
<td>-0.006</td>
<td>0.000</td>
<td>16.00</td>
<td>0.000</td>
</tr>
<tr>
<td>638769.63</td>
<td>0.1552</td>
<td>-0.006</td>
<td>0.000</td>
<td>16.77</td>
<td>0.000</td>
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<tr>
<td>696561.46</td>
<td>0.1445</td>
<td>-0.006</td>
<td>0.000</td>
<td>17.73</td>
<td>0.000</td>
</tr>
</tbody>
</table>

First Peak (Distance, Value): 234226.83, 9.595792
Max Peak (Distance, Value): 234226.83, 9.595792
Distance measured in Meters

The p-value (0.751704) and z-score (-0.316394) analysis of daily rainfall data indicated the spatial distribution and variability of high values and low values in the daily rainfall data is more spatially dispersed than would be expected the rainfall spatial processes were random in Iran(Fig. 5). The High/Low Clustering (Getis-Ord General G) in the daily rainfall data average values are shown in Fig. 6. Getis-Ord General G analysis on rainfall series indicated random patterns and the rainfall spatial processes supporting the observed pattern of values is random chance in daily rainfall data for most of the stations (Fig. 6). Getis-Ord General G analysis on rainfall series indicated the p-value is not statistically significant. The p-value (0.782158) and z-
score (-0.276508) analysis of daily rainfall data revealed the spatial distribution and variability of high values and low values in the daily rainfall data is more spatially dispersed than would be expected the spatial processes were truly random in Iran (Fig. 6). In general, the results showed through Getis-Ord General G analysis is similar to each other on Global Moran's I index (Figs. 5 and 6).

**Fig. 5:** Global Moran's I analysis on rainfall series

**Fig. 6:** The High/Low Clustering (Getis-Ord General G) in the daily rainfall data
The Cluster and Outlier Analysis (Local Moran's I) in the daily rainfall data average values are shown in Fig. 7.

The cluster analysis on rainfall series revealed spatial clusters of daily rainfall data for most of the stations with low values (Fig. 7) and the cluster analysis on rainfall series revealed spatial clusters of daily rainfall data for some of the stations with high values. Daily rainfall data as well as the cluster high values were predicated in the southwestern parts of the Caspian Sea and western parts for some of the stations in Iran (Fig. 7). In addition, the Outlier analysis in the daily rainfall data average values is shown in Fig. 7. Outlier analysis on rainfall series revealed that there aren’t the outlier series in the daily rainfall data average values and the rainfall spatial processes supporting the observed pattern of values have homogeneity, homogeneity in which a high value isn’t surrounded primarily by low values (High outlier), and homogeneity in which a low value isn’t surrounded primarily by high values (Low outlier) in daily rainfall data for all of the stations in Iran (Fig. 7) and there is weak heteroscedasticity in the daily rainfall data. The Hot Spot analysis (Getis-Ord Gi) in the daily rainfall data average values are shown in Fig. 8.
Hot Spot analysis of daily rainfall data by different distribution and variability indicated dissimilar daily patterns in Iran (Fig. 8). Southwestern of the Caspian Sea and western parts of the Iran revealed that statistically significant positive z-scores, the larger the z-score is, the more intense the clustering of high values (hot spot) in the daily rainfall data and in central parts of the Iran indicated that statistically significant negative z-scores, the smaller the z-score is, the more intense the clustering of high values (cold spot) in the daily rainfall data (Fig. 8). The result of Geographically Weighted Regression (GWR) with significant distribution and variability in Iran is shown in Fig. 9.

Fig. 8: The Hot Spot analysis (Getis-Ord Gi) in the daily rainfall data

Fig. 9: Geographically Weighted Regression of the daily rainfall data
GWR, a local pattern of linear regression used to model spatially varying relationships in the daily rainfall data in Iran. In Fig. 9, the red areas are locations where the daily rainfall data are larger than the model estimated. The blue areas are locations where the daily rainfall data are smaller than the model estimated. Statistically significant clustering of high and low residuals in daily rainfall data analysis with series period suggested that the GWR model is specified (Fig. 9). The residuals of GWR analysis revealed that the residuals are normally distributed (Fig. 9). The result of Ordinary Least Squares (OLS) to generate forecasts in daily rainfall data of its relationships to stations elevations in Iran is shown in Fig. 10.

![GWR analysis](image)

**Fig.10:** Ordinary Least Squares of the daily rainfall data

OLS, a best known of all regression techniques used to model spatially varying relationships in the daily rainfall data in Iran. It provides a global model of the daily rainfall data to predict. OLS testing, investigate spatial relationships between the stations elevation points and daily rainfall data spatial distribution and variability (Table.2). The result of OLS analysis with significant spatial relationships in Iran is shown in Fig. 11.

**Table.2: OLS**

<table>
<thead>
<tr>
<th>NAME</th>
<th>VALUES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth</td>
<td>215.5017401</td>
</tr>
<tr>
<td>ResidualSquares</td>
<td>0.822804607</td>
</tr>
<tr>
<td>EffectiveNumber</td>
<td>5.006650239</td>
</tr>
<tr>
<td>Sigma</td>
<td>0.070617955</td>
</tr>
<tr>
<td>AICc</td>
<td>-411.2803096</td>
</tr>
<tr>
<td>R2</td>
<td>0.99130413</td>
</tr>
<tr>
<td>R2Adjusted</td>
<td>0.991092962</td>
</tr>
</tbody>
</table>
In OLS analysis, significant spatial relationships ($R^2=0.72$) was observed between the stations elevation distribution and variability and daily rainfall data distribution and variability in Iran (Fig.11). In addition, number of stations elevation distribution and variability down as the number of daily rainfall data distribution and variability goes up in Iran, however, the relationship is negative (Fig.11). The result of OLS analysis, strong negative relationship was reflected in the northern parts, while the weak negative relationship between the central and south regions. However, a significant relationship (72 percent of the model's predicted values explains the variation in the observed daily rainfall data values) was observed in the daily rainfall data spatial distribution and variability in Iran. In addition, the result of OLS coefficients (a statistically significant p-value [$p < 0.01$] indicated the strength and type of relationship between stations elevation distribution and variability and the daily rainfall data distribution and variability. The result of probability and robust probability indicated a coefficient is statistically significant ($p < 0.01$). The result of variance inflation factor (VIF) indicated (large variance inflation factor (VIF) values (> 7.5)) revealed redundancy among stations elevation distribution and variability and Joint F and Wald statistics presented overall model significance ($p < 0.01$). In addition, Jarque-Bera Statistic displayed statistically significant ($p < 0.01$) model monitoring are unbiased (the residuals are normally distributed). However, the Spatial Autocorrelation (Moran's I) displayed residuals of daily rainfall data are spatially autocorrelated. The standard distance of daily rainfall data values is shown in Fig. 12.
The standard distance the degree to which daily rainfall data are concentrated or dispersed around the geometric mean center. The result of daily rainfall data values standard distance analysis was observed the circle size 1 and 2 standard deviations in the majority parts of Iran (Fig.12). The multi-distance spatial cluster analysis (MDSCA), based on Ripley's K-function in the daily rainfall data average values are shown in Fig. 13.
MDSCA is another method to analyze the spatial pattern of point daily rainfall data average values. The result of Ripley's K-function analysis, distribution and variability is more clustered than a random distribution and variability at that distance was reflected in the central and eastern parts, while the distribution and variability is more dispersed than a random distribution and variability at that distance in the north and western regions (Fig. 13). In general, result of Ripley's K-function analysis was observed the observed K value is larger than the upper confidence envelope value, spatial clustering (western and southwestern of Caspian Sea) for daily rainfall data values that are statistically significant (Fig. 13). However, result of Ripley's K-function analysis was reflected spatial clustering (western and southwestern of Caspian Sea) and spatial dispersion (central and southeastern of Iran) for daily rainfall data that are statistically significant (Fig. 13). The ordinary least squares prediction (OLSP), based on kriging-ordinary least squares function in the daily rainfall data average values for stations 170 are shown in Fig. 14.

The result of OLSP analysis, was reflected the scatter plot of daily rainfall data predicted values versus daily rainfall data true values in Iran. The fitted line through the scatter of daily rainfall points was observed in blue with the OLSP equation given just below the plot. The scattering of daily rainfall data predicted values was reflected (R^2=0.703 and RMSE=0.505) statistically significant in Iran (Fig. 14). The variance
cloud, based on empirical crosscovariance in the daily rainfall data average values for stations 170 is shown in Fig.15.

![Fig.15: The empirical crosscovariance in the daily rainfall data](image)

In this study, the variance cloud is used to examine the local characteristics of spatial distribution and variability and dispersed between daily rainfall series. The variance cloud results with significant pattern for different stations are shown in Fig. 15. In the Fig.15, each cross shows the empirical crosscovariance between a pair of locations, with the daily rainfall of one point taken from the first daily rainfall series and the daily rainfall of the second point taken from the second daily rainfall series. However, in rainfall variability is important the spatial distribution and variability in Iran.

**CONCLUSION:**

This study demonstrates the spatial distribution and variability in Iran. In this study, the rainfall spatial distribution and variability calculates the distance between each station cell centroid and its nearest neighbor's centroid station cell location. It then rainfall averages all station cells nearest neighbor distances. Spatial autocorrelation of daily rainfall in different stations of a year was analyzed in this study. Fuzzy Gaussian function analysis at daily rainfall scale indicated increasing trends in probability of daily rainfall values in Fuzzy Gaussian values from western north to eastern south in Iran. Global Moran's I analysis on rainfalls series indicated the p-value is not statistically significant and the daily rainfalls series has random pattern and the rainfall spatial processes supporting the observed pattern of values is random chance in daily rainfall data for most of the stations. Getis-Ord General G analysis on rainfall series indicated random patterns and the rainfall spatial processes supporting the
observed pattern of values is random chance in daily rainfall data for most of the stations. GWR, a local pattern of linear regression used to model spatially varying relationships in the daily rainfall data in Iran. In general, result of Ripley's K-function analysis was observed the observed K value is larger than the upper confidence envelope value, spatial clustering (western and southwestern of Caspian Sea) for daily rainfall data values that are statistically significant. However, in rainfall variability is important the spatial distribution and variability in Iran.

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**Author Contributions:**
Spatial Distribution and variability of Rainfall in Iran was done by Majid Javari. All figures and tables were done by Majid Javari. Manuscript writing was made by Majid Javari.

**Conflicts of Interest:** The authors declare no conflict of interest.

**REFERENCES**


