

Full Length Research Paper

Spatial rainfall analysis for an urbanized tropical river basin

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Spatial distributions of the storms are important since it is a major factor influencing flood formation in urban areas. However, the spatial allocations of rainfall data obtained from the interpolation method have many uncertainties. Thus, it is the objective of this research to derive the spatial distribution of storm events by using grid-based Kriging method. The best semi-variogram (SV) model is found for Kriging interpolation technique. Rectified skew orthomorphic (RSO) coordinates of 28 rainfall stations, located at upper part of the Klang river basin (675 km²) Malaysia, were used for generating a continuous storm event map using raster GIS software. The standard indicator for spatial correlations, Geary's C, Moran's I and SV were calculated for all events. These correlation coefficients are indicative of the spatial structure of point data. Continuous theoretical variogram models were plotted by using experimental variogram model. Positive correlation was found at average distance class of 6273 m for the pair-points. Based on the spatial correlation, maximum effective radius for a gauging station was found to be 3136 m. It was found that Gaussian model gave slightly better rainfall estimation at the position of samples as compared to the exponential and spherical models.

Key words: Kriging, spatial correlation, rainfall pattern, Gaussian model, Klang river basin.

INTRODUCTION

Hydrological modeling requires rainfall coverage data as an important variable. However, most of the rainfall data is measured using rain gauges that are considered as point measurement. The spatially explicit data are often obtained using different interpolation methods. The interpolated rainfall data and its accuracy is controlled by the spatial distribution of the rainfall stations and the spatial interpolation methods used which may or may not reflect reality (Earls and Dixon, 2007). Spatial distribution of the storms are important because it has been shown in many countries that the spatial variability of rainfall is a major factor influencing flood formation in urban areas (Niemczynowicz, 1984; Obled et al., 1994; Watts and Calver, 1991; Bell and Moore, 2000; Faures et al., 2006). In the recent past, several studies concentrating on

characterizing short-term rainfall properties have been carried out in Klang river basin (Niemczynowicz, 1987; Desa and Niemczynowicz, 1996b). More recently, an attempt has been made to propose an adaptive neuro-fuzzy inference system (ANFIS) model to forecast the monthly rainfall for Klang river in Malaysia (El-Shafie, 2011). Effects of meteorological, orographic and space-time aggregation scales, and a discussion on network design, areal mean calculations and storm velocities on spatial correlation functions have been explained (Bacchi and Kottegoda, 1995). The results indicated that the spatial correlation of rainfall generally decreases with distance, and different correlation structures are observed during different rainfall events. The areal extension of thunderstorms, which create most floods, is limited and there are no routines to account for this in design (Desa and Niemczynowicz, 1996c). There are also errors attached to such estimated areal rainfall due to the effects of inadequate temporal resolution, inadequate spatial coverage or network configuration, inadequate gauge density and instrument error (Peters-

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Lidard and Wood, 1994). Moreover, storm velocity enlarges the uncertainty of the point data at the stations. The importance of these issues has been reported on localized study by Desa and Niemczynowicz (1996a), in a small-urbanized sub-catchment (23 km²) of Klang river basin equipped with sixteen rain gauges. They reported that there was no clearly preferred direction for the storm movement and propagation is chaotic in direction. Due to complexity of the storm patterns in time and space over the small distances, description of these variations is important to hydrologists for the accurate study and understanding of rainfall events (Patrick and Stephenson, 1990). Estimating a smooth spatial distribution from noisy observations and constructing smoothed maps and predicting at locations for which no data are available have been the focus of researchers for many years. Fuentes and Smith (2001) have proposed a new methodology for spatial interpolation of nonstationary processes, based on a convolution of local stationary processes. However, two of the most prominent approaches have been Kriging and thin plate splines (Paciorek and Schervish, 2006).

The objective of this research is to derive the spatial distribution of storm events by using grid-based Kriging. Several researches have stated that Kriging is a powerful method for point pattern analysis. Goovaerts (2000) used simple Kriging to interpolate rainfall incorporates with elevation in Portugal. The prediction performance was compared by using cross validation method, and it has been found that ordinary Kriging yields more accurate predictions than linear regression when the correlation between rainfall and elevation is moderate. Barancourt et al. (1992) provided a comparison of rainfall assessments by a global Kriging and geo-statistical model. Karamouz and Araghinejad (2005) applied the Kriging method to evaluate monthly regional rainfall in the central part of Iran. Thavorntam et al. (2007) indicated ordinary Kriging with spherical model performed better for interpolation of rainfall within the Thailand region. The application of Kriging has also been reported in the study of drought (Yildiz, 2009) and velocity dispersion profiles (Ünal and Özçakal, 2011).

MATERIALS AND METHODS

Kriging is a method invented by geostatisticians to provide the best local estimate of the value of the mean value of a regionalized variable. It can be seen as a point interpolation, which requires a point map as input and produces a raster map with estimations and an error map. The estimations are based on weighted averaged input point values. The weight factors are determined using a user-specified structure function of the regionalized variables. More details on the geo-statistical theory, Kriging and its algorithm (Matheron, 1971; Journel and Huijbregts, 1987; Cressie, 1991; Isaaks and Srivastava, 1990; Webster and Oliver, 2007). The important parameters in Kriging are described as follows.

Semi-variogram (SV)

The heart of Kriging is the semi-variogram (SV) or structure function of the regionalized variables that needs to be estimated. Basically

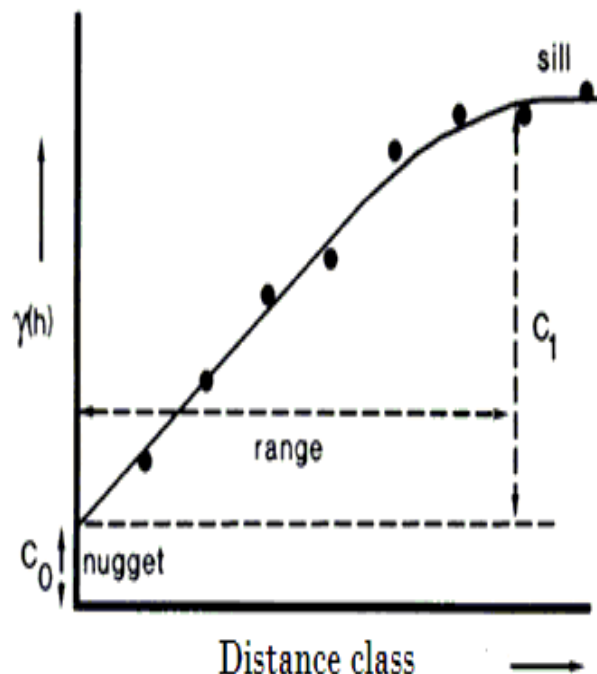


Figure 1. Semi-variogram model parameters.

the idea is to have an estimate of the distance one would need to travel before data points separated by that much distance are uncorrelated. This information is usually presented in the form of the variogram, which is a function of the semivariance versus this distance lag. SV model, which is the output of spatial correlation and cross variogram result in an empirical SV. Empirical SV values are defined by Equation 1.

$$\gamma(h) = \frac{\sum_i \sum_j W_{ij} (X_i - X_j)^2}{2 (\sum_i \sum_j W_{ij})} \quad (1)$$

Where $\gamma(h)$ is SV values, X is the value of a point, $(X_i - X_j)^2$ is the squared difference of the values of point i and point j ; this is calculated for all point pairs within a distance class and then summed.

W_{ij} is the weight of a point pair. When using the *omnidirectional* method, $W_{ij} = 1$ when a point pair belongs to a certain distance class, otherwise $W_{ij} = 0$.

When using the *bidirectional* method, $W_{ij} = 1$, when a point pair belongs to a certain distance class and when within the direction, tolerance and bandwidth as specified.

The available SV models in ILWIS software are spherical, exponential, Gaussian, wave, rational quadratic, circular and power (Koolhoven et al., 2007). In this paper, three commonly used SV models, which are the Gaussian, the spherical, and the exponential model (Thavorntam et al., 2007) were employed. A typical SV model is shown in Figure 1. The related parameters, such as nugget, sill and range are found using experimental data.

A nugget (C_0) effect is the vertical jump from value 0 at the origin to the SV value $\gamma(h)$ at extremely small separation distances. Sill

$(C_0 + C_1)$ is the plateau that the SV values $\gamma(h)$ reach at the range. The range is the distance at which the SV values do not increase anymore and reach a plateau. The statistical indicator, such as Moran's I and Geary's C can be used to indicate the reliability of SV. These indicators explain the correlation of the point pairs at the certain distance class. It becomes important when the data are noisy and the variance is high. Moreover, empirical distribution of the data can be used to refine the estimate.

2nd order stationary

When there is no trend, that is, the mean of the field is the same in all sub-regions, data fields are said to be first order stationary. When the variance is constant from one sub-region to the next, data field are realized as second order stationary.

Isotropic and anisotropic data

When the sill and range values are always the same, regardless of the direction being considered, the easiest SV model is used to visualize the data. In practice, that is not always the case and it is often found that data display anisotropic behavior in their range. Rainfall distribution in space and time is one clear example. Knowing these anisotropies is necessary when designing an appropriate SV model of the data prior to Kriging.

Moran's I

Moran's I is one of the oldest indicators of spatial autocorrelation. It is a weighted correlation coefficient used to determine whether neighboring areas are more similar than would be expected under the null hypothesis. Similar to other correlation coefficient, the value ranges from -1 to +1. The correlation coefficient measures the strength and the direction of a linear relationship between two variables, while Moran's I measures spatial autocorrelation using information only from specified pairs of spatial observations for one variable. The standardized Moran's I is positive when the observed value of locations within a certain distance tend to be similar, negative when they tend to be dissimilar, and approximately zero when the observed values are arranged randomly and independently over space. If the number of sample sizes is n , then the expected values and variance of Moran's I can be calculated according to the assumed pattern of spatial data distribution. The normal test for the null hypothesis of no spatial autocorrelation between observed values over the n locations can be conducted based on the standardized I, which express the Moran's I indicator (Equation 2).

$$I = \frac{n}{\sum_i \sum_j W_{ij}} \frac{\sum_i \sum_j W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \quad (2)$$

Where I is the Moran indicator, X is the value of a point, \bar{X} is the average value of all available point values, $(X_i - \bar{X})(X_j - \bar{X})$ is the product of the difference of the value of point i and the mean value of all points, and the difference of the value of point j and the average value of all points, $(X_i - \bar{X})^2$ is the squared difference of the value of point i and the mean values of all points; this is calculated for all points and then summed, n is the total number of points, W_{ij} is the weight of a point pair. When using the *omnidirectional* method, $W_{ij} = 1$

when a point pair belongs to a certain distance class, otherwise $W_{ij} = 0$.

When using the *bidirectional* method, $W_{ij} = 1$, when a point pair belongs to a certain distance class and when within the direction, tolerance and bandwidth as specified.

Geary's C

Similar to Moran's I, Geary's C interaction is not the cross product of the deviations from the mean, but the deviations in intensities of each observation location with one another. The value typically ranges between 0 and 2. If the value of any one zone is spatially unrelated to any other zone, the expected value of C will be one. Values less than 1 indicate negative spatial autocorrelation. Geary's C does not provide identical inference, because it emphasizes the differences in values between pairs of observations, rather than the co-variation between the pairs (Shekar and Xiong, 2008). This factor is inversely related to the Moran's I. Geary equation is defined as follows (Equation 3):

$$C = \frac{n-1}{2 \sum_i \sum_j W_{ij}} \frac{\sum_i \sum_j W_{ij} (X_i - X_j)^2}{\sum_i (X_i - \bar{X})^2} \quad (3)$$

Where X is the value of a point, \bar{X} is the average value of all available point values, $(X_i - \bar{X})(X_j - \bar{X})$ is the product of the difference of the value of point i and the mean value of all points, and the difference of the value of point j and the average value of all points, $(X_i - X_j)^2$ is the squared difference of the values of point i and point j ; this is calculated for all point pairs within a distance class and then summed, $(X_i - \bar{X})^2$ is the squared difference of the value of point i and the mean values of all points; this is calculated for all points and then summed, n is the total number of points, W_{ij} is the weight of a point pair.

When using the *Omni directional* method, $W_{ij} = 1$ when a point pair belongs to a certain distance class, otherwise $W_{ij} = 0$. When using the *bidirectional* method, $W_{ij} = 1$, when a point pair belongs to a certain distance class and when within the direction, tolerance and bandwidth as specified. It is noted that according to Desa and Niemczynowicz (1996a), there is no clearly preferred direction for the storm movement, and propagation is chaotic in direction, therefore, we use *omnidirectional* method to define the weight of point pairs.

Geary's C compares the squared differences of point pair values to the mean of all values, while Moran's I relates the product of differences of point pair values to the overall difference. Moran's I gives a more global indicator, whereas the Geary coefficient is more sensitive to differences in small neighborhoods (Shekar and Xiong, 2008). In Table 1 the relationship of both correlation indicators are shown as explained in the ILWIS software user manual (Koolhoven et al., 2007).

In the SV, the discrete experimental SV value is modeled by a continuous function so that SV values $\gamma(h)$ are available for any desired distance h for the Kriging operation.

Table 1. Moran's I and Geary's C indicators and their relationship.

Geyr's C	Statements	Moran's I
$0 < C < 1$	Strong positive autocorrelation	$I > 0$
$C > 1$	Strong negative autocorrelation	$I < 0$
$C = 1$	Random distribution of values	$I = 0$

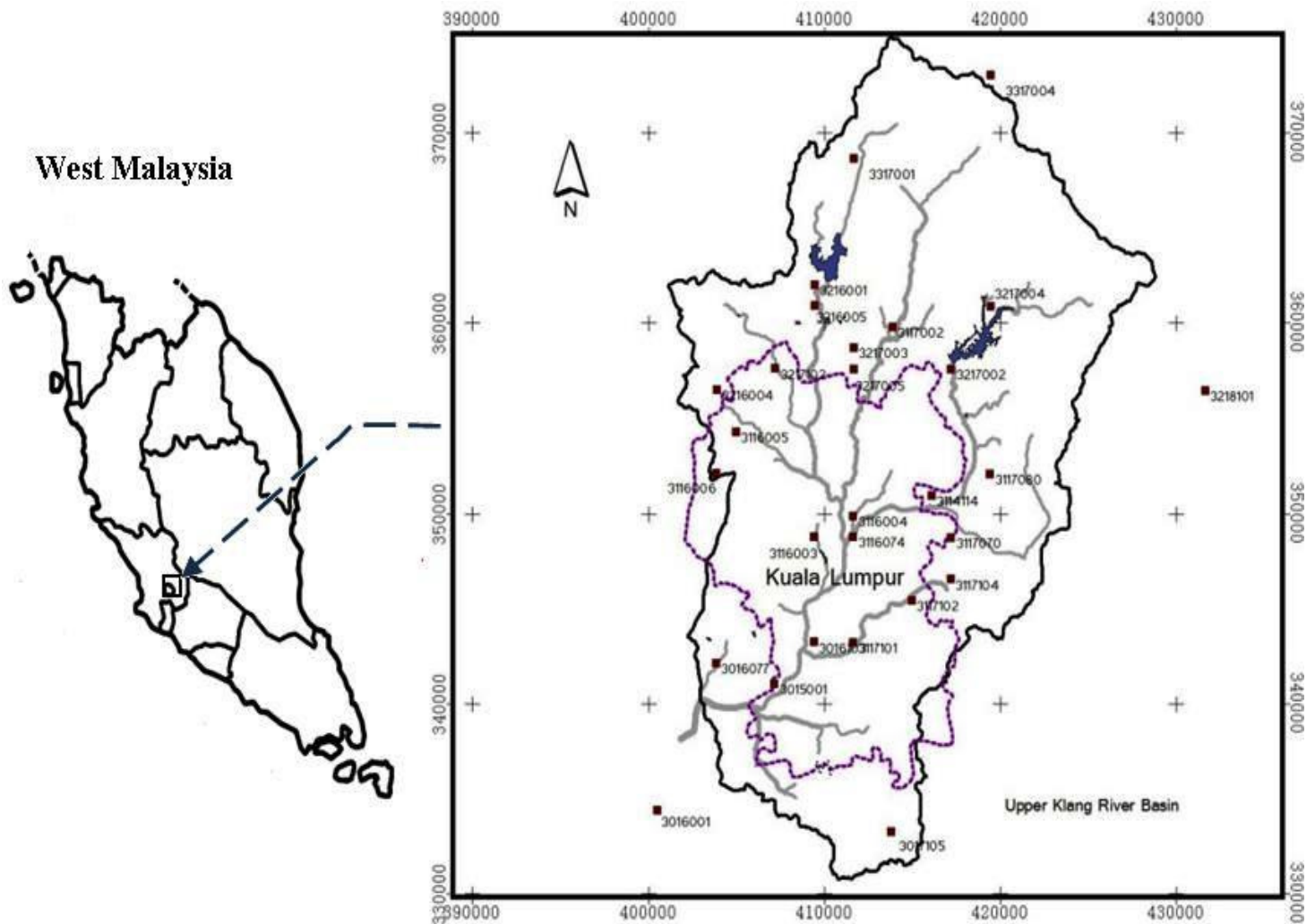


Figure 2. Study area.

Study area

The study was conducted on the upper part of the Klang river basin in Malaysia. This covers an area of 675 km². The Klang valley falls largely within the state of Selangor and encompasses the entire Federal Territory of Kuala Lumpur as shown in Figure 2. The climate of Klang river basin is warm and humid tropical with little variation in temperature or relative humidity throughout the year. Temperature varies daily between 32 and 23°C and relative humidity averages about 80 (Tick and Samah, 2004). Mean annual rainfall over the catchment averages about 2350 mm. The most significant heavy rainfall had been observed during the months of

October, November and December (Desa and Niemczynowicz, 1996b).

Data used

Rainfall data for the twenty-eight gauge stations located at the upper Klang river basin were collected from the Department of Irrigation and Drainage (DID) of Malaysia. General characteristics of the rainfall stations such as ID numbers that are the key code indicated by DID and geographic coordinates of the stations are provided in Table 2.

Table 2. General information of the gauging stations.

Number	Station IDs	Longitude°	Latitude°	Number	Station IDs	Longitude°	Latitude°
1	3216005	101.68	3.26	15	3016077	101.63	3.09
2	3015001	101.66	3.08	16	3016001	101.6	3.02
3	3217102	101.66	3.23	17	3017105	101.72	3.01
4	3117070	101.75	3.15	18	3218101	101.88	3.22
5	3116004	101.7	3.16	19	3217005	101.7	3.23
6	3217002	101.75	3.23	20	3216001	101.68	3.27
7	3217004	101.77	3.26	21	3216004	101.63	3.22
8	3116006	101.63	3.18	22	3317004	101.77	3.37
9	3116074	101.7	3.15	23	3016103	101.68	3.1
10	3117104	101.75	3.13	24	3116005	101.64	3.2
11	3317001	101.7	3.33	25	3117102	101.73	3.12
12	3117002	101.72	3.25	26	3114114	101.74	3.17
13	3217003	101.7	3.24	27	3116003	101.68	3.15
14	3117080	101.77	3.18	28	3117101	101.7	3.1

Table 3. General properties of the selected storm events.

Date	Number of stations	Variance	Average (mm)	Minimum (mm)	Maximum (mm)
6 May 2002	18	349.7	39.2	6	65.5
2 June 2002	18	1375.2	30	0	100
11 June 2002	18	1128.8	44.4	8.5	138
6 September 2002	20	990.2	32.4	2	97
8 October 2002	20	1252.8	43.9	0.5	110
8 November 2002	19	533.8	19.3	0	76
9 November 2002	16	839.5	69.4	28	123
18 November 2002	16	1073.9	83.5	32	148
19 November 2002	16	629.3	35	13	95
18 December 2002	16	151.4	15.8	1	52
21 December 2002	18	358.1	30.1	7.5	74

RESULTS

Eleven historical events were randomly selected in the year 2002 for the stations listed in Table 2. Number of active stations and statistical values of the events are provided in Table 3. A primary quality control such as detecting physically impossible values, improbable zero values, unusually low values and unusually high values (Michaelides, 2008) was performed to the observed data. The attribute point map was generated in RSO coordinate system according to the gauge coordinates and total rainfall values. The SV and value for Moran's I, Geary' C and number of pair points, which fall into the certain distance class, were calculated using the Equations 1 to 3 accordingly.

According to Table 3 the observed data are not stationary in both variance and mean. It also displays anisotropic behavior in their range. This is the case that occurs more frequently, which may be related to a seasonal rainfall data. A point map for the rainfall stations

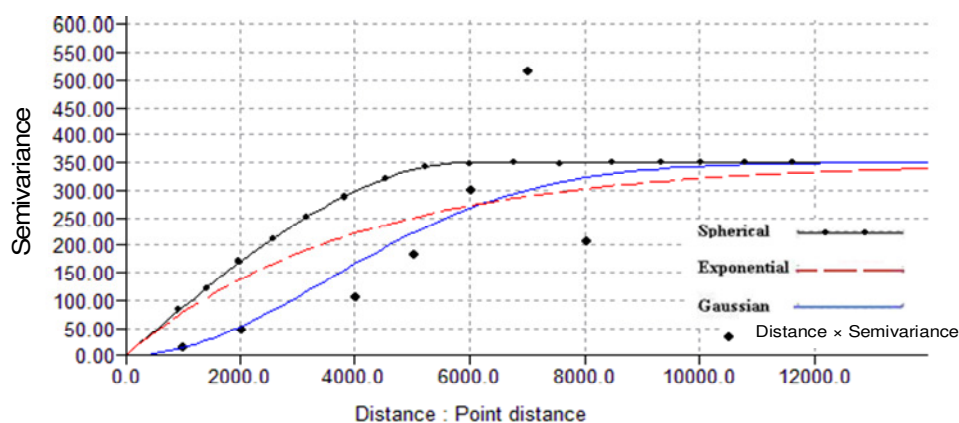
was generated and then converted to attribute raster map with pixel size of 250 m. Result of spatial correlation for selected events which are Moran's I, Geary' C and distance was used to indicate the distance classes with the positive correlation. The distances with the positive correlation are listed in Table 4. The average influence range with positive correlation for selected storms was found to be 6273 m. As a result, it could be concluded that the effective radius of gauges is about 3136 m. The positive correlations range was used as a key factor to find the other SV parameters. Three types of SV model were examined at the stated range using the storm events listed in Table 4. The estimated rainfalls based on the three types of SV model at the position of rainfall stations have been obtained and the results for storm event of 21 December, 2002 are shown in Table 5. It can be seen from the table that the values given by the three models are more or less the same as the actual values. Similar results have been obtained using other storm events.

Table 4. Positive correlation ranges based on spatial correlation analysis for the selected storm events in 2002.

Date	6-May-02	2-June-02	11-June-02	6-September-02	8-October-02	8-November-02	9-November-02	18-November-02	19-November-02	18-December-02	21-December-02	Mean (m)
Distance (m)	9000	6000	6000	9000	5000	6000	5000	5000	7000	5000	6000	6273

Table 5. Rainfall estimation at the stations for the event of 21 December, 2002 (using different SV models).

Station ID	Actual (mm)	Gaussian (mm)	Exponential (mm)	Spherical (mm)
3116006	7.50	7.38	7.89	7.95
3216004	8.50	8.29	8.78	8.74
3317004	12.00	12.03	12.61	12.60
3116074	18.00	18.30	18.38	18.26
3217102	19.00	19.00	19.06	19.16
3117002	20.00	20.36	20.43	20.39
3317001	22.00	22.00	22.05	22.06
3217003	22.50	22.56	22.51	22.52
3116004	24.00	24.29	24.08	24.23
3116003	24.50	24.38	24.57	24.33
3217004	25.00	24.93	25.02	25.04
3117070	28.00	28.44	28.49	28.50
3217002	32.50	32.23	32.18	32.23
3117102	41.50	41.35	41.51	41.50
3015001	46.00	45.96	46.02	45.61
3117104	48.00	48.87	47.73	47.68
3117101	69.50	69.83	68.74	68.71
3016001	74.00	74.00	73.46	73.43
Variance	360.85	360.85	346.82	345.74
Min	7.50	7.38	7.89	7.95
Max	74.00	74.00	73.46	73.43
Average	30.14	30.23	30.20	30.16
Std	18.92	19.00	18.62	18.59

**Figure 3.** Experimental and continuance SV models for the event of 21 December, 2002.

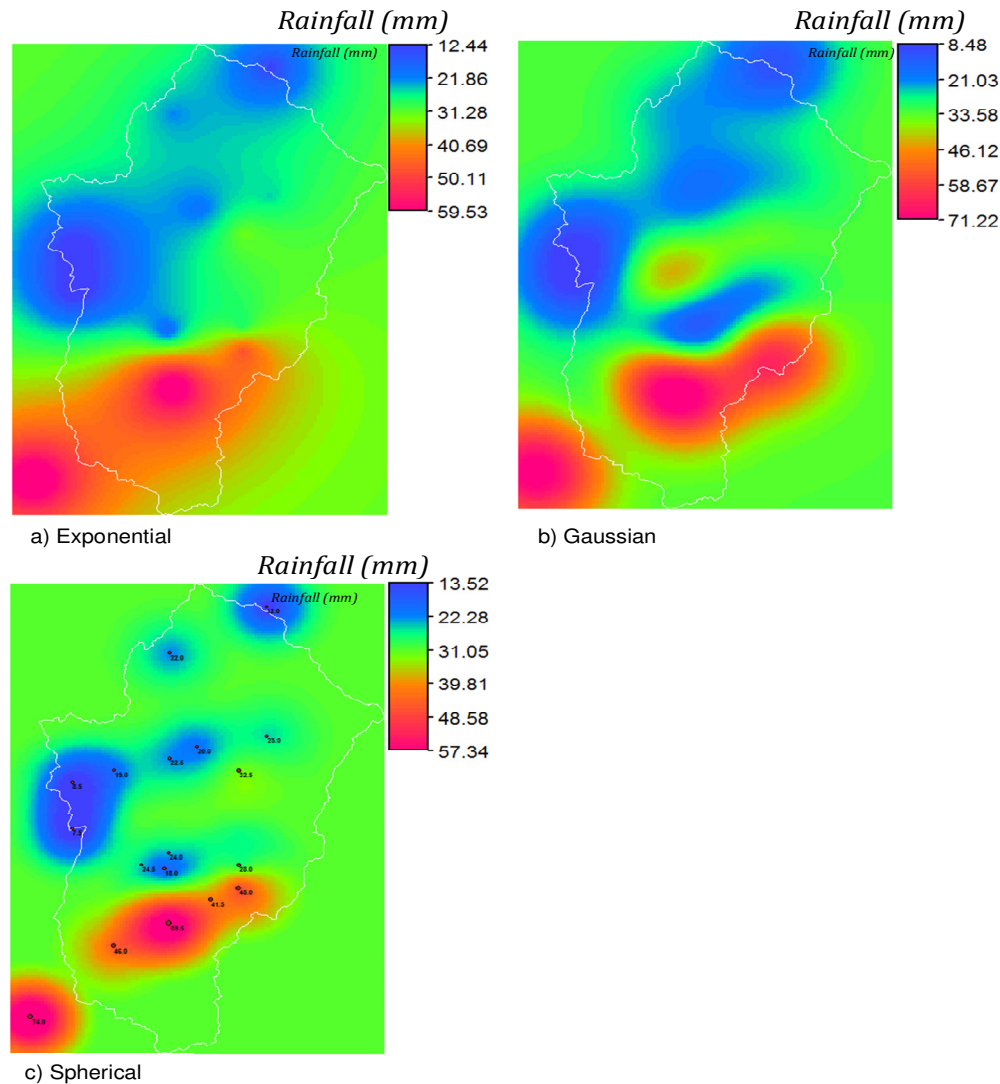


Figure 4. Spatial distribution of storm event (21 December, 2002) using: (a) exponential SV model, (b) Gaussian SV model and (c) spherical SV model.

Results of the experimental SV and the selected theoretical SV for a selected storm event (21 December, 2002) are presented in Figure 3. This figure shows that there is no good positive correlation between the sample points. This is because of the high variance, in which the correlation between the samples is very low. In this case, fitting best SV model is quite difficult. However, according to the derived SV for the investigated events, it was found that in most cases the Gaussian model illustrate a slightly more reasonable variogram model. As an example, SV models for the storm event of 21 December, 2002, are shown in Figure 4. It can be seen from the figure that the Gaussian model fits better through the points as compared to the exponential and spherical models. Similar trends have been found for other storm events which show a better fit when Gaussian model was employed.

DISCUSSION

There is a high variability of storms in space in the Klang river basin (Malaysia) even for the events occurring in the northeast monsoon season, which commences from October and ends by January. From the spatial pattern analysis, it was found that the effective range of influence is about 6273 m, from which it can be concluded that effective radius of the gauging stations is about 3136 m. Other SV parameters were found using the stated range, and there types of SV models, namely the Gaussian, exponential and spherical were examined. Comparison between these three SV models with the actual values is given in Table 5.

It can be seen from this table that the values given by the three models does not differ very much from the actual values. Although, fitting the best SV model is rather

difficult due to high variance, the Gaussian model gave slightly better estimation as compared to exponential and spherical models. The Gaussian model also propagates much lesser standard error at the effective influence range.

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