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Effect of Pixel Size on the Areal Storm Pattern Analysis using Kriging

A. Akbari, A. Abu Samah and F. Othman
Department of Civil Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia

Abstract: Several factors influence the interpolation accuracy of point source rainfall data during storms. Types of storm, network density and interpolation method are the most significant factors. Usually, random distributed point source data is converted into regular distributed grids, through the appropriate method. Kriging is a stochastic method that simulates the spatial surface using sample points, based on best-fit Semi-Variogram (SV) models. This study assesses the effect of pixel size on the performance of Kriging interpolation using the Gaussian SV model. Twenty eight rainfall stations located at the upper part of the Klang River Basin (KRB), Malaysia are selected and three storm events are investigated. Simple Kriging interpolation is applied using different pixel size ranges from 50 to 3000 m. This study shows that pixel size is important issue when explaining the spatial pattern of rainfall. Optimal pixel size depends on the variance, minimum distance of pair points or rainfall network density and the visualization requirement. It is difficult to maintain a certain pixel size but based on the drawn result, it can be concluded that a pixel size at the range of 200 to 500 m is more appropriate for this region.

Key words: Pixel size, Kriging, rainfall pattern, point interpolation

INTRODUCTION

Representing geo-spatial data in a raster data model requires grid cells definition. The cell size is sensitive to map scale, computer processing power, positional accuracy, point density, spatial autocorrelation structure and complexity of terrain (Hengl, 2006). It also depends on the desired quality of the output map. Pixel size and its impacts on the spatial analysis particularly in rainfall runoff modeling are the focus of several studies. The majority of research focuses on the influence of grid size of Digital Elevation Models (DEMs) for the calculation of the topographic indices (Cai and Wang, 2006) and watershed runoff simulation (Molnar and Julien, 2000). Hengl (2006) showed that using resolution coarser than the coarsest legible resolution means that we are either not respecting the scale of work, positional accuracy, inspection density, size of objects being mapped or the complexity of terrain. Hydrological modeling employs rainfall data as an important variable. As stated by Earls and Dixon (2007), the representation of rainfall data and its accuracy are controlled by the spatial distribution of the rainfall stations and the spatial interpolation methods used which may or may not reflect the reality. Several factors may affect the accuracy of point source rainfall data interpolation such as type of storm, network/gauge density and interpolation methods are important factors. A number of studies on characterizing of rainfall has been carried out in Klang River Basin (KRB) (Niemczynowicz, 1987; Bacchi and Kottegoda, 1995). The results indicate that generally, the spatial correlation of rainfall decreases with distance and different correlation structures are observed during different rainfall events. The spatial extension of thunderstorms, which create most floods, is limited and there are no routines to account for this in design of rainfall (Desa and Niemczynowicz, 1996). There are also errors attached to estimating localized rainfall due to the effects of inadequate temporal resolution, inadequate spatial coverage or network configuration, inadequate gauge density and instrument error (Peters-Lidard and Wood, 1994).

KRIGING THEORY AND APPLICATIONS

Kriging is named after D.G. Krige, a South African mining engineer and pioneer in the application of statistical techniques to mine evaluation. The Kriging technique is derived from the theory of regionalized variables which is the invent of Matheron (1971). This theory is formed based on the observation that the variabilities of all regionalized variables have a particular structure (Journel and Huijbregts, 1978). As an example, a storm event can be characterized by the spatial distribution of a certain number of measurements. More details on the geo-statistical theory, Kriging and its

Corresponding Author: Abolghasem Akbari, Department of Civil Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia

algorithm can be found in (Matheron, 1971; Journel and Huijbregts, 1978; Cressie, 1993; Isaaks and Srivastava, 1990; Webster and Oliver, 2007). Here, some important elements of this theory are presented, according to the Journel and Huijbregts (1978):

Regionalized variable (ReV): When a variable is distributed in space, it is said to be ReV and the phnomeno that the ReV is used to represent is called regionalization (Journel and Huijbregts, 1978). This definition can be extended to almost; all geo-referenced data or spatial variables such as population density, canopy density, water quality, air pollution and so on. In mathematic language, a ReV is a function f (x) which takes a value at every point x, in space. ReV takes two contradictory characteristics, which are a Random Variable (RV) and a certain functional representation. A RV is a variable, which takes a certain number of numerical values according to a certain probability distribution (Journel and Huijbregts, 1978).

Random function (RF): Random function expresses the random and structured aspects of a ReV. These aspects are as follows:

- In each point x_1,Z(x) is the RV
- Z(x) is also a RF in the sense that for each pair of points x_1 and x_1+h, the corresponding RFs $Z(x_1)$ and $Z(x_1+h)$ are not, in general, dependent but are related by a correlation expressing the spatial structure of the initial ReV Z(x)

Mathematical expectation (first order moment): Consider a random function Z(x) at point x. if the distribution function of Z(x) has an expectation then, this expectation is generally a function of x and is written as:

$$E\ \{Z(x)\} = m(x) \tag{1}$$

Second order moments: The three second-order moments considered in geostatistic are as follows:

- The variance of Z(x). when this variance exists, it is defined as the second-order moment about the expectation m (x) of the RV Z(x), i.e.,

$$\mathrm{Var}\ \{Z(x)\} = E\{[Z(x)-m(x)]^2\} \tag{2}$$

As with the expectation m(x), the variance is generally a function of x.

- The covariance. It can be shown that if the two RVs $Z(x_1)$ and $Z(x_2)$ have variances at the point x_1 and x_2, then they also have a covariance which is a function of two locations x_1 and x_2 and is written as:

$$C(x_1 , x_2) = E\{[Z(x_1)-m(x_1)]\ [Z(x_2)-m(x_2)]\} \tag{3}$$

- The variogram. The variogram function is defined as the variance of the increment $[Z(x_1)-Z(x_2)]$ and is written as:

$$2\gamma(x_1 , x_2) = \mathrm{Var}\ \{Z(x_1)-Z(x_2)]\} \tag{4}$$

The function $\gamma(x_1 , x_2)$ is then the semi-variogram (SV). When the RF is stationary of order 2, mathematical expectation exists and does not depend on the support point x, thus, E {Z(x)} = m. For each pair of RV $\{Z(x_1), Z(x_1+h)\}$ the covariance exists and depends on the separation distance h. according to the Eq. 2 and 3 can be drive as follow:

$$C(h) = E\{Z(x+h)\ Z(x)\}-m^2 \tag{5}$$

where, h represent vector of coordinates.

The stationarity of the covariance implies the stationarity of the variance and the variogram. The following relations are immediately evident:

$$\mathrm{Var}\ \{Z(x) = C(h) = E\ \{Z(x)-m]^2\} = C\ (0) \tag{6}$$

$$\gamma(h) =1/2\ E\ \{[Z(x+h)-Z(x)]^2\} = C(0)-C(h) \tag{7}$$

The Eq. 4 indicate that under the hypothesis of second-order stationarity, the covariance and the variogram are two equal tools for characterizing the auto-correlations between two variable Z(x+h) and Z(x) separated by a distance h.

Covariance and correlation are measures of the similarity between two different variables, where the data pairs represent measurements of the same variable made some distance apart from each other. The separation distance is usually referred to as lag. The correlation versus lag is referred to as the correlogram and the semi-variance versus lag is the SV. Kriging employs SV model (Bohling, 2005).

In GIS environment, Kriging can be seen as a point interpolation, which requires a point map as input and returns a raster map with estimations and optionally an error map. The estimations are weighted averaged input point values. The weight factors in Kriging are determined by using a user-specified SV model. The estimated values are thus a linear combination of the input values and have a minimum estimation error. The optional error map contains the standard errors of the estimates.

Characteristics of the typical SV are shown in Fig. 1. Sill is the semi-variance value at which the variogram levels off. Range is the lag distance at which the reaches the sill value. Presumably, autocorrelation is essentially zero beyond the range. Nugget is, in theory, the value at the origin (0 lag) should be zero. If it is significantly different from zero for lags very close to zero, then this value is referred to as the nugget, which represents variability at distances smaller than the typical sample spacing, including measurement error. For the sake of it is necessary to replace the empirical SV with an acceptable SV model. Part of the reason for this is that the Kriging algorithm will need access to SV values for lag distances other than those used in the empirical SV. More importantly, the SV models used in the Kriging process need to obey certain numerical properties in order for the Kriging equations to be solvable. Most frequently used models are spherical, exponential, Gaussian and power model.

Barancourt *et al.* (1992) have provided a comparison of rainfall assessments by a global Kriging and geo-statistical model. The prediction performance is compared by using cross validation. It is found that ordinary Kriging yields more accurate predictions than linear regression when the correlation between rainfall and elevation is reasonable. Karamouz and Araghinejad (2005) applied the Kriging method to evaluate monthly regional rainfall in the central part of Iran. Thavorntam *et al.* (2007) studied spatial interpolation of mean annual rainfall in a 29 year period using interpolation methods such as Inverse Distance Weighting (IDW), radial basis function and ordinary Kriging. They indicated that ordinary Kriging with

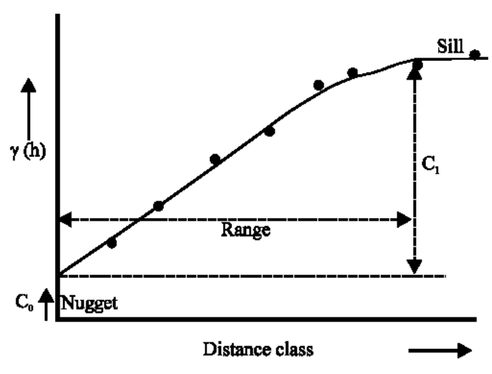

Fig. 1: Characteristics of the typical SVSemi-variogram

IDW a spherical model has better performance for interpolation of rainfall within the region of Thailand. However, Dirks *et al.* (1998) studied interpolation of rainfall data on the Norfolk Island, Australia. Thirteen rain gauges on the area of 35 km^2 are used. They found that Kriging did not provide a significant improvement over simple methods like the IDW, the Thiessen and the area mean methods because of the demanding on computations.

MATERIALS AND METHOD

Study area: This study is conducted at University Malaya as a part of postgraduate research project within 6 month started from November, 2008. The study is carried out on the upper parts of the Klang River Basin located in Kuala Lumpur/Malaysia. The Klang Valley is located between 101° 30′- 101° 55′ longitude and 3°- 3° 30′ latitude. It falls largely within the state of Selangor and encompasses the entire Federal Territory of Kuala Lumpur (Fig. 2). The basin area at the outlet is about 675 km^2. The mean annual rainfall based on the Association of Southeast Asian Nations Climate Atlas for Peninsular Malaysia is about 2400 mm (Tick and Samah, 2004). The elevation above sea level ranges from 20 m at the outlet to 1420 m upstream.

Data set used: Rainfall data for 28 stations located at the upper Klang river basin are collected form Department of Irrigation and Drainage (DID) of Malaysia. General characteristics of the rainfall stations such as ID that is the key code indicated by DID and geographic coordinates of stations are provided in Table 1.

Software used: The Integrated Land and Water Information System (ILWIS) which is free raster-GIS software, developed by International Institute for Geo-

Table 1: General information of rainfall stations used in this study

No.	Station ID	Longitude	Latitude	No.	Station ID	Longitude	Latitude
1	3216005	101.68	3.26	15	3016077	101.63	3.09
2	3015001	101.66	3.08	16	3016001	101.60	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	101.70	3.16	19	3217005	101.70	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	101.70	3.15	23	3016103	101.68	3.10
10	3117104	101.75	3.13	24	3116005	101.64	3.20
11	3317001	101.70	3.33	25	3117102	101.73	3.12
12	3117002	101.72	3.25	26	3114114	101.74	3.17
13	3217003	101.70	3.24	27	3116003	101.68	3.15
14	3117080	101.77	3.18	28	3117101	101.70	3.10

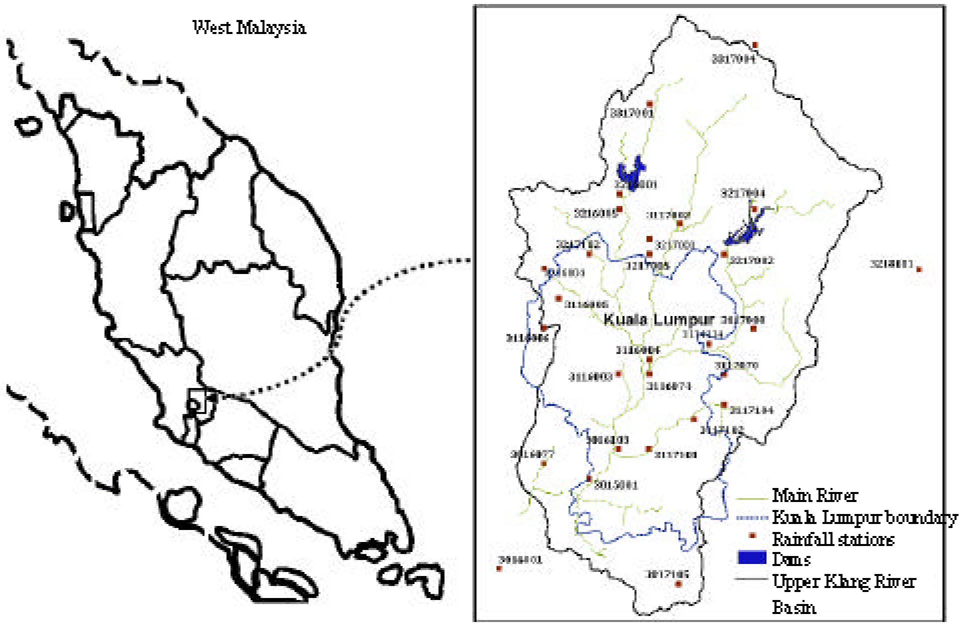

Fig. 2: Study area and rainfall stations network at upper Klang River Basin

Information Science and Earth Observation (ITC), The Netherlands (Koolhoven *et al*., 2007) is used for this study. Available at http://www.itc.nl/ilwis/default.asp.

RESULTS AND DISCUSSION

The three random rainfall events occurred on May 6, Sep. 6 and Dec. 21 in the year 2002, are selected. General statistics such as minimum, maximum, average, standard derivation and variance are calculated for the selected events (Table 2). A point map is generated based on available rainfall stations shown in Fig. 2. Total recorded rainfall in each station for that particular date is then linked to the point map as attribute. Spatial autocorrelation (Odland, 1988) applied to estimate the Kriging parameters included nugget, sill and range effects (Borga and Vizzaccaro, 1997). As shown in Fig. 3, Gaussian SV model fits through the experimental SV, resulted from spatial autocorrelation as better model compared to the exponential and spherical model (Akbari *et al*., 2008). Simple Kriging is used, because no certain direction can be found in the storm propagation in this region (Desa and Niemczynowicz, 1996). Kriging interpolation technique is then applied to the selected storms. Different Pixel size range from 50 to 3000 m is examined for all storms. Kriging interpolation using point map in ILWIS provides raster map with predefined pixel size. A histogram is made for the raster map including pixel values and the corresponding number of pixels, the

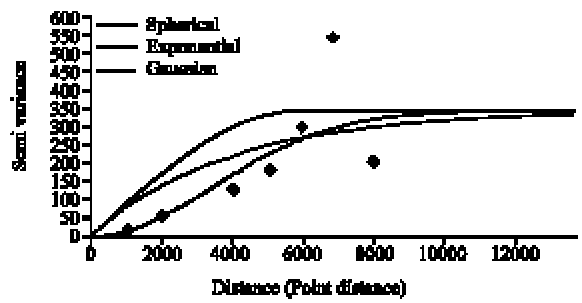

Fig. 3: Experimental and empirical SVs for the event of 21 December, 2002

Table 2: Statistical summaries of investigated storm events

Statistics	Dec 21,2002	May 6, 2002	Sept. 6,2002
Minimum (mm)	7.5	6.0	2.0
Maximum (mm)	74.0	65.5	97.0
Average (mm)	30.1	39.8	35.9
STDEV (mm)	18.9	19.1	30.8
Variance (mm^2)	358.0	365.0	945.0
No.	18.0	18.0	20.0

fraction of total pixels, the area and statistical summaries including minimum, maximum, average, standard deviation and summation of cell values. Table 3 is provided as an example for derived statistical summaries of rainfall event of Dec 21, 2002. This table does not provide for the two other events. However, a comparison is presented to show the variation of pixel size with the estimated average rainfall (Fig. 3, 4), standard deviation (Fig. 5), area allocated by average rainfall (Fig. 6). One can see the

Table 3: Statistical summaries of raster map showing Kriging interpolation based on different pixel size for the Storm Dec 21 2002

A	B	C	D	E	F	G	A	B	C	D	E	F	G
50	Min	4.5	31	0.01	53	8	1250	Min	4.6	1	0.11	1	156
	Max	74.5	43676	8.22	531600	10919		Max	74.3	99	10.7	925	15469
	Avg	39.5	758	0.14	323421	190		Avg	34.4	3	0.29	487	420
	StD	20.3	1998	0.38	212091	500		Std	15.7	6	0.63	342	918
	Sum		531600	99.88	-	-		Sum		925	100.39	-	-
100	Min	4.5	6	0	13	6	1500	Min	4.9	1	0.15	1	225
	Max	74.5	11206	8.38	133644	11206		Max	73.5	71	10.91	651	15975
	Avg	39.5	191	0.14	81292	191		Avg	34.1	2	0.35	343	519
	Std	20.3	510	0.38	53345	510		Std	14.6	5	0.72	233	1052
	Sum		133644	99.99	-	-		Sum		651	99.5	-	-
250	Min	4.5	1	0	2	6	1750	Min	5.1	1	0.19	1	306
	Max	74.4	1855	8.61	21538	11594		Max	72.7	75	14.62	513	22969
	Avg	39.3	31	0.14	13045	194		Avg	33.3	2	0.42	257	660
	Std	20.1	84	0.39	8598	527		Std	14.3	5	0.99	184	1547
	Sum		21538	100.02	-	-		Sum		513	99.18	-	-
500	Min	4.6	1	0.02	2	25	2000	Min	5.4	1	0.26	1	400
	Max	74.3	502	9.14	5490	12550		Max	74.2	48	12.5	384	19200
	Avg	38.4	9	0.16	3266	216		Avg	33.3	2	0.5	194	776
	Std	19.3	23	0.43	2172	586		Std	13.7	4	0.95	134	1453
	Sum		5490	100.07	-	-		Sum		384	99.87	-	-
750	Min	4.7	1	0.04	1	56	2500	Min	5.4	1	0.4	1	625
	Max	74.2	237	9.63	2460	13331		Max	71	32	12.96	247	20000
	Avg	36.2	5	0.2	1376	275		Avg	32.9	2	0.65	122	1009
	Std	17.9	12	0.49	954	683		Std	13.1	3	1.08	83	1662
	Sum		2460	99.55	-	-		Sum		247	99.43	-	-
1000	Min	4.7	1	0.07	1	100	3000	Min	6.6	1	0.57	1	900
	Max	73.5	147	10.31	1426	14700		Max	73.5	25	14.2	176	22500
	Avg	35.5	3	0.24	788	343		Avg	32.3	2	0.87	85	1377
	Std	16.5	8	0.57	536	813		Std	12.7	2	1.34	59	2124
	Sum		1426	99.85	-	-		Sum		176	100.21	-	

A: Pixel size (m), B: Statistical terms, C: Total rainfall during the storm (mm), D: The number of pixels with a certain value or meaning (pixel frequencies), E: The cumulative percentage of pixels with this value or a smaller value (%), F: The relative cumulative numbers of pixels with this value or a smaller value as a percentage of the total number of pixels in the map, G: The area of pixels with a certain value or meaning as D* pixel size *pixel size (m^2)

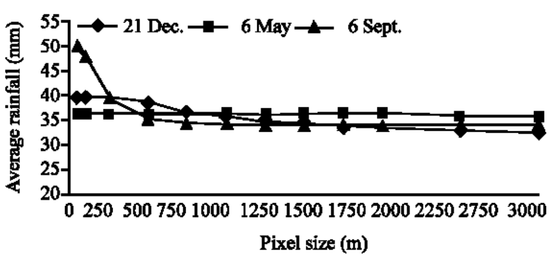

Fig. 4: Variations of average rainfall vs. pixel size

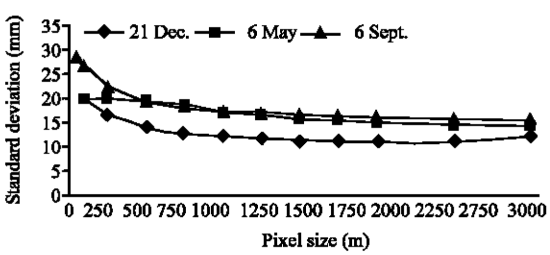

Fig. 5: Standard deviation of cell values vs. pixel size

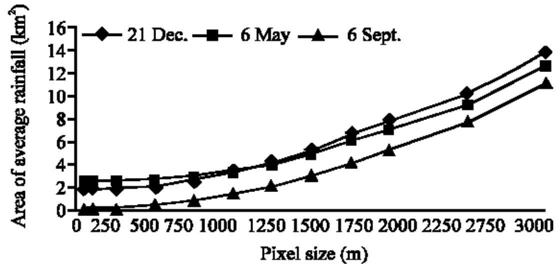

Fig. 6: Variation of area representing the average rainfall vs. pixel size

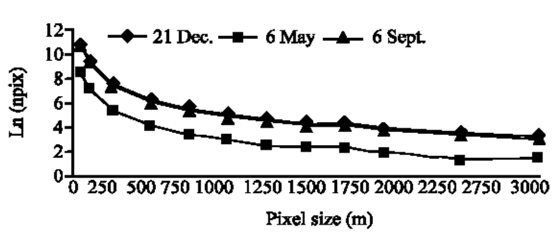

Fig. 7: Variation of number of pixel assigned by maximum value vs. pixel size

variation of pixel size with the total number of pixels assigned by maximum value in that particular pixel size in Fig. 7 and file size, which is important in computer processing and allocating memory in Fig. 8. Finally, we examined the effect of pixel size on the visualization,

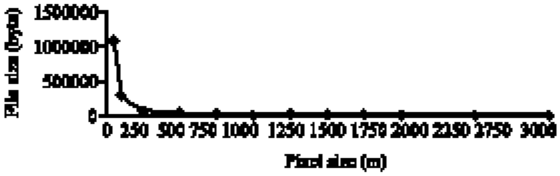

Fig. 8: Variation of file size vs. pixel size

which is shown in Fig. 9a and b and 10. These maps are based on the storm event of Dec 21, 2002.

Rainfall distribution in space can be explained by the standard deviation and variance of samples. Statistical analysis for the recorded rainfall at the rainfall stations indicates the high variance for the event of Sept. 6, 2002 compare to the 2 other investigated events. Based on the results of the interpolations, it is possible to interpret the spatial variation of rainfall based on the investigated pixel size and its effect on the statistical terms such as average, standard deviation and area related to the maximum value in each map. As shown in Fig. 4, the average rainfall is sensitive to the pixel sizes at about 50-750 m. Almost in three tested storms, average rainfall does not change by taking the pixel size larger than 750 m. Based on the variance of the events; different trends can be seen for each event. For example, for the event of Sept. 6, 2002 that is the highest variance (945) among the samples, average value is more sensitive to the pixel size. However, for the storm event on the Dec. 21, 2002 that has the lowest variance, variation of the average value is not sensitive to the pixel size. That means the enlargement of grid resolution leads to aggregation or up scaling and the decrease of grid resolution leads to disaggregation or down scaling (Hengl, 2006). As the grid becomes coarser, the overall information content in the map decreases progressively and vice versa (Hengle, 2006). Figure 5 shows almost the same trend for the variaton of pixle size with standard deviation. The trends shown in this figure imply on the sensitivity of the standard deviation to the pixel size from 50 to 750 m. The number of pixels in the raster map also expresses the surface values. Figure 6 shows the variation of pixel size in relation to the area coreponding to the mean value for three storms. It can be seen that the area related to the mean value increases by selecting coarser pixel size at an exponential rate. This is due to the smoothing effect of a mean value increases by selecting coarser pixel size at an exponential rate. This is due to the smoothing effect of a larger pixel size. The smoothing effect is confirmed by Fig. 7, which illustrates the variation of the number of pixeles assigned by the maximum value for different pixel size in three investigated events. High sensitivity can be found for the pixel sizes at about 50 to 500 m. Figure 8 shows clearly the

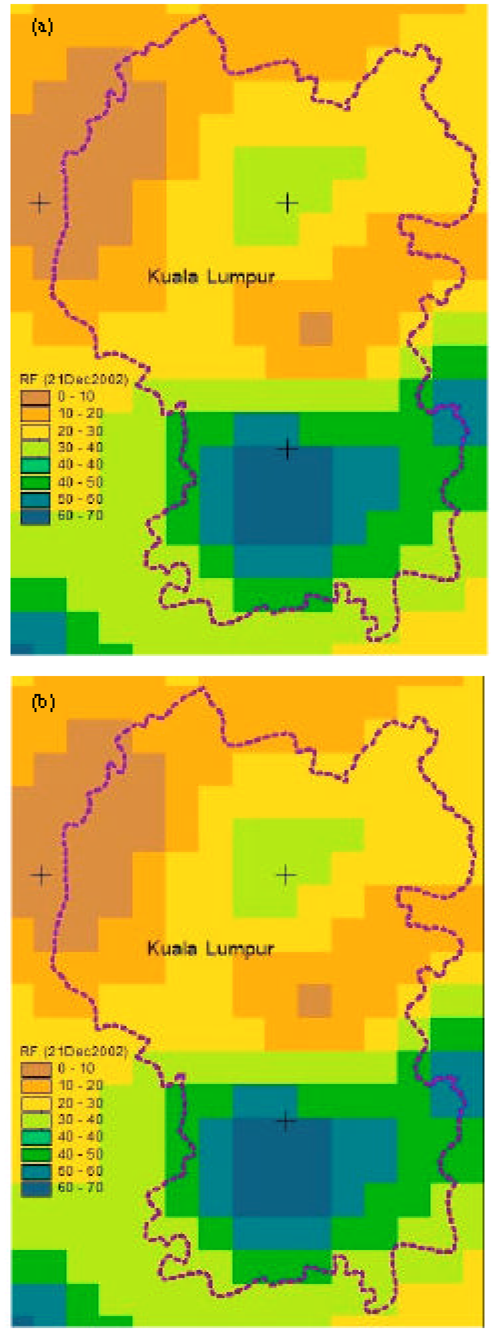

Fig. 9: Storm distribution based on the Kriging interpolation for different pixel size (a) (1250 m) and (b) (50 m)

effect of the pixel size on the size of file. This become important issue when working with database and transfering and analyzing raster data. Selection of the optimal pixel size facilitates the easier transfer and processing. Eventually, a comparison is made to show

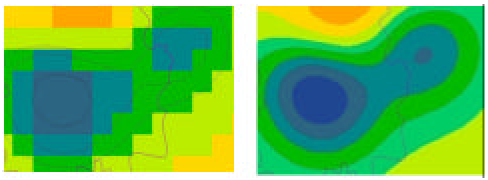

Fig. 10: Isorain lines derived from the Kriging interpolation for different pixel size (1250 m), left, (50 m), right

the performance of pixel size on the spatial distribution of rainfall derived from kriging interpolation (Fig. 9). These two maps emphesize the effect of pixel size on the visualization especially when isoline is derived (Fig. 10).

CONCLUSION

This study shows clearly that pixel size has a significant influence on storm pattern analysis. Variance of the rainfall over the area has a meaningful effect on the selection of the legible pixel size and therefore, on the result of points interpolation. In fact, variance is comparable with the complexity of terrain when Digital Elevation Model (DEM) is generated from the points or contour lines. It can be concluded that the rainfall variance over the space is important factor in selecting appropriate pixel size when using Kriging interpolation. High variance leads to take the small pixel sizes and low variance leads to take larger pixel size. It is because of the fact that small pixel size is more able to explain the rainfall variation. No ideal pixel size exists, but rather a range of suitable pixel size. Optimal pixel size will depend on the variance, minimum distance and the visualization requirement. It is recommended to select a smaller pixel size when the variance of the source point values is high. Small pixel size provide better visualization but generates larger file size. Raster maps in Fig. 9, results from Kriging interpolation for the rainfall event of 21 Dec. 2002. As shown in Fig. 10, small grid size is more advisable when contour line drawing is required from the raster map. Hence, one can report that variation of average rainfall to the pixel size illasterates sensitivity of the pixel size to the rainfall variance and recommended range of pixel size at 200 to 500 m scale in this region. Pixel size has a cosiderble effect on the visualization and the file size.

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