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SPATIAL PATTERN OF RAINFALL EVENTS: A BACKGROUND STUDY TO MODELLING AND FORECASTING RAINFALL

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Abstract. The study of extreme rainfall events and their spatial coverage is important in identifying areas with high and low extreme events. It has been widely known that extreme rainfall is responsible for major flash flood and landslide events that have caused significant loss of life and economic losses. Unfortunately, the dynamics of extreme rainfall events still received less concern. This study scrutinized the characteristics of extreme rainfall and their spatial coverage in Peninsular Malaysia using rain gauge data. Eight indices of climate extremes based on daily precipitation data defined and adopted by the Joint Expert Team on Climate Change Detection and Indices (ETCCDI) were calculated. The selected indices captured the precipitation intensity, the frequency and length of heavy rainfall events. The geostatistical method of Ordinary Kriging (OK) is applied to the indices calculated. The results from OK method give a pictorial representation of the structure of extreme rainfall spatial variability which helps in deriving rainfall patterns, quantifying rainfall amounts or help in identifying areas with high risk of extreme rainfall event. This result could provide to researchers and decision makers a case study area that needs adequate attention.

Keywords Extreme Rainfall Events, Ordinary Kriging, Spatial Dependence, Rainfall Indices and Rclimdex

1.0 INTRODUCTION

One of the key steps in analysing hydrological extremes is to decide on the hydrological variable to be studied. Extreme precipitation events have resulted in several flash floods, landslides and property damages in Peninsular Malaysia. For example, the extensive rainfall in the mid-January 2007 triggered severe flooding in southern peninsular Malaysia, with some areas submerged under three meters of water. The heavy rains that begin in December 2006 reportedly resulted in the worst flooding in the area in more than a century, particularly affecting the southern states of Johor and Pahang. According to the Government of Malaysia, the flooding killed 17 people, forced the evacuation of more than 100,000 others, and caused more than $28.6 million in property damage. As of January 17, approximately 98,000 people remained displaced in 268 flood evacuation centres in Johor and Pahang states. Historical rainfall data are very important to many problems in hydrological issues. For example the ability of obtaining estimates of spatial variability in rainfall fields becomes important for identification of locally intense rainfall which could lead to floods and other hazardous events. Precipitation patterns are highly variable concerning space, time, amount and duration of events [1]. A large amount of the variability of rainfall is related to the occurrence of extreme rainfall events and their intensities.

Climatic changes affect all aspects of weather and climate [2], including the extreme precipitation events [3]. Extreme rainfall events have a substantial effect on society and may lead to loss of life and property. Hazardous situations related to extreme rainfall events can be due to very intense rainfall, or to the persistence of rainfall over a long period of time. Such events may give rise to an exceedence of the capacity of drainage systems resulting in destruction of roads and basements which may lead to landslides or flooding. Therefore, there is a need to know the magnitudes of extreme rainfall events over different part of an area under study [4].

Extreme rainfall events have been examined and defined in various studies using different criteria, for example, Brooks et al. [5] defined extreme rainfall as the hourly rainfall totals over one inch; The accumulation of rain greater than two inches in a 48-hour time period [6]. "Extreme events are those that fall in the top 0.1 percent of all precipitation events" [7] where the 24-hour precipitation total at one or more stations surpassed a 50-year recurrence level [8]; the top 1 percent of 24-hour precipitation measurements for each year [9]. Moreover, Indices of climate extremes based on daily precipitation data were defined by the Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI). ETCCDMI defined 27 indices with 11 assessing extremes in precipitation; thus, make a global adaptation [10].

Most of the studies analyzing extreme precipitation indices over Peninsular Malaysia concentrated on temporal trends, rather than spatial patterns, because most of them aimed at assessing climate changes, for example, Wan Zawiah et al. [11] applied a Bayesian approach based on a single shifting model to assess the recent changes in extremes of annual rainfall in Peninsular Malaysia based on daily rainfall data for 50 rain-gauged stations over the period 1975-2004 using eight indices representing extreme events. The results of the analysis showed that half of the stations considered displayed significant changes, and more than 75% of the stations which recorded significant changes are situated on the west coast of the peninsular. In the study, [12] several extreme rainfall indices were calculated using linear regression analysis at the station level to study the hourly trends of extreme events across Peninsular Malaysia using 36 year period at 25 local stations. The results show an increasing trend between the year 1975 and 2010. The study by Diong et al. [13] provides a comprehensive analysis of the spatial and temporal patterns of changes in the precipitation at 22 stations across Malaysia for the period 1951 to 2009 using the following indices; RX1, RX5, SDII, R10, R20, R30, CDD, CWD, R95, R99 and PRCPTOT. The finding of the study was that the intensity and frequency of extreme precipitation events are on the rise. The summer monsoon season is becoming wetter, at the same time prolonged dry spells are more frequent. Other works on extreme rainfall events in peninsular Malaysia can be found in ([14]; [15]; [16] and [17]).

For others, spatial analysis is not feasible due to the limited number of monitoring stations over large study regions (e.g. [18]). However, that kind of analysis is extremely important for impact studies related to the flood phenomenon [19]. Therefore, to achieve full and effective understanding of spatial pattern of extreme rainfall events, we propose to use a technique based on geostatistics method of Ordinary Kriging (OK) to capture the spatial pattern of extreme rainfall. The method of OK is chosen in this study because it provides an estimate of the error at each interpolated point, therefore providing a measure of confidence in the modeled surface.

Mair and Fares [20] assessed rainfall spatial variability over a 34-month period of 21 gauges across the mountainous leeward portion of the island of O'ahu, Hawai'i, Traditional and geostatistical interpolation methods, including Thiessen polygon, inverse distance weighting, linear regression, OK, and simple kriging with varying local means, were used to estimate wet and dry season rainfall. The OK method produced more accurate predictions than linear regression of rainfall against elevation. Other applications of the OK method can be seen in ([21]; [22]; [23]; [24] and [25]).

The objective of this work is to determine the spatial patterns of extreme rainfall events in peninsular Malaysia for identifying areas that are more related to risk of extreme rainfall event. The identification of the structure of extreme rainfall spatial variability will help in setting a case study area that needs adequate attention. A detailed study would be practically useful for planners and other users.

In a related study, Wong et al. [26] analysed and quantified the spatial patterns and time-variability of rainfall in Peninsular Malaysia on monthly, yearly and monsoon temporal scales. The result of the spatial variation analysis shows that the east coast region, which substantially has higher amounts of rainfall during the northeast monsoon, and has lower spatial rainfall variability and a more uniform rainfall distribution than other regions. Our study is different because it specifically targeted towards station base not on regions. The rest of this paper is organized as follows: Section 2 presents the data used and a brief discussion on the methodology. The results obtained in the study are presented and discussed in section 3. Section 4 gives the conclusion and recommendations for further research.

2.0 PROBLEM STATEMENT

IPCC [27] reported that "wet extremes are projected to become more severe in many areas where mean precipitation is expected to increase, and dry extremes are projected to become more severe in areas where mean precipitation is projected to decrease. In the Asian monsoon region and other tropical areas there will be more flooding". "It is still difficult to draw a consistent picture of changes in the tropics and subtropics, where many areas are not analyzed and data are not readily available". Since 1980s, there are an increasing number of days of extreme rainfall events for several stations over the peninsular Malaysia [28]. In view of this, therefore, a detailed study of extreme rainfall events covering the entire peninsular Malaysia using rain-gauge data is urgently needed to obtain a clear insight about the impact of climate change on the extreme weather events of the region.

3.0 DATA AND METHODOLOGY

3.1 Data Used

The daily rainfall data sets of 75 rain-gauge monitoring stations across peninsular Malaysia for the period January 1975 to November 2008 obtained from the Malaysian Meteorological Department is used in this study. Figure 1 displayed the pictorial representation of the study area. The extreme rainfall indices were calculated from these data sets using RClimdex developed by Zhang and Yang [29]. To begin and to ensure that our plan sustain well, the schedule of the methodology is given.

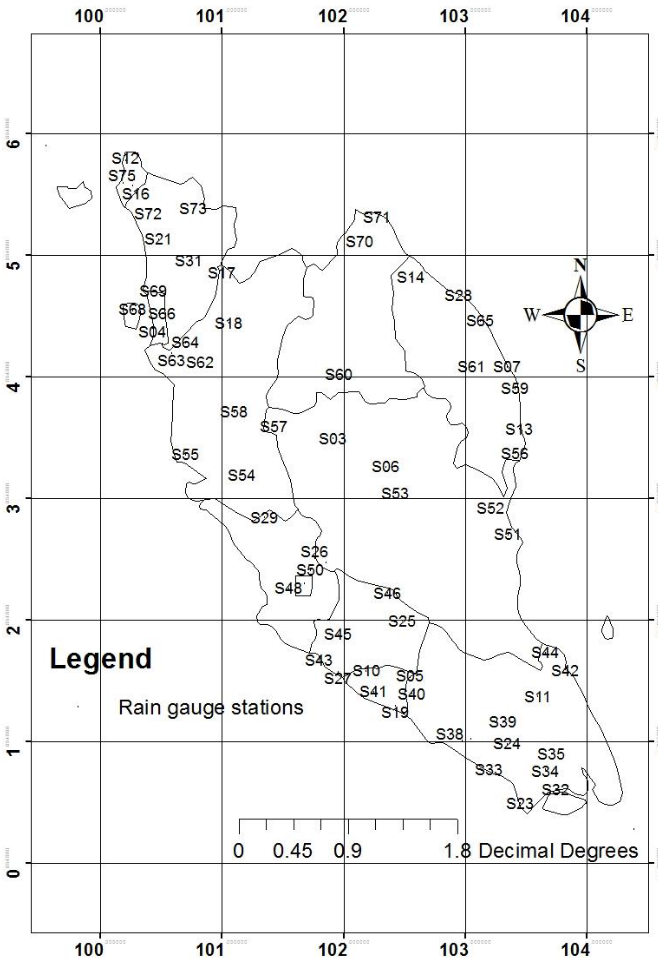

Figure 1 Geographical map of the Peninsular Malaysia with the rainfall stations considered

3.2 Extreme rainfall Indices Calculation

RClimDex (1.0) is designed to provide a user friendly interface in R software to compute indices of climate extremes. An exhaustive data quality control (QC) is first applied, because indices of extremes are sensitive to changes in stations, exposure, equipment, and observer practice [30], QC is a prerequisite for determining climatic indices. The RClimdex software performs the following procedure:

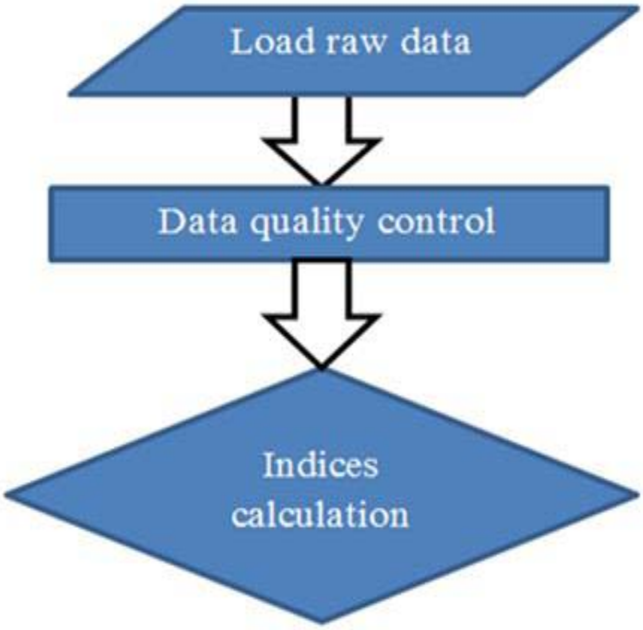

Figure 2 RClimDex climate indices calculation stages

The RClimDex QC performs the following procedure:

- Replace all missing values (currently coded as -99.9) into an internal format that R recognizes (i.e. NA, not available),
- Replace all unreasonable values into NA. Those values include daily precipitation amounts less than zero, daily maximum temperature less than the daily minimum temperature.

The indices to be used for this study are summarized in Table 1. The indices were selected based on the criteria that they represent extreme rainfall situations under different perspectives, such as; frequency, intensity and amount. "The use of annual indices greatly simplifies the analysis of extremes and provides useful measures for impact analysis as they can be related with extreme events that affect human society and the natural environment" [18] and [1].

Table 1: List of 8 selected ETCCDMI Extreme Rainfall Indices

ID	Indicator name	Definition	Unit
R10	Frequency of heavy precipitation days	Annual count of days when PRCP>=10mm	mm
R20	Frequency of very heavy precipitation	Annual count of days when PRCP>=20mm	mm
R30	Frequency of extremely heavy precipitation	Annual count of days when PRCP>=30mm	mm
SDII	Simple daily intensity index	Let RR_{wj} be the daily precipitation amount on wet days, where *w(RR ≥ 1mm)*, in period *j*. If *W* is the number of wet days during period *j*, then: $SDII_j = \sum_{w=1}^{W}(RR_{wj})/W$	mm/day
CWD	Consecutive wet days	Let RR_{ij} be the daily precipitation amount on day *i* during period *j*. Count the largest number of consecutive days where: $RR_{ij} \geq$ 1mm	Days
R95p	Very wet days	Let RR_{wj} be the daily precipitation amount on a wet day *w (RR ≥ 1mm)* during time period *i*, and let $RR_{wn}95$ be the 95th percentile of precipitation on wet days during the comparison period of climate base. Let *W* be the number of wet days during this period, then: $R95_{Pj} = \sum_{w=1}^{W} RR_{wj}$, for all $RR_{wj} > RR_{wn}95$	mm
R99p	Extreme wet days	Let RR_{wj} be the daily precipitation amount on a wet day *w (RR ≥ 1mm)* during time period *i*, and let $RR_{wn}99$ be the 99th percentile of precipitation on wet days during the comparison period of climate	mm

		base. Let W be the number of wet days during this period, then: $R99_{Pj} = \sum_{w=1}^{W} RR_{wj}$, for all $RR_{wj} > RR_{wn}99$	
PRCPTOT	Annual total wet-day precipitation	Let RR_{ij} be the daily precipitation amount on day i in period j. If I represent the number of days in j, then: $PRCPTOT_j = \sum_{i=1}^{J} (RR_{ij})$	mm

3.3 Spatial Dependence

Kriging uses semivariance to measure the spatially correlated component, a component that is also called spatial dependence or spatial autocorrelation which expresses the spatial dependence between neighboring observations. The semivariogram quantifies the relationship between the semivariance and the distance between sampling pairs. A semivariogram, plots the average semivariance against the average distance, this function may be used alone as a measure of spatial autocorrelation [31]. The semivariance is computed by:

$$\gamma(h) = \tfrac{1}{2n} \sum_{i=1}^{n} [z(s_i) - z(s_j + h)]^2$$

where $\gamma(h)$ is the average semivariance between known points, s_i and s_j separated by distance h; n is the number of pairs of sample points sorted by direction in the bin; and z is the attribute value. Semivariogram is modeled by fitting a theoretical function such as: Spherical, Exponential, Gaussian or Linear models to ensure that the solution is unbiased and has minimum variance.

If spatial dependence does exist among the sample points, then pairs of points that are closer in distance will have more similar values than pairs that are farther apart [31]. Having assumed a suitable semivariogram model, the adequacy of the chosen model is to be tested using cross-validation, where an acceptable fit appears by a mean estimation error (MEE) between measured and estimated values of approximately zero [32]:

$$MEE = \tfrac{1}{n}\sum_{i=1}^{n}\{[z(s_i) - \hat{z}(s_i)] / \sigma_i^2 \approx 0$$

where $z(s_i)$ is the measured value of regional value (ReV) at the location s_i, $\hat{z}(s_i)$ is the estimated value of ReV at the location s_i, σ_i is the calculated Kriging estimation error variance for $\hat{z}(s_i)$, and n is the number of estimated values. On the other hand, the root mean square error (RMSE) is close to one as follows:

$$RMSE = \tfrac{1}{n}\{(z(s_i) - \hat{z}(s_i)) / \sigma_i]^2\}^{\frac{1}{2}} \approx 1.$$

After a suitable semivariogram model fitting and its parameter estimations, the Kriging technique is applied to estimate the value of a variable at every grid point, where no observation is available.

3.4 Ordinary Kriging

Ordinary Kriging (OK) is a geostatistical technique to modelling. OK relies on the spatial correlation structure of the data in determining the weighting values. This is a more rigorous approach to modelling, as correlation between data points determines the estimated value at an unsampled point. The semivariograms provides estimated values of the correlation structure for a finite number of distances. In performing OK, semivariogram values for any distance are required. The kriging estimators are but variants of the basic linear regression estimator $Z^*(u)$ defined as [33]:

$$Z^*(u) - m(u) = \sum_{\alpha=1}^{n(u)} \lambda_\alpha [Z(u_\alpha) - m(u_\alpha)] \tag{1}$$

with u and u_α: location vectors for estimation point and one of the neighbouring data points, indexed by α, where $n(u)$ is the number of data points in local neighbourhood used for estimation of $Z^*(u)$, $m(u)$ and $m(u_\alpha)$ are the expected values of $Z(u)$ and $Z(u_\alpha)$ respectively, $\lambda_\alpha(u)$ is the Kriging weight assigned to datum $z(u_\alpha)$ for estimation location u; same datum will receive different weight for different estimation location. $Z(u)$ is treated as a random field with a trend component $m(u)$, and a residual component $\varepsilon(u) = Z(u) - m(u)$.

Kriging estimates residual at u as weighted sum of residuals at surrounding data points. The Kriging weights λ_α, are derived from covariance function or semivariogram.

The main goal of (Eq. 1) is to determine weights λ_α that minimize the variance of the estimator: $\sigma_E^2(u) = Var\{Z^*(u) - Z(u)\}$, under the unbiased constraint $E\{Z^*(u) - Z(u)\} = 0$.

The random field $Z(u)$ is decomposed into residual and trend components given as:

$$Z(u) = \varepsilon(u) + m(u),$$

with the residual component treated as a field with a stationary mean 0 and a stationary covariance (a function of lag *h*, but not of position, u):

$$E\{\varepsilon(u)\} = 0$$

$$Cov(\varepsilon(u), \varepsilon(u+h)\} = E(\varepsilon(u) \cdot \varepsilon(u+h)\} = C_\varepsilon(h)$$

The residual covariance function is generally derived from the input semivariogram model:

$$C_\varepsilon(h) = C_\varepsilon(0) - \gamma(h) = Sill - \gamma(h).$$

In ordinary Kriging, rather than assuming that the mean is constant over the entire domain, following [34] it is assumed that it is constant in the local neighbourhood of each estimation point that is $m(u_\alpha) = m(u)$ for each nearby data value $z(u_\alpha)$ used in estimating $Z(u)$. In this case, the Kriging estimator can be written in the following form:

$$Z^*(u) = m(u) + \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u)[Z(u_\alpha) - m(u_\alpha)]$$

$$= \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u) Z(u_\alpha) + \left[1 - \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u)\right] m(u)$$

Filtering the unknown local mean by requiring that the Kriging weights sum to 1, leading to an ordinary kriging estimator [21];

$$Z_{OK}^*(u) = \sum_{\alpha=1}^{n(u)} \lambda_\alpha^{OK}(u) Z(u_\alpha) \qquad (2)$$

with

$$\sum_{\alpha=1}^{n(u)} \lambda_\alpha^{OK}(u) = 1.$$

3.0 RESULTS AND DISCUSSIONS

The daily rainfall data sets of 75 rain-gauge stations across peninsular Malaysia for the period January 1975 to November 2008 were used to calculate the rainfall indices selected in this study given (Table 1). The first important step in performing OK is modelling the spatial dependence through either of the semivariogram models. A semivariogram is an important function to indicate spatial correlation in observations measured at sample locations. Three semivariogram models such as: Gaussian, Spherical and Exponential were employed in this study. The cross validation result from the fitted models is given (Table 2).

Table 2: Summary results for cross validation of semivariogram models

	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential
		R10			R99p	
ME	0.4164	0.3386	0.2235	1.1766	1.5304	2.5952
MS	0.0353	0.0276	0.0159	-0.0009	0.0181	0.0308
RMSE	9.4283	9.4861	9.6764	36.655	34.079	36.981
RMSSE	1.1166	1.0407	1.0322	1.9549	1.1150	1.0967
ASE	7.9042	8.5744	8.9394	31.207	32.838	37.714
		R20			PRCPTOT	
ME	0.3121	0.3048	0.1088	12.808	15.383	9.8375
MS	0.0506	0.0370	0.0118	0.0261	0.0362	0.0175
RMSE	6.9152	6.5397	6.9931	288.42	290.65	305.29
RMSSE	1.6330	1.2142	1.0331	1.0635	1.1663	1.0019
ASE	5.4260	5.9315	6.3691	272.07	275.23	301.64
		R30			CWD	
ME	0.1841	0.1707	0.1243	0.0415	0.0528	0.0335
MS	0.0401	0.0252	0.0179	0.0280	0.3364	0.0183
RMSE	4.7733	4.4754	4.6075	1.9647	1.9396	1.9010
RMSSE	1.4532	1.0520	1.1135	1.1775	1.2059	1.1303
ASE	4.0452	4.2152	4.4585	1.5806	1.5503	1.6183
		R95p			SDII	
ME	2.7937	4.3032	6.6857	-0.0795	0.0139	0.0133
MS	-0.0003	0.0199	0.0373	-0.0286	0.0013	0.0043
RMSE	83.482	76.847	79.018	2.9048	2.8894	2.9223
RMSSE	1.1750	0.9235	0.9520	1.2357	1.2132	1.1644
ASE	73.960	86.798	93.696	2.3879	2.3574	2.4658

The cross validation, is used to find the best model among the competing models. The goal is to have standardized mean prediction errors near 0, small root-mean-squared prediction errors, average standard error near root-mean-squared prediction errors, and standardized root-mean-squared prediction errors near 1 (ArcGis Desktop 10). From (Table. 2) it can be seen that the Exponential semivariogram model best fits the data sets, therefore, is chosen as the best model for the spatial interpolation.

According to the previous analysis, the exponential semivariogram model is chosen to realize the OK interpolation using the eight adapted rainfall events. The OK is used to estimate the spatial pattern of the representative precipitation indices, producing one map for each index. The climatological pattern of the indices over the peninsular Malaysia indicates some areas that recorded low and high values for both the frequency and intensity indicators.

Considering the objective of this study, the study is limited to only area with the highest value of extreme, meanwhile, high value was observed for each representative index. The estimated maps of R10, R20 and R30 representing the frequency of heavy, very heavy and extremely heavy precipitation events, defined as the number of days per year with precipitation amount above or equal to 10, 20 and 30mm respectively is presented in Fig. 3(a, b and c). Based on the results of the maps, the Chui Chak station realised the most extreme rainfall events, moreover, it has also being identified as the area with the highest annual total precipitation (PRCPTOT) seen in Fig. 4d. The area identified with extreme precipitation exceeding the 95^{th} (R95p) and 99^{th} (R99p) percentiles is the K.g Menerong, depicted in Fig 4(a & b). The result of CWD index that reflects time-series variations that can lead to wetter conditions is given in Fig. 3d. Pusat Kesihatan Bt.Kurau is the station identified that realised the highest CWD precipitation. In Figure 4c, the station Pintu Kawalan Tampok Batu Pahat has the highest SDII.

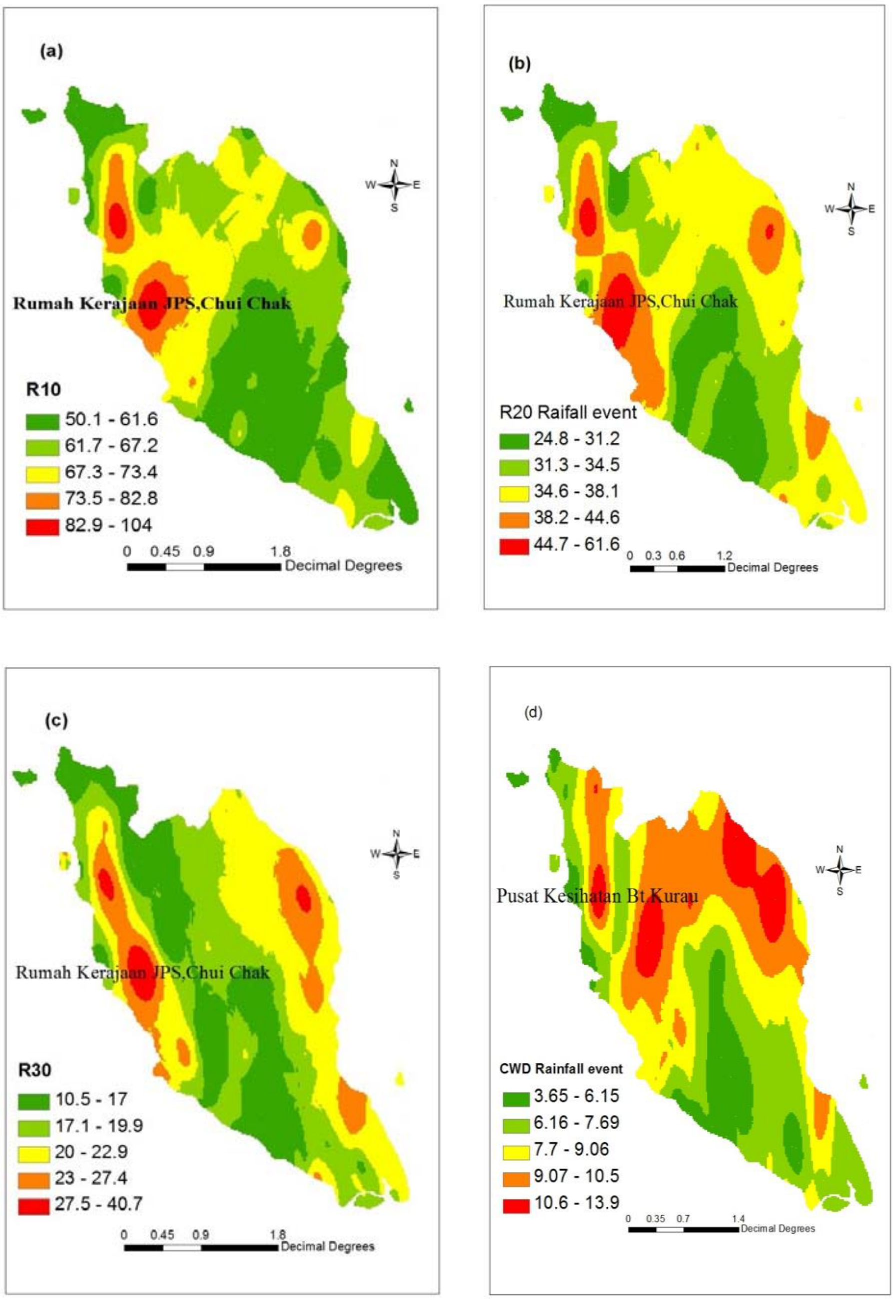

Figure 3 OK prediction map of peninsular Malaysia (Jan 1975-Nov 2008) for precipitation events exceeding defined threshold

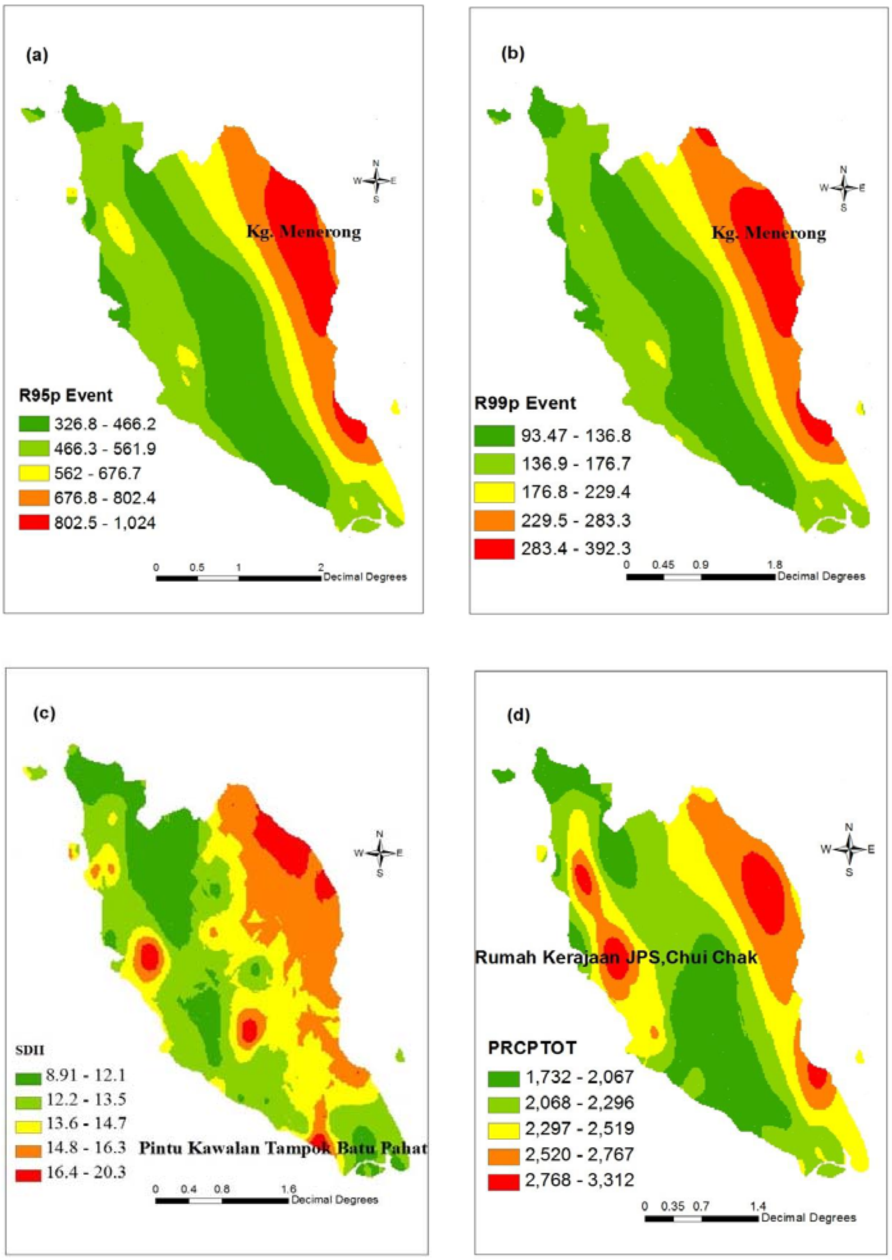

Figure 4 OK prediction map of peninsular Malaysia (Jan 1975-Nov 2008) for the amount and intensity of extreme precipitation events

4.0 SUMMARY AND CONCLUSION

The main objective of this work is to analyse the spatial patterns of eight rainfall indices in peninsular Malaysia in identifying areas that are more related to risk of extreme rainfall event. First, the indices were calculated from the daily rainfall data sets using RClimDex. The indices were grouped into two: The first group calculates the frequency of the event exceeding a defined threshold (CWD, R10mm, R20mm and R30). The second group measures the precipitation depth or intensity (PRCPTOT, SDII, R95P and R99P). Based on the results in this work, the following conclusions were made:

1. The Chui Chak station realised the most extremely rainfall events based on the indices R10, R20 and R30. Moreover, it has also being identified as the area with the highest annual total precipitation in wet days (PRCPTOT). This is not surprising, as aforementioned, IPCC [27] reported that "wet extremes are projected to become more severe in many areas where mean precipitation is expected to increase", this is in line with the findings [35] "Based on the values of descriptive statistics, the five highest mean rainfall amounts among the stations are Chui Chak (W10), followed by Kg Menerong (E06), Endau (E13), …".
2. Kg Menerong station realised the highest value for the indices that measure heavy precipitation that exceeds the 95 and 99 percentile thresholds, expressed by the 95^{th} and 99^{th} percentiles (R95p and R99p) indices.
3. Pusat Kesihatan Bt.Kurau is the station identified with the highest CWD precipitation.
4. Pintu Kawalan Tampok Batu Pahat is the station with highest SDII.

The CWD, PRCPTOT and SDII are not necessarily associated with climate extremes but provide useful information about the relationship between changes in extreme conditions and other aspects of the distribution of the daily precipitation [36]. Finally, the Kg Menerong and Chui Chak are the areas identified that are more related to risk of extreme rainfall events. Therefore, we strongly recommend that researchers should give more attention to the identified areas in knowing the dynamics of the rainfall data generating the extreme events.

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Appendix

Stations code and name

1	PINTU A.BAGAN,AIR ITAM	40	Tangkak
2	ARAU	41	Malacca
3	S. K. KG. AUR GADING	42	Mersing
4	LDG. BATU KAWAN	43	Hospital Port Dickson
5	LDG. BKT. ASAHAN	44	Endau
6	KG. CHEBONG	45	Setor JPS Sikamat Seremban
7	GUAR NANGKA	46	Sg.Lui Halt
8	KLINIK BIDAN ,JAMBU BONGKOK	47	Petaling Jaya
9	JANDA BAIK	48	Subang
10	JAM. SG. SIMPANGN ,JLN. EMPAT	49	Empangan Genting Kelang
11	IBU BEKALAN KAHANG , KLUANG	50	Gombak
12	KAKI BUKIT	51	Rumah Pam Pahang Tua,Pekan
13	SEK. KEB. KEMASEK	52	Kuantan
14	SEK. KEB. KG. JABI	53	Rumah Pam Paya Kangsar
15	LDG. KIAN HOE , KLUANG	54	Rumah Kerajaan JPS,Chui Chak
16	KODIANG	55	Sitiawan
17	DISPENSARI KROH	56	JPS Kemaman
18	STN. PEMEREKSAAN HUTAN ,LAWIN	57	Ldg Boh
19	PEKAN MERLIMAU	58	Ipoh
20	RUMAH PENJAGA JPS. PARIT NIBONG	59	Sek.Men. Sultan Omar, Dungun
21	PENDANG	60	Gua Musang
22	JPS. WILAYAH PERSEKUTU	61	Kg. Menerong
23	LDG. GETAH KUKUP , PONTIAN	62	Pusat Kesihatan Bt.Kurau
24	LDG. BENUT ,RENGAM	63	Rumah JPS, Alor Pongsu
25	LDG. SG. SABALING	64	Selama
26	GENTING SEMPAH	65	Stor JPS Kuala Trengganu
27	LDG. SENGKANG	66	Bkt Berapit
28	KG. MERANG ,SETIU	67	Kolam Takongan Air Itam
29	IBU BEKALAN SG. BERNAM	68	Klinik Bkt. Bendera
30	KG. SG. TUA	69	Rumah Pam Bumbong Lima
31	SIK	70	To' Uban

32	Stor JPS Johor Bahru	71	Kota Bharu
33	Pintu Kawalan Tampok Batu Pahat	72	Alor Star
34	Senai	73	Ampang Pedu
35	Sek.Men.Bkt Besar di Kota Tinggi	74	Padang Katong ,Kangar
36	Sek.Men.Inggeris Batu Pahat	75	Abi Kg. Bahru
37	Pintu Kawalan Sembrong		
38	Pintu Kawalan Separap Batu Pahat		
39	Kluang		