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The Use of BLRP Model for Disaggregating Daily Rainfall Affected by Monsoon in Peninsular Malaysia

(Penggunaan Model BLRP untuk Mengasingkan Curahan Hujan Harian Terjejas oleh Monsun di Semenanjung Malaysia)

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ABSTRACT

Rainfall intensity is the main input variable in various hydrological analysis and modeling. Unfortunately, the quality of rainfall data is often poor and reliable data records are available at coarse intervals such as yearly, monthly and daily. Short interval rainfall records are scarce because of high cost and low reliability of the measurement and the monitoring systems. One way to solve this problem is by disaggregating the coarse intervals to generate the short one using the stochastic method. This paper describes the use of the Bartlett Lewis Rectangular Pulse (BLRP) model. The method was used to disaggregate 10 years of daily data for generating hourly data from 5 rainfall stations in Kelantan as representative area affected by monsoon period and 5 rainfall stations in Damansara affected by inter-monsoon period. The models were evaluated on their ability to reproduce standard and extreme rainfall model statistics derived from the historical record over disaggregation simulation results. The disaggregation of daily to hourly rainfall produced monthly and daily means and variances that closely match the historical records. However, for the disaggregation of daily to hourly rainfall, the standard deviation values are lower than the historical ones. Despite the marked differences in the standard deviation, both data series exhibit similar patterns and the model adequately preserve the trends of all the properties used in evaluating its performances.

Keywords: Bartlett Lewis rectangular pulse model; daily to hourly; disaggregation; Inter-monsoon; monsoon

ABSTRAK

Keamatan hujan adalah pemboleh ubah input utama dalam pelbagai analisis hidrologi dan pemodelan. Malangnya, kualiti data hujan selalunya lemah dan rekod data yang boleh dipercayai diperoleh pada jangka masa kasar seperti tahunan, bulanan dan harian. Rekod hujan selang pendek adalah terhad kerana kos yang tinggi serta kebolehpercayaan pengukuran yang rendah dan sistem pemantauan. Salah satu cara untuk menyelesaikan masalah ini adalah dengan mengasingkan selang kasar untuk menghasilkan yang pendek menggunakan kaedah stokastik. Kertas kerja ini menghuraikan penggunaan model segiempat denyut Bartlett Lewis (BLRP). Kaedah ini digunakan untuk mengumpul data 10 tahun setiap hari untuk menjana data setiap jam dari 5 stesen hujan di Kelantan sebagai kawasan wakil dipengaruhi oleh tempoh monsun dan 5 stesen hujan di Damansara dipengaruhi oleh tempoh antara monsun. Model dinilai berdasarkan keupayaan mereka untuk menghasilkan semula statistik model piawai dan hujan melampau yang diperoleh daripada rekod lampau ke atas penyampaian simulasi pengasingan. Pengasingan daripada setiap hari untuk hujan setiap jam dihasilkan melalui cara bulanan dan harian dan perbezaan yang rapat sepadan dengan rekod lampau. Walau bagaimanapun, bagi pengasingan daripada setiap hari untuk hujan setiap jam, nilai sisihan piawai adalah lebih rendah daripada rekod lampau. Walaupun perbezaan ketara dalam sisihan piawai, kedua-dua siri data menunjukkan corak yang sama dan model mengekalkan trend semua sifat secukupnya yang digunakan dalam menilai prestasinya.

Kata kunci: Antara-monsun; harian kepada jam; model segiempat denyut Bartlett Lewis; monsun; pengasingan

INTRODUCTION

Rainfall intensity is the main input variable in various hydrological analysis and modeling. Many hydrologic analyses especially on flood prediction require short time interval rainfall data. Unfortunately, short interval rainfall records especially in the past are scarce because of high cost, low reliability of the measurement and the monitoring systems. One way to solve this lack of data problem is by disaggregating the historical daily rainfall data using stochastic methods. Work along this direction was pioneered by Ashraf et al. (2011) and Valencia and Schaake Jr. (1973). The technique basically produces synthetic short interval data from long interval variable data as an input. The stochastic approaches were utilized in order to reproduce the appropriate statistical characteristics of the data at the required time scale (Salapour et al. 2014).

The modeling of rainfall has a long history in literature with significant advances being made in the statistical methods and techniques used and subsequent accuracies achieved. The purpose of such modeling is to produce simulated series of data. Stochastic models are important tools in providing fine or short time scale rainfall data for analysis and design. Stochastic models, sometimes also known as 'stochastic weather generators' are commonly used to generate synthetic sequences of weather variables that are statistically consistent with the observed characteristics of the historical record (Koutsoyiannis et al. 2003).

Different rainfall disaggregation models have been developed in the last few decades. Many researchers have been studying the disaggregation technique for modifying a lower scale time series from a higher scale series; such as daily to hourly. With today's computer power it is not be a big problem to compute these long-interval simulations. Hershenhorn and Woolhiser (1987) proposed a disaggregation model for daily rainfall. It is a method to simulate the number of rainfall events in a day with amount, duration and starting time of each event from daily data. But, this method is described as complicated and not appropriate for common engineering purposes (Koutsoyiannis 1994). It was due to the disaggregation model in general are not exact in a strict sense but they only provide sufficient approximations of important properties of the short time series variables that need to be preserved from the long time series data (Koutsoyiannis 1994).

There are several methods available to generate short time scale rainfall data and researches about this are still on-going in many parts of the world. Koutsoyiannis and Xanthopoulos (1990) developed a dynamic disaggregation model for solving stochastic disaggregation problems. The model development was intended for application to short-scale rainfall disaggregation problems and when it combined with a rainfall model it is possible to disaggregate monthly rainfall into events and hourly amounts. However, this research only focused on one of the most proven methods in the stochastic cluster models to disaggregate daily into hourly rainfall data, which is known as Bartlett Lewis Rectangular Pulse (BLRP) model. BLRP model was pioneered by Rodriguez-Iturbe et al. (1987). Then, Bo and Islam (1994) developed and used the modified Bartlett Lewis Rectangular Pulse (BLRP) model (Rodriguez-Iturbe et al. 1987) to capture the statistics of short timescale rainfall from the observed daily rainfall statistics in Arno basin central Italy. Their approach used the statistical parameter of daily data such as their mean, standard deviation, auto-correlation and probability of dry day to estimate parameter of the model and then simulate the sequence of rainfall events at any desired time-scale. That model is a stochastic point process model to generate artificial rainfall. A point process rainfall model generates storm origins from a Poisson process. Other researchers also make use of such models for disaggregation such as (Glasbey et al. 1995) applied the modified BLRP model to disaggregate daily rainfall data by conditional simulation in Edinburgh, United Kingdom. They found that the generated hourly rainfalls are consistent with the historical daily totals (Cowpertwait et al. 1996a, 1996b; Gyasi-Agyei 1999).

In the early 2000, the use of BLRP model was further improved by adding a proportional adjusting procedure on it to preserve the individual observed daily totals while disaggregating rainfall into fine time scale (Koutsoyiannis & Onof (2001). This research continued into multivariate rainfall disaggregation schemes (Koutsoyiannis et al. 2003). Gyasi-Agyei and Mahbub (2007) extended the original stochastic model Gyasi-Agyei (2005) by disaggregating daily rainfall data throughout Australia to any desired short timescale down to 6 min.

However, the use of rainfall disaggregation model for short timescale based on stochastic point processes have not been widely applied for tropical region where the storms behave differently from those of the climate that ever used. First application of BLRP model in tropical region was reported by Hanaish et al. (2011), Hidayah et al. (2010) and Lu and Qin (2012). Hidayah et al. (2010) applied BLRP model to disaggregate daily into hourly rainfall in Sampean catchment, Indonesia, Hanaish et al. (2011) fitted the BLRP model to disaggregate the daily data to hourly data using observed data from the rain gauge data in Petaling, Peninsular Malaysia, while Lu and Qin (2012) applied the BLRP model to disaggregate rainfall data in Changi airport, Singapore. Three of them utilized short time scale rainfall data generation using BLRP model only and chose one single site or region which was presumed to have similar climatic condition and rainfall pattern. The technique to fit any data generation model such as to simulate daily rainfall and disaggregate it into hourly rainfall amounts using BLRP at various sites with different rainfall pattern is still not applied yet. Tropical region experiences more intense rainfall with shorter duration and known as convectional type. Hence, this paper describes the technique and applicability of Bartlett Lewis Rectangular Pulse (BLRP) as one of stochastic model for disaggregating daily rainfall data into hourly rainfall during monsoon and inter-monsoon periods in two region of Peninsular Malaysia. Short timescale rainfall data is crucial for various hydrological design and risk assessment and by using disaggregation technique it could minimize the scarce of short timescale data problem.

DATA

THE STUDY AREA

Peninsular Malaysia experiences a tropical climate due to its location close to the equator and it was influenced by two monsoons seasons. The two monsoons that contribute to rainy seasons are the South-West (SW) monsoon, occurring normally from May to September and North-East (NE) monsoon from November to March. The latter brings about heavier rainfall in Peninsular, especially in east and south while the South-West monsoon is a drier period for the whole country. The transition period also known as inter monsoons period bring more rainfall in the central region and characterized by bimodal monthly rainfall pattern with peaks normally in April and October.

Two study sites were selected, namely Sungai Kelantan River Basin representing the eastern region which affecting by SW and NE monsoons and Damansara catchment for the central region which affected by inter-monsoon period. Five rainfall stations from Kelantan and Damansara respectively were selected based on the completeness and length of rainfall data (Table 1 & Figure 1). The data was obtained from the Department of Irrigation and Drainage (DID), Malaysia.

QUALITY OF DATA

The data used in this study was considered good because less than 10% of the data was missing throughout the 10 year period. As it was known, rainfall time series data were often affected by the presence of missing data. But when dealing statistically with data, the need to fill in the gaps estimating the missing values must be considered because it can produce biased results and it can also prevent important analyses of the considered variables from being carried out (Lo Presti et al. 2010; Sultana et al. 2015). Hence, for this study, the missing values were estimated using weighting methods known as the inverse distance method. Inverse distance methods are based on the assumption that the missing value at one rainfall station should be influenced most by the nearby stations and less by the more distant stations. The estimation error for missing data calculation could be highly reduced by adjusting the order of distances to reach the optimal value (Chang et al. 2006).

TABLE 1. Selected rainfall stations and the station code

No	Station Name	Station Code
	Damansara	
1.	SMK Taman Sea	3110007
2.	Tropicana Golf	3110009
3	SR Damansara Utama	3110008
4.	Bukit Kiara Golf Resort	3110016
5.	Balai Polis Sea Park	3110004
	Kelantan	
6.	Blau	4717001
7.	Gua Musang	4819027
8.	Kg Lalok	5322044
9.	Pasik	5217001
10.	Ulu Sekor	5520001

DATA DISTRIBUTION

Checking of rainfall data distributions is crucial because most of hydrologic analysis deal with uncertainties. Distribution identification allows development of robust models from random process that deal with uncertainties and probabilities. It also protect from time and money lost which arise due to invalid model selection and enabling to make better decision in developing the model or in choosing the method that will be applied.

This study used the most acceptable distribution models to fit the distribution of daily data, namely, Gamma, Weibull, Beta, Log Pearson Type 3 and Generalized Pareto (Burgueño et al. 2005; Deidda & Puliga 2006; Duan et al. 1995; Noor et al. 2014; Olofintoye et al. 2009; Suhaila & Jemain 2008, 2007). In order to check the best distribution that can represent the daily rainfall data there were three goodness-of-fit tests used. They were Kolmogorov-Smirnov (K-S), Anderson-Darling (A-D) and Chi-Squared tests. Kolmogorov-Smirnov test was used to decide if a sample comes from a hypothesized continuous distribution whereas the Anderson-Darling procedure was a general test to compare the fit of an observed cumulative distribution function to an expected cumulative distribution function. Meanwhile, the Chi-Squared test was used to determine if a sample comes from a population with a specific distribution.

The idea behind the goodness of fit tests was to measure the distance between the data and the distribution that were tested and compare that distance to some

FIGURE 1. Location of selected rainfall stations in Kelantan and Damansara River basins

threshold value. If the distance (called the test statistic) was less than the threshold value (the critical value), that distribution was considered good and it was obvious that the distribution with the lowest statistic value was the best fitting model. Based on the fact in this study, the three goodness of fit was compared with each other and at the end choose the fitted models and the most valid one.

MATERIALS AND METHODS

MODEL DESCRIPTION

The Bartlett-Lewis Rectangular Pulses (BLRP) model was used in this study to simulate the rainfall data. This model was chosen because its wide applicability for several climatic conditions as stated by Debele et al. (2009). Evidences on its ability to reproduce important features of observed rainfall from hourly to the daily scale and above can be found in Onof and Wheater (1994) and Rodriguez-Iturbe et al. (1987).

The general assumption of the BLRP model as proposed by Onof and Wheater (1993) and Rodriguez-Iturbe et al. (1987) are as follows: Storm origins *ti* occurs following a Poisson process rate λ; cell origins *tij* arrive following a Poisson process rate β; cell arrivals terminate after a time *vi* are exponentially distributed with parameter γ; each cell has a duration *wij* exponentially distributed with parameter η; and each cell has a uniform intensity *Xij* with a specified distribution μx.

In Rodriguez-Iturbe et al. (1987) it was stated that rainfall intensity was treated as a random variable that remains constant throughout the lifetime of a rain cell, so that rain cells were modeled using rectangular profiles and characterized by 5 parameters (λ, β, γ, η and μx) stated periodically. When applied, Rodriguez-Iturbe et al. (1987) found that the model has an inability to preserve the properties of dry and wet periods and noted as one of weaknesses of the cluster based rectangular pulse model. In order to overcome this problem, Rodriguez-Iturbe et al. (1988) improved the model and introduced an extra parameter into the model to give a better fit to the statistics. For the extra parameter, Rodriguez-Iturbe et al. (1988) put the mean cell duration, 1/Ø, which it was allowed to vary randomly from storm to storm. The parameter η now follows two parameter gamma distributions with shape parameter α and scale parameter *v*. Subsequently, parameters β and γ also vary in a manner that the ratios $\kappa = \beta/\eta$ and $\emptyset = \gamma/\eta$ become constant. Each cell depth is a random constant that is exponentially distributed with mean *E[x]*. This results in a six-parameter model for a new modified BLRP model (λ, κ, Ø, μ_x, α and *v*).

The rainfall disaggregation for this study was performed using the Hyetos software developed by Koutsoyiannis and Onof (2001). Hyetos uses the BLRP model as a background stochastic model for rainfall disaggregation. It uses repetition to derive a synthetic rainfall series, which resembles the given series at daily scale. Inputs required in Hyetos were parameters from the BLRP model and the actual historical rainfall time series. Then, the disaggregated results that were produce by Hyetos simulation can be compared with the historical one. The easiest way to compare the simulation results by Hyetos with historical data is by using graphical plot of statistical value such as mean and standard deviation.

PARAMETER ESTIMATION

For parameter estimation at least four statistical characteristics of the historical data were required to estimate these parameters. These statistical characteristics were mean, variance, lag-1 autocorrelation coefficient and proportion dry / probability of the dry day at 1, 24 and 48 h levels of aggregation (altogether 12 statistic values). For statistical simulated model with five parameter by Koutsoyiannis and Onof (2001), it can be calculated as follows where (1) gives the analytical values of mean, (2) for variance, (3) for covariance and (4) for proportion dry.

$$E\left[Y_t^{(T)}\right] = \lambda E[X]\mu c \frac{\upsilon}{\alpha - 1} T \tag{1}$$

$$\begin{aligned} Var\left[Y_t^{(T)}\right] &= \frac{2\upsilon^{2-\alpha}T}{\alpha-2}\left(k_1 - \frac{k_2}{\Phi}\right) - \frac{2\upsilon^{3-\alpha}}{(\alpha-2)(\alpha-3)} \cdot \\ &\left(k_1 - \frac{k_2}{\Phi^2}\right) + \frac{2}{(\alpha-2)(\alpha-3)} \\ &\cdot\left[k_1(T+\upsilon)^{3-\alpha} - \frac{k_2}{\Phi}(\Phi T+\upsilon)^{3-\alpha}\right]. \end{aligned} \tag{2}$$

$$\begin{aligned} Cov\left[Y_t^{(T)}, Y_{t+s}^{(T)}\right] &= Y_{Y(s)}^{T} \\ &= \frac{k_1}{(\alpha-2)(\alpha-3)}\left\{\left[T(s-1)\_\upsilon\right]^{3-\alpha}\right. \\ &\left. + \left(T(s+1)+\upsilon\right)^{3-\alpha} - 2(Ts+\upsilon)^{3-\alpha}\right\} \\ &+ \frac{k_2}{\Phi^2(\alpha-2)(\alpha-3)}\left\{2(\Phi Ts+\upsilon)^{3-\alpha}\right. \\ &\left. - \left[\Phi T(s-1)+\upsilon\right]^{3-\alpha}\right\} \\ &- \left\{\left[\Phi T(s+1)+\upsilon\right]^{3-\alpha}\right\} \quad s \geq 1, \end{aligned} \tag{3}$$

prob [zero rainfall]

$$\begin{aligned} &= \exp\left\{-\lambda T - \left[\frac{\lambda\upsilon}{\Phi(\alpha-1)}\left(1+\Phi(k+\Phi) - \frac{1}{4}\Phi(k+\Phi)\right)\right.\right. \\ &\left. .(k+4\Phi) + \frac{\Phi(k+\Phi)\left(4k^2+27k\Phi+72\Phi^2\right)}{72}\right] \\ &+ \frac{\lambda\upsilon}{(\alpha-1)(k+\Phi)}\left(1-k-\Phi+\frac{3}{2}k\Phi+\Phi^2+\frac{k^2}{2}\right) \\ &+ \frac{\lambda\upsilon}{(\alpha-1)(k+\Phi)}\left(\frac{\upsilon}{\upsilon+(k+\Phi)T}\right)^{\alpha-1} \\ &\left. .\frac{k}{\Phi}\left(1-k-\Phi+\frac{3}{2}k\Phi+\Phi^2+\frac{k^2}{2}\right)\right\}, \end{aligned} \tag{4}$$

where,

$$k_1 = \left(2\lambda\mu CE^2[x] + \frac{\lambda\mu C^k \Phi E^2[x]}{\Phi^2 - 1}\right)\left(\frac{\upsilon^\alpha}{\alpha - 1}\right). \tag{5}$$

$$k_2 = \left(\frac{\lambda\mu C^k E^2[x]}{\Phi^2 - 1}\right)\left(\frac{\upsilon^\alpha}{\alpha - 1}\right). \tag{6}$$

Parameter estimation procedure was achieved by minimizing the sum of squares, where the squared terms were the differences between the selected expressions of the model and their equivalent historical sampled values. The method of moment's approach has been frequently adopted when fitting time series models to historical data (Bo & Islam 1994; Cowpertwait 1991; Cowpertwait et al. 1996a; Entekhabi et al. 1989; Onof & Wheater 1993; Rodriguez-Iturbe et al. 1987; Verhoest et al. 1997).

$$Z = \min\left[\sum_{i=1}^{N} W_i \left(\frac{F_i(x)}{F_i'} - 1\right)^2\right]. \tag{7}$$

The above equation was used to calibrate the models to the historical rainfall observed where *Fi (X)* is the corresponding analytical expression for statistic *i* as a function of the parameter vector X. F'_i the statistic *i* estimated from historical data at various levels of aggregation. *N* is the number of statistics used in parameter determination; and W_i is the weight assigned to statistic *i*. W_i is the weight attributed to all the 12 statistical values; sum of weighted mean, variance, probability dry and lag-1 auto covariance of 1, 24 and 48 h level of aggregation. For the original BLRP model, let the five parameters $F_i = F_i$ (λ, μ_c, β, η and μ_x) be a function of the BLRP model, and let be its historical sampled value. Verhoest et al. (1997) use $W_i = 1$ for all statistic while Cowpertwait et al. (1996a) set $W_i = 100$ for the mean and used $W_i = 1$ for all other moments.

Results

Data Distribution

Statistically, the behavior of rainfall can be described by the type of the distribution that the data belongs too. The distributions that can best fit the daily rainfall data for various stations at selected areas of study that governed by those monsoons in percentage displayed as follows:

Based on the results above, it shows that most of the rainfall distribution for each monsoon in selected area is Weibull, followed by Log Pearson 3, Gamma, Generalized Pareto and Beta distribution. Based on previous research by Koutsoyiannis (2001), Bartlett Lewis rectangular pulse (BLRP) model that was applied in Hyetos program has been successfully applied in the area that tends to have Gamma and exponential distribution.

Statistical Characteristics & Parameter Estimation

Table 3 provides the example of statistical properties and the calculated parameter estimate for the BLRP rainfall model (provided in the lower rows of the table). It takes from SMK Taman Sea (3110007) data as representatives.

Model Performance

The performance of the model was evaluated using daily and hourly rainfall series for 10 years. The model was evaluated by comparing the statistical properties; the monthly mean and standard deviation between the historical data and the disaggregated results. The comparison between the disaggregated and the historical series for the monthly means are shown in Figure 2(a) for each rainfall station in Kelantan while Figure 3(a) for Damansara. Meanwhile, the comparison of standard deviations for each rainfall station is shown next to the means Figure (Figures 2(b) & Figure 3(b)).

Discussion

The data distribution was also strongly affected the performance of the model. As stated previously, the BLRP model that develops into Hyetos program used gamma and exponential distribution data. However, the distribution of rainfall data in tropical area varies very much and made the BLRP model through the Hyetos program cannot fully applied (Hidayah et al. 2010). As found in the result, the daily rainfall distribution varied between stations (Table 2). The result of data distribution for both of selected areas of study shows that most of them fitted to Weibull, Log Pearson 3 and Gamma distribution and only small percentage fitted with Generalized Pareto and Beta distribution. Weibull, Log Pearson 3, Generalized Pareto and Beta distribution tend to gamma structure and have similarity structure with it. Hence, for some of the rainfall station, the application of BLRP model through Hyetos can be applied and has good performance and some of them did not perform well.

Another constraint which was used to evaluate the performance of model was by comparing the statistical properties; mean and standard deviation. The result showed that most of the stations have means very closely match with the historical means except for station Blau for July mean (Figure 2(a)), Kg Lalok for January, April and December means (Figure 2(a)), SR Damansara Utama for March, July and Augustus means (Figure 3(a)) and Tropicana Golf station for April mean (Figure 3(a)). For SR Damansara Utama station, the entire mean shows that the BLRP model tended to overestimate the historical mean where others reverse was true.

This error was caused by inaccuracy on parameter estimate and disaggregation of hourly period. The sum weighted error for those months also relatively high where it was in the range 0.74 to 2.25. According to Gupta et al.

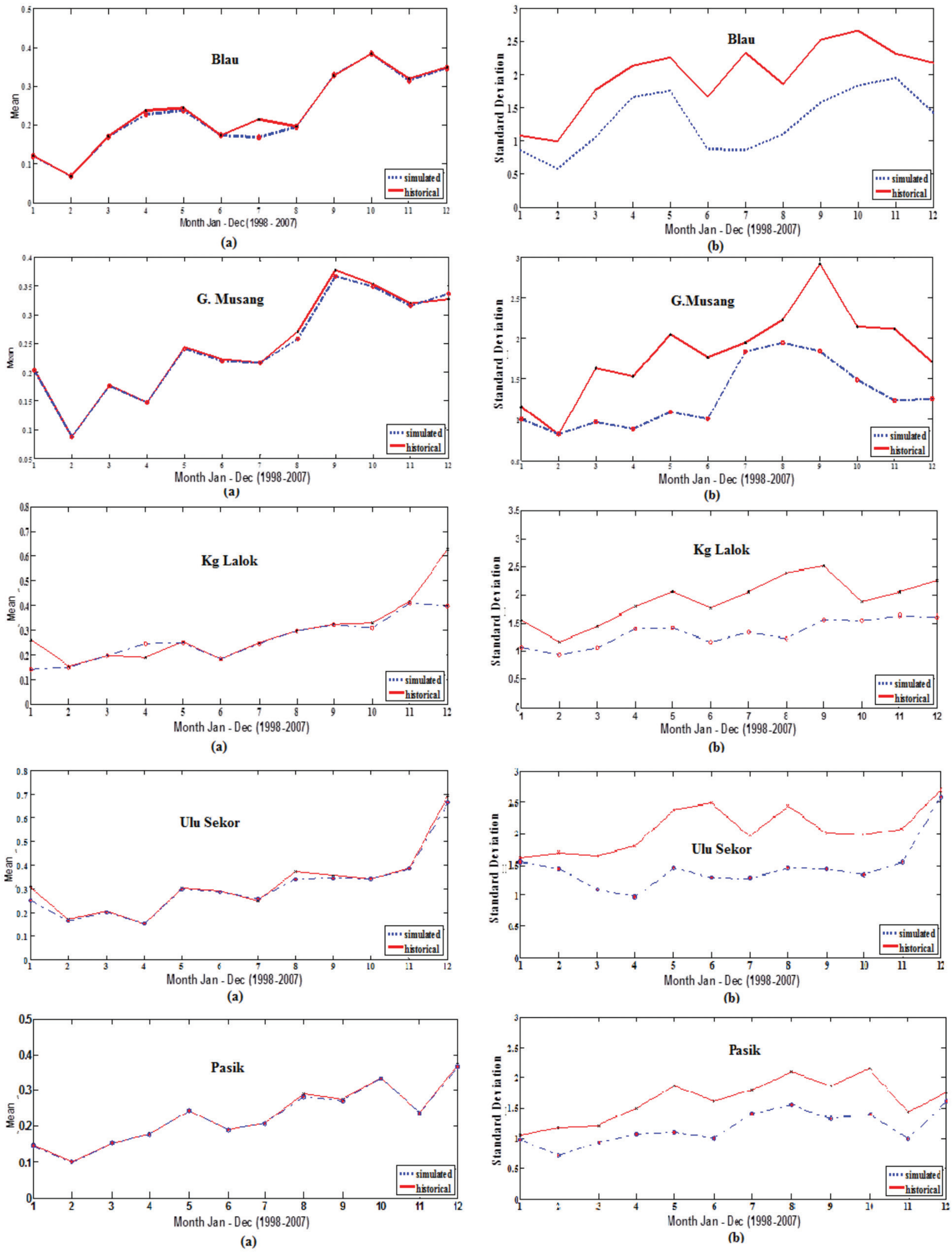

FIGURE 2. Comparison of mean (on the left) and standard deviation (on the right) of the disaggregated and historical hourly rainfall for the selected stations in Kelantan

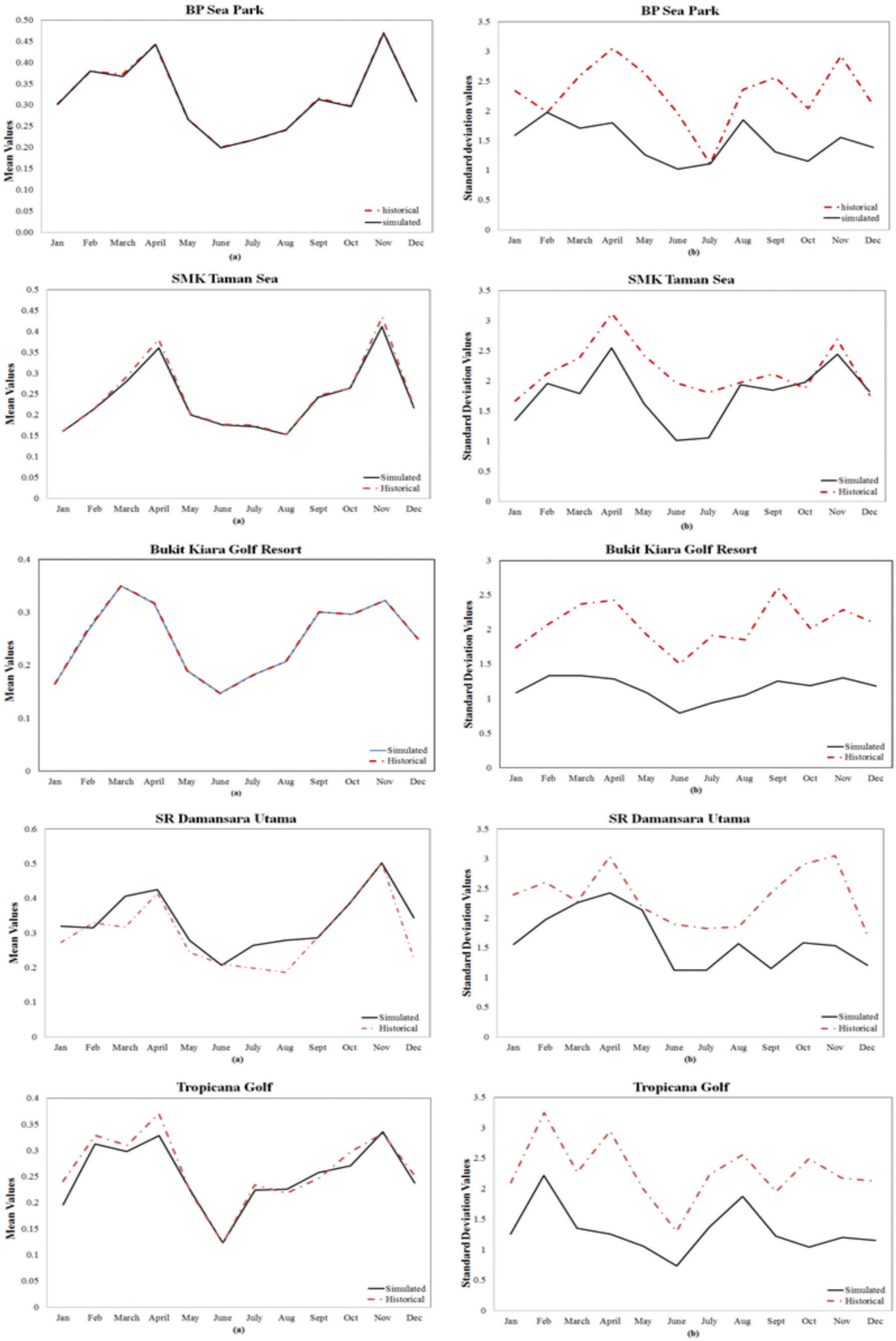

FIGURE 3. Comparison of means (on the left) and standard deviations (on the right) of disaggregated and historical hourly rainfall for the selected stations in Damansara

TABLE 2. Distribution of selected rainfall stations for each season

Areas	Season	Distribution				
		Generalized Pareto (GP)	Weibull	Log Pearson 3	Gamma	Beta
Damansara	NE monsoon	14%	44%	8%	28%	6%
	SW monsoon	2%	40%	30%	20%	8%
	Inter-Monsoon	15%	40%	25%	20%	0
Kelantan	NE monsoon	7.5%	45%	32.5%	15%	0
	SW monsoon	0	62.5%	31.25%	6.25%	0
	Inter-Monsoon	0	55%	17.5%	15%	12.5%

(1999), in order to achieve good simulation result the weighted of error should be close to 0 (zero) because the values of 0 (zero) indicated that as a perfect fit or indicated as accurate model simulation. The less sum weighted error generated in the dry season and the BLRP model perform better than high sum weighted error which mostly generated in the wet season. This happened because during the wet months, the amount of rainfall fluctuated from the rainstorm and suddenly became lower, or just from heavy rain to less rain or vice versa. This caused many data anomalies discovered during the wet months and resulted in high sum weighted errors. As the rainfall during dry months was not very volatile, this resulted in fewer data anomalies and the sums of weighted errors were also not too high. Hence, the BLRP model applied in the Hyetos could perform better in dry months.

Other than that, BLRP model produced much lower standard deviation compared to the historical series. The standard deviation provides measure of the degree of dispersion of the data from the mean. A large standard deviation than mean indicates that the data were spread out over a large range of values. On the other hand a small standard deviation indicates that the data were clustered closely around the mean. The results showed that most of the standard deviations were higher than the means but the trends of the simulated and the historical data were quite similar and some of them closely match. For rainfall station where BLRP model tend to overestimate the historical mean as described earlier also has deviated for the standard deviation value. The result of standard deviation for those stations did not follow the historical pattern.

Referring to the mean and standard deviation graph as presented in Figures 2, 3 and in discussion section earlier, it shows that the BLRP model were not fully applied and did not perform well. The failure of the BLRP model coupled with Hyetos presentation to perform well might be a real limitation of the model when applied in tropical region. Rainfalls in the tropics were mainly convective that characterized by sudden burst, very high intensities and short duration. The intensities also fluctuate but decrease rapidly as the storm progress. However, the result of this study showed that the BLRP model coupled with the Hyetos could fulfill the objective to disaggregate data from long resolution into short time resolution. In addition, It also has a good ability to preserve the statistical properties of the rainfall even when the performance was not too good.

CONCLUSION AND RECOMMENDATION

This paper demonstrates the using of Bartlett Lewis Rectangular Pulse (BLRP) model to disaggregate the rainfall data in the area affected by inter-monsoon and monsoon period in Central and East region of Peninsular Malaysia; Damansara and Kelantan. The model was used to disaggregate daily rainfall into hourly rainfall using 10 years data. Four statistic properties for monthly hourly rainfall data were used to estimate the model parameters. The problem of parameter stability or sensitivity with respect to the choice of the four statistics for parameter estimates was addressed through the estimating parameters from a large number of statistic properties that have to be calculated.

From the statistic descriptive comparison results, it was found that the mean of the disaggregated results can match the historical mean. For the standard deviation, the disaggregated results were lower than the historical data but the trend was there. Therefore, in general the BLRP model has good ability to disaggregate daily rainfall into hourly rainfall in the two selected areas even though those two areas were affected by monsoon and inter-monsoon. It is compelling to test the BLRP model for different region in Malaysia to ensure consistency of results or do some improvement for statistical model such as for parameter estimating, data clustering or using other time series model. We also aim to compare the model performance with other established rainfall disaggregation models such as Artificial Neural Network (ANN) model.

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TABLE 3. Example of statistical properties and the estimated parameters for rainfall station SMK Taman Sea

Statistical properties	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1 h												
Mean	0.16	0.22	0.29	0.38	0.2	0.18	0.18	0.15	0.25	0.26	0.43	0.22
Variance	2.78	4.51	5.69	9.75	5.88	3.88	3.27	3.9	4.48	3.52	7.22	3.12
Lag1 autocovariance	0.06	1.19	1.51	1.7	1.92	0.56	0.7	0.76	1.15	0.9	1.58	0.7
Proportion dry	0.97	0.96	0.95	0.94	0.97	0.97	0.97	0.97	0.95	0.94	0.92	0.95
24 h												
Mean	4.68	5.84	7.66	10.36	5.41	5.19	4.94	4.24	6.43	7.34	11.07	5.62
Variance	130.86	184.43	260.55	370.75	283.1	146.49	124.8	160.36	180.26	156.51	264.53	136.6
Lag1 autocovariance	3.24	1.6	5.6	-5.87	24.35	8.53	7.64	-8.77	27.96	14.8	32.94	11.94
Proportion dry	0.63	0.54	0.46	0.4	0.63	0.59	0.61	0.63	0.51	0.43	0.31	0.45
48 h												
Mean	7.79	10.4	14.13	18.31	9.8	8.53	8.51	7.42	11.83	12.72	20.87	10.19
Variance	251.79	372.88	496.5	699.34	588.07	240.84	242.9	274.72	383.87	314.56	554.72	246.03
Lag1 autocovariance	7.11	18.53	55.46	-56.15	91.11	39.95	6.95	30.24	77.98	-3.74	155.21	13.44
Proportion dry	0.55	0.45	0.29	0.23	0.49	0.47	0.51	0.47	0.39	0.25	0.21	0.35
Parameter estimates												
Lamda (λ)	3.81	0.35	0.55	0.71	0.19	0.58	0.56	0.24	0.46	0.74	0.95	0.53
Kappa ($\varkappa = \beta/\eta$)	1.00E-07	99	99	99	89.96	1.00E-07	19.93	99	99	99	99	99
Phi ($\phi = \gamma/\eta$)	99	9.48	32.08	8.33	43.41	99	99	6.85	11.24	12.99	10.8	14.87
Alpha (α)	99	77.31	32.22	99	12.98	14.14	16.26	99	76.28	99	92.68	78.82
Sum of weighted squared error	2.83	1.98	2.03	2.47	2.07	2.14	1.91	2.31	2.22	2.37	2.21	2.19

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