



UNIVERSITI PUTRA MALAYSIA

***DEVELOPMENT OF A STOCHASTIC RAINFALL GENERATOR AND ITS
UNCERTAINTY QUANTIFICATION FOR THE KELANTAN RIVER BASIN,
MALAYSIA***

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BASIN, MALAYSIA**

By

NG JING LIN

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia,
in Fulfilment of the Requirements for the Degree of Doctor of Philosophy**

October 2017

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Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Stochastic simulation of rainfall is challenging due to incomplete rainfall series and high variability of rainfall. Furthermore, the quantification of uncertainty is often ignored in the current practice of hydrological modelling and lead to inappropriate decisions. Accordingly, this research intends to develop a stochastic rainfall generator, consisting of rainfall occurrence models and rainfall amount models and perform its uncertainty quantification for the Kelantan River Basin, Malaysia. Seventeen rainfall stations with rainfall series within the period from 1954 to 2013 were selected.

The first until fifth order Markov chains were utilized to simulate the rainfall occurrences. The results showed that the first until fourth order Markov chains gave similarly good performances in simulating the mean, frequency distribution, standard deviation and extreme values of wet spells, dry spells, wet day frequency and dry day frequency, while the fifth order Markov chain gave poor results. The first until fourth order Markov chains passed most of the Wilcoxon rank sum (82.4 – 100% passing rate), Kolmogorov-Smirnov (K-S) (70.6 – 100% passing rate) and squared ranks tests (70.6 – 100% passing rate). They reproduced lower values of mean absolute percentage error (MAPE) for the mean (0.4 – 5.2%), standard deviation (1.4 – 7.5%) and extreme values (2.3 – 16.4%). However, the results of the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) suggested that the monthly, seasonal and yearly rainfall occurrences were simulated fairly using the second (35.3 – 82.4% selection rate), fourth (58.8 – 100% selection rate) and third (100% selection rate) order Markov chains.

The exponential, gamma, log-normal, skew normal, mixed exponential and generalized Pareto distributions were used to simulate the rainfall amounts. It was found that all the distributions were capable of simulating the mean, frequency

distribution and standard deviation of the rainfall amounts by reproducing high passing rates of the Wilcoxon rank sum (100%), K-S (86.8 – 100%) and squared ranks tests (88.2 – 100%). They obtained relatively low values of MAPE for the mean (2.5 – 4.7%), standard deviation (2.8 – 10.4%) of rainfall amounts and low values of variance overdispersion (-7.9 – -1.7%). For the extreme rainfall amounts, the exponential, gamma, log-normal and mixed exponential distributions were consistently better than the skew normal and generalized Pareto distributions. The log-normal distribution (41.2 – 100% selection rate) was chosen as the best fitting distribution based on the results of AIC and BIC.

The uncertainty quantification was performed on the synthetic rainfall series simulated from the best formulations for the monthly, seasonal and yearly rainfall series. The uncertainty of the rainfall depth duration frequency (DDF) curves was quantified using the 95% confidence interval. The results showed that there was uncertainty ranged from -10.0% to 12.4% for return periods up to 100 years in the DDF curves. The uncertainty increases with the return period.

Overall, the stochastic rainfall generator is considered a convenient tool to simulate the rainfall characteristics over the Kelantan River Basin and the uncertainty quantification framework is straightforward and useful. The outcomes of this study can be used for flood control, climate change assessment, hydrological modelling and decision making.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PEMBANGUNAN PENJANA HUJAN STOKASTIK DAN KUANTIFIKASI KETIDAKPASTIAN UNTUK LEMBANGAN SUNGAI KELANTAN

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Simulasi stokastik hujan adalah mencabar disebabkan oleh siri hujan yang tidak lengkap dan kebolehubahan hujan yang tinggi. Tambahan pula, kuantifikasi ketidakpastian sering diabaikan dalam amalan semasa pemodelan hidrologi dan menghasilkan keputusan yang tidak sesuai. Oleh demikian, kajian ini bertujuan untuk membangunkan penjana hujan stokastik yang terdiri daripada model kejadian hujan dan model jumlah hujan dan melaksanakan kuantifikasi ketidakpastian untuk Lembangan Sungai Kelantan di Malaysia. Tujuh belas stesen hujan dengan siri hujan dari tempoh 1954 - 2013 telah dipilih dalam kajian ini.

Rantaian Markov dari perintah pertama sehingga kelima telah digunakan untuk mensimulasikan kejadian hujan. Hasil kajian menunjukkan bahawa perintah rantaian Markov pertama sehingga keempat memberikan keputusan yang sama baik dalam mensimulasikan min, taburan kekerapan, sisihan piawai dan nilai ekstrem rentetan hari basah, rentetan hari kering, kekerapan hari basah dan kekerapan hari kering, manakala perintah kelima rantaian Markov memberikan keputusan yang tidak memuaskan. Perintah rantaian Markov pertama sehingga keempat lulus sebahagian besar daripada uji jumlah peringkat Wilcoxon (kadar kelulusan 82.4 – 100%), Kolmogorov-Smirnov (K-S) (kadar kelulusan 70.6 – 100%) dan ujian pangkat dua (kadar kelulusan 70.6 – 100%). Mereka menghasilkan semula nilai-nilai peratusan ralat min mutlak yang lebih rendah (MAPE) untuk min (0.4 – 5.2%), sisihan piawai (1.4 – 7.5%) dan nilai-nilai ekstrem (2.3 – 16.4%). Walau bagaimanapun, keputusan daripada kriteria maklumat Akaike (AIC) dan kriteria maklumat Bayesian (BIC) mencadangkan bahawa kejadian hujan bulanan, bermusim dan tahunan telah disimulasikan agak memuaskan dengan menggunakan perintah rantaian Markov kedua (kadar pemilihan 35.3 – 82.4%), keempat (kadar pemilihan 58.8 – 100 %) dan ketiga (kadar pemilihan 100%).

Taburan eksponen, gamma, log-normal, kemiringan kurva normal, eksponen bercampur dan Pareto umum telah digunakan untuk mensimulasikan jumlah hujan. Kajian menunjukkan bahawa semua taburan mampu mensimulasikan min, taburan kekerapan dan sisihan piawai jumlah hujan dengan menghasilkan semula kadar kelulusan uji jumlah peringkat Wilcoxon yang tinggi (100%), K-S (86.8 – 100%) dan ujian pangkat dua (88.2 – 100%). Mereka menghasilkan nilai MAPE yang agak rendah untuk min (2.5 – 4.7%), sisihan piawai (2.8 – 10.4%) daripada jumlah hujan dan varians overdispersion (-7.9 – -1.7%). Untuk jumlah hujan yang ekstrem, taburan eksponen, gamma, log-normal dan eksponen bercampur adalah lebih baik daripada taburan kemiringan kurva normal dan Pareto umum. Taburan log-normal (kadar pemilihan 41.2 – 100%) telah dipilih sebagai taburan penyesuaian yang terbaik berdasarkan keputusan AIC dan BIC.

Kuantifikasi ketidaktentuan telah dilakukan pada siri hujan sintetik yang disimulasikan daripada formula yang terbaik untuk siri hujan bulanan, bermusim dan tahunan. Ketidaktentuan daripada lengkung kekerapan tempoh kedalaman hujan (DDF) telah diquantifikasikan dengan menggunakan 95% selang keyakinan. Hasil kajian menunjukkan bahawa ketidaktentuan adalah dari antara -10.0% dengan 12.4% untuk tempoh pulangan sehingga 100 tahun dalam lengkung DDF. Ini menunjukkan bahawa ketidaktentuan meningkat dengan tempoh pulangan.

Secara keseluruhan, penjana hujan stokastik dianggap sebagai satu alat yang mudah untuk mensimulasikan ciri-ciri hujan di Lembangan Sungai Kelantan dan rangka kerja kuantifikasi ketidaktentuan adalah jelas dan berguna. Hasil kajian ini boleh digunakan untuk kawalan banjir, penilaian perubahan iklim, pemodelan hidrologi dan membuat keputusan.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

AIC	Akaike information criterion
ANFIS	Adaptive network-based fuzzy inference system
ANN	Artificial neural networks
BIC	Bayesian information criterion
BLRP	Barlett-Lewis Rectangular Pulses
BRT	Buishand range test
DDF	Depth duration frequency
DSC	Direct Search Complex
FFT	Fast Fourier Transform
DYNIA	Dynamic identifiability analysis
GCM	Global climate models
GEV	Generalized extreme value
GLM	Generalized linear models
GLUE	Generalized Likelihood Uncertainty Estimation
IDF	Intensity duration frequency
ITM	Inter-monsoon
K-NN	K-nearest neighbors
K-S	Kolmogorov-Smirnov
LARS-WG	Long Ashton Research Station weather generator
MA	Moving average
MAPE	Mean absolute percentage error
MCMC	Markov Chain Monte Carlo
MLE	Maximum likelihood estimation

NEM	Northeast monsoon
NSRP	Neyman-Scott Rectangular Pulses
OBL	Original Barlett-Lewis
PET	Pettitt test
RCM	Regional climate models
SDSM	Statistical downscaling model
SNHT	Standard Normal Homogeneity test
SSA	Singular spectrum analysis
SWM	Southwest monsoon
VNRT	Von Neumann ratio test

LIST OF NOTATIONS

$\hat{\beta}_{gls}$	Generalized least squares estimators
$\hat{\beta}_{ols}$	Ordinary least squares estimator
$\log L$	Log-likelihood function
\hat{F}	Proportion of tested variables
\hat{P}	Conditional relative frequency
P_m	Probability weighted moment
P_r	Transitional probability of Markov chain
T_0	Test statistic of SNHT
T_{KS}	Test statistic of K-S test
T_{OW}	Owen's T function
T_k	Statistic of homogeneity tests
T_s	Test statistic of squared ranks test
T_w	Test statistic of Wilcoxon rank sum test
X'	Original rainfall samples
X^*	Stochastic rainfall estimates
X_E	Maximum values of PET
X_M	Matrix of full rank
X_t	Rainfall state
\bar{x}	Mean
x_c	Contraction point
x_e	Expansion point
x_r	Reflection point

x_s	Shrunk point
x_z	Quantile function of GEV distribution
δ_c	Contraction coefficient
δ_e	Expansion coefficient
δ_p	Reflection coefficient
δ_s	Shrink coefficient
ω_0	Fundamental frequency
hrs	Hours
ℓ	Sample L-moments
Φ	Cumulative density function of the normal distribution
A	Measure of skewness
D	Rainfall duration
$F(x)$	Cumulative density function
G	Frequency domain component
L	Likelihood function
Q	Log-likelihoods of Markov chains
R	Rescaled adjusted range
S	State space of the values 0 and 1
T	Return period
V	Test statistic of VNRT
W	Sum of ranks
a, b	Real numbers
c	General complex number
e	Random error

$f(x)$	Probability density function
g	Time domain component
j	Imaginary unit
k	Number of years, number of parameters
m	Order of the Markov model
n	Observed frequency of the transition counts, sample size, number of observations, total length of data series
nn	Size of stochastic replication
p	Mixing probability
q	Weather state
r	Ranks of the tested variables
rr	Rate parameter
s	Number of states
ss	Adjusted partial sums
t	Days
x	Rainfall series to be tested, daily rainfall amount
z	Cumulative probability of GEV distribution
Γ	Gamma function
β	Regression coefficient
γ	Shape parameter
ε	Tolerance level
θ	Phase
λ	Vector of GEV parameters
μ	Location parameter

ξ	Scale parameter
ρ	Magnitude
σ	Standard deviation
ϕ	Standard normal probability density function of the normal distribution



CHAPTER 1

INTRODUCTION

1.1 Research background

Rainfall is a highly significant piece of hydrological data that initiates the whole chain of hydrological events occurring in river basins and watersheds. The rainfall occurrence and rainfall amounts have great influences on the hydrological cycle and environment. The prolong periods of intense rainfall occurrence can cause flooding that can lead to destruction of properties and loss of lives. On the other hand, the continuous dry weather condition with no rain can cause the rivers and dams to dry up, affecting the welfare and the livelihoods of people. Therefore, the probability of rainfall occurrence and the distribution of rainfall events are important for analyzing and understanding the hydrological responses in the system.

Stochastic rainfall generators are stochastic simulation tools used to simulate synthetic rainfall series at a particular location that are statistically consistent with the observed rainfall series (Lee, 2016; Chen et al., 2015; Kenabatho et al., 2012). They are not weather forecasting models that rely on initial conditions and numerically integrate the partial differential equation. Specifically, the stochastic rainfall outputs are not associated with the duplications of weather at a specific real dates either for the past or future. Rather, they are statistical and random representations of the observed rainfall series and it is expected that they can closely mimic the statistical properties of the present day condition. The stochastic modelling of rainfall series is based on a stochastic process where the sequences of random numbers simulated from computer algorithms are transformed into sequences of synthetic data series. One of the main advantages of the stochastic rainfall generator is that the long and complete sequences of rainfall series can be generated under limited availability of rainfall series. Therefore, the stochastic rainfall generators are used frequently in a wide range of fields, such as water resources management, climate change assessment, flood control, drought forecasting and hydrological modelling.

The modelling procedures of any hydrological models are exposed to uncertainty. The uncertainty of the models is inherent due to possible errors and imperfections that arise beyond human control. Uncertainty refers to a state of imperfect knowledge where it is difficult to represent the process and outcome of a particular system. In general, the measurements or the estimates of any model will not be perfectly accurate. Errors in the measurement process, inappropriate parameter estimation method and errors in the data used for modelling procedures are the main sources of uncertainty (Zahmatkesh et al., 2015; Chandra et al., 2015; Gronewold et al., 2013). Therefore, the uncertainty quantification is performed to examine the potential source of errors in a process and to identify the uncertainty bounds of the relevant variables.

It is now being broadly recognized that the stochastic simulation of rainfall series and the proper investigation of uncertainty are important for the purpose of research works and operational planning. The tremendous advance of computational power and the rapid growth of the hydrological field have improved the understanding of the hydrologic phenomena and permit more advanced models to be developed. As with any model, it is essential to examine the model structure depending on the understanding of the hydrologic phenomena and the computational ability. This helps to increase the accuracy and reliability of simulation procedures.

1.2 Problem statement

The availability of long and complete rainfall series is essential in hydrological modelling. It is noted that rainfall series of a minimum 20–25 years are desirable for rainfall modelling to allow a good representation of the rainfall characteristics (Jones et al., 2016; Fodor et al., 2013). However, in many regions, the rainfall series are often too short, possess considerable amounts of missing or simply unavailable values (Bárdossy & Pegram, 2014; Lo Presti et al., 2010; McKague et al., 2005). In Malaysia, rainfall stations with particularly long observed rainfall series are very scarce. The current available observed weather series are usually inconsistent and incomplete due to some systematic and random errors or missing values. The reliability and accuracy of the results of the hydrological modelling could be affected by inputting the short and incomplete rainfall series to the hydrological models. This creates difficulty for the hydrologists and engineers to carry out their research and operational analysis. Therefore, it is very useful to employ a stochastic rainfall generator to simulate long and complete synthetic rainfall series based on the statistical characteristics of the observed rainfall series.

Although Malaysia is known to be one of the countries with low risk of natural disasters, uncontrolled urban developments, poor drainage, intense monsoon rain storms and heavy convection rainfall have caused floods to become a significant natural hazard in Malaysia (Hai et al., 2017; Perera & Lahat, 2015; Ariff et al., 2012). Flooding in Malaysia usually occurs during the monsoon season and can last for a month. This issue has raised considerable concern to analyze the characteristics of rainfall occurrence and rainfall amount to understand the responses of hydrological cycle and cope with the flood hazards and other natural disasters. The wet day rainfall amount is simulated based on the rainfall occurrence. The rainfall occurrence and rainfall amount are the crucial factors of the flood events as they affect the infiltration, flow accumulation and rate of runoff directly. Therefore, the formulation of the rainfall occurrence models and rainfall amount models is crucial to study the rainfall behavior and consequently aid in flood mitigation and hydrological modelling.

Many of the stochastic rainfall generators that had been developed are site-specific where the formulation of the rainfall occurrence model and rainfall amount model is carried out based on the condition of that particular region. The existing stochastic weather generators WGEN (Richardson 1981) and WeaGETS (Chen et al., 2012) were developed and applied in diverse climate regions, United States and Canada,

respectively. Unlike other countries that experience spring, summer, autumn and winter, the study area of this research, Kelantan River Basin is located near to the equator which receives abundant rainfall throughout the year. Therefore, there is a need to formulate and develop a stochastic rainfall generator based on the rainfall characteristics of this specific study area. The presence of different climatic conditions and geographical factors in each study area also further adds to the interesting variety of findings and results. Therefore, a thorough model evaluation procedure should be performed to examine the capability of the rainfall occurrence model and the accompanying rainfall amount model in reproducing the characteristics of rainfall.

Malaysia has a tropical climate and experiences seasonal variations which are dominated by monsoon seasons. The definition of seasonal in some of the studies refers to spring, summer, autumn and winter, which are different from the monsoon seasons in a tropical area like Malaysia. The monsoon seasons of Malaysia consist of the southwest monsoon (SWM), the northeast monsoon (NEM), and the two inter-monsoon seasons (ITM). The rainfall characteristics for different monsoon seasons are different. For example, SWM implies drier and warmer climate conditions. The NEM is the major rainy season in Malaysia that brings heavy rains and strong winds. Although a considerable amount of literature has been published on stochastic rainfall studies in tropical region (Jones & Thornton, 2013; Cowden et al., 2008; Tingem et al., 2007; Jones & Thornton, 2000; Jones & Thornton, 1993), those studies were carried out based on the overall basis where the monsoon seasonal components are not included in the formulation and validation process. Specifically, most of the stochastic rainfall studies in Malaysia are conducted on daily, monthly and yearly basis (Dlamini et al., 2015; Hassan & Harun, 2013; Shui & Haque, 2004). It would be interesting to carry out the model evaluation procedure and the selection of the best rainfall model by considering the monsoon seasons in Malaysia.

In general, there is no single model being deemed as ideal or perfect for use. By definition, the stochastic rainfall generator simulates synthetic rainfall series (output) based on parameters generated from the observed rainfall series (input). No matter how well the model is formulated, there is always an inconsistency between the model output and the corresponding model input. Uncertainty is equally as vital as the estimates themselves in any hydrological simulations. However, current stochastic rainfall studies are putting more emphasis on assessing the model performance where the quantification of uncertainty is rarely presented (Lee, 2016; Li et al., 2014; Abas et al., 2014; Kenabatho et al., 2012). Lacking of the uncertainty information may lead to inappropriate predictions in the hydrological models and consequently pose much higher risk of failures in project design and implementation. This highlighted an urgent need to include the quantification of uncertainty as part of any hydrological simulation procedures. Accordingly, this study attempts to address the aforementioned gaps by developing a stochastic rainfall generator incorporating the quantification of uncertainty.

1.3 Objectives

The aim of this study is to develop a stochastic rainfall generator, which consists of rainfall occurrence models and rainfall amount models with its uncertainty quantification for Kelantan River Basin. The specific objectives are as follow:

1. To formulate the rainfall occurrence models using Markov chains of different orders;
2. To evaluate the performances of the rainfall occurrence models through monthly, seasonal and yearly rainfall series;
3. To formulate the rainfall amount models based on the selected rainfall occurrence models using different probability distributions;
4. To determine the best rainfall amount models for the monthly, seasonal and yearly rainfall series;
5. To quantify the uncertainty in rainfall depth duration frequency (DDF) curves associated with the synthetic extreme rainfall series.

1.4 Scope of study and thesis outline

The scope of this research covers two model frameworks, and they are developing a parametric stochastic rainfall generator and quantifying its uncertainty specifically for the Kelantan River Basin, Malaysia. The former framework is directed towards formulating an efficient stochastic rainfall simulation procedure which is able to produce long synthetic rainfall series that have similar statistical characteristics as the observed rainfall series for any duration as required. The proposed stochastic rainfall generator consists of two main components, which are the rainfall occurrence models and rainfall amount models. The research works will be focused on simulating rainfall occurrences using five Markov chain models, simulating rainfall amounts using six rainfall amount models and correcting low-frequency variability using spectral correction method. Ultimately, the stochastic rainfall generator is evaluated for its ability to simulate the synthetic rainfall series. The latter framework simulates synthetic rainfall series using the best formulations from the former model framework and assesses the parameter uncertainty features of rainfall DDF curves. The objectives of this research have been listed with respect to the research problems and the thesis is organized as follows.

Chapter 2 provides the introduction of rainfall modelling and gives a brief description of kinds of rainfall and types of rainfall modelling. An overview of stochastic rainfall generator is given. The important aspects of stochastic rainfall generator, such as principles, purposes, classification and challenges are explained. The types of stochastic rainfall generator are reviewed. Their strengths and limitations are discussed to allow an appropriate model for this research to be selected. The descriptions of the notion, classification and reduction of uncertainty are discussed in the context of hydrological modelling. It also discusses the evolution of the uncertainty quantification approaches and reviews the uncertainty quantification of rainfall DDF curves.

Chapter 3 gives a description of the study area, data sets used for simulation and the procedures of data quality control. The methodological framework of stochastic rainfall generator, which consists of rainfall occurrence simulation, rainfall amount simulation and correction of low-frequency variability is formulated, presented and explained. The evaluation of model performance by using various statistical tests and graphical analysis is discussed. This chapter also thoroughly explains the steps of stochastic replication of synthetic rainfall series using the best formulations and the uncertainty quantification of rainfall DDF curves.

Chapter 4 begins with presenting the results of homogeneity tests. Then, it evaluates and discusses the performance of stochastic rainfall generator in simulating the statistical properties of rainfall occurrences and rainfall amounts. The best rainfall occurrence model and rainfall amount model are selected. The derivation of the rainfall DDF curves is discussed and the results of uncertainty quantification are presented. All the results are accompanied by in depth discussions and descriptions in accordance to the significance of findings.

Chapter 5 presents the summary and main conclusions of the research. The contributions and significant findings of this research are also discussed. Finally, the recommendations for further work are presented.

1.5 Significance of study

The major contribution of this study is the development of a simple yet effective stochastic rainfall generator for the simulation of rainfall occurrences and rainfall amounts in a tropical area, specifically for the Kelantan River Basin, Malaysia. The stochastic rainfall generator is able to generate an infinite length of synthetic rainfall series for different research works and operations. The stochastic generation of rainfall series can be used to complement the inadequate length of rainfall records. This is especially advantageous for Malaysia as the rainfall stations with available complete rainfall series for a long duration are limited. The stochastic rainfall generator has been validated thoroughly, thus the research outcomes can be used as the foundation bases to improve the conceptualization and specifications of the stochastic rainfall studies. Also, through the simulation results, the developed stochastic rainfall generator presented its significant contribution in providing important information about the statistics and characteristics of monthly, seasonal and yearly rainfall series derived from the aggregation of synthetic daily time series. The major concern of Kelantan River Basin is monsoon flood, which is characterized by heavy and long duration rainfall. For the flood control, long and complete monthly, seasonal and rainfall series are required to calibrate the flood forecasting model and the flood control system. They are used as important inputs to simulate the hydrographs and predict runoff for the flood events. Besides, the time series of the monthly, seasonal and yearly rainfall series are necessary for the climate change assessment and optimum planning, designing and management of water resources engineering, such as the irrigation systems, reservoir operation and urban water supply.

In addition, the significance of this study is the quantification of the uncertainty of rainfall DDF curves based on the replications of 10^4 synthetic rainfall series generated solely from the stochastic rainfall generator so as to become the novelty of this study. A comprehensive uncertainty assessment has been performed to obtain the uncertainty bounds of extreme rainfall series, which is often neglected or overlooked during practice. The results of this study can contribute to a better understanding of the impact of uncertainty in hydrological process. Also, the quantification of uncertainty can benefit the decision makers to react wisely to the uncertainty arise from the model output and make a reliable decision.



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LIST OF PUBLICATIONS

Journals Published/ Accepted

- Ng, J. L., Abd Aziz, S., Huang, Y. F., Wayayok, A., & Rowshon, M. D. (2015). Homogeneity analysis of rainfall in Kelantan, Malaysia. *Jurnal Teknologi*, 76(15), 1–6. (Q3, Indexed by SCOPUS)
- Ng, J. L., Abd Aziz, S., Huang, Y. F., Wayayok, A., & Rowshon, M. K. (2016). Stochastic modelling of seasonal and yearly rainfalls with low-frequency variability. *Stochastic Environmental Research and Risk Assessment*, 1–19. (Q1, IF=2.629, Indexed by SCOPUS & ISI)
- Ng, J. L., Abd Aziz, S., Huang, Y. F., Wayayok, A., & Rowshon, M. K. (2017). Generation of stochastic precipitation model for tropical climate. *Theoretical and Applied Climatology*, 1–21. (Q2, IF=2.64, Indexed by SCOPUS & ISI)

Journals Submitted

- Ng, J. L., Abd Aziz, S., Huang, Y. F., Mirzaei, M., Wayayok, A., & Rowshon, M. D. Uncertainty analysis of rainfall depth duration frequency curves using bootstrap resampling technique. *Journal of Earth System Science*.

Conference papers presented

- Ng, J. L., Abd Aziz, S., Huang, Y. F., Wayayok, A., & Rowshon, M. D. (2015). Homogeneity analysis of rainfall in Kelantan, Malaysia. PAWEES-INWEPF Joint International Conference 2015. Kuala Lumpur. 19-21 August 2015.
- Ng, J. L., Abd Aziz, S., Huang, Y. F., Wayayok, A., & Rowshon, M. D. (2016). Analysis of annual maximum rainfall in Kelantan, Malaysia. 3rd International Conference on Agricultural and Food Engineering (CAFEi2016). Kuala Lumpur. 23-25 August 2016.



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