STREAMFLOW ESTIMATION AT UNGAUGED SITE USING WAVELET GROUP METHOD OF DATA HANDLING IN PENINSULAR MALAYSIA

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To my beloved father and mother and family

Badyalina b. Badron, Sae`di Bt Reff, Reff, Doremon, Haikal, Firdaus,

Rezaaomi Reff, Zamani, Asnal, Bahar, Hadzimah, Harith Shah.

To my supportive friends

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ABSTRACT

This study investigates the ability of wavelet group method (WGM) of data handling conjunction model in the estimation of flood quantiles in ungauged sites in Peninsular Malaysia. The conjunction method was obtained by combining two methods, discrete wavelet transform and group method of data handling. Comparison between the WGM model, group method (GM) of data handling model, wavelet regression (WR) model and linear regression (LR) model were done. To assess the effectiveness of this model, 70 catchments in the province of Peninsular Malaysia were used as case studies. The performance of WGM model was compared with the conventional LR, GM and WR models using various statistical measures such as the mean absolute error, root mean square error and Nash-Sutcliffe coefficient of efficiency. Jackknife procedure was required for the evaluation of the performance of the four approaches. The jackknife procedure was needed to simulate the ungauged sites. The results of the comparison indicate that the WGM model was more accurate and perform better than the traditional LR, GM and WR models. Thus, WGM model is a promising new method for estimation of flood quantiles in ungauged sites.

ABSTRAK

Kajian ini menyelidik keupayaan model gabungan kaedah berkumpulan wavelet (WGM) untuk menangani data dalam anggaran kuantil banjir di stesen tiada data di Semenanjung Malaysia. Kaedah ini diperoleh dengan menggabungkan dua kaedah yang berlainan iaitu jelmaan wavelet diskrit (DWT) dan kaedah berkumpulan (GM) bagi menangani data. Kaedah gabungan ini kemudiannya diuji dengan menbandingkan model tradisional iaitu model GM, model regresi wavelet (WR) dan model regresi linear (LR). Untuk menilai keberkesanan model ini, 70 kawasan tadahan di wilayah Semenanjung Malaysia telah digunakan sebagai kajian kes. Prestasi model WGM dibandingkan dengan model konvensional LR, model GM dan model WR dengan menggunakan pelbagai ukuran statistik iaitu ralat mutlak, ralat kuasa dua dan pekali Nash-Sutcliffe bagi kecekapan. Prosedur Jackknife diperlukan untuk menilai prestasi bagi empat pendekatan. Prosedur Jackknife diperlukan untuk membuat simulasi stesen yang tiada data. Keputusan perbandingan menunjukkan bahawa model WGM adalah lebih tepat dan lebih baik daripada model tradisional LR, model GM dan model WR. Maka, model WGM adalah satu kaedah baharu yang menjanjikan hasil yang baik untuk anggaran kuantil banjir di tapak stesen tiada data.

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LIST OF SYMBOLS

α, σ	-	scale parameter
ξ, μ	-	location parameter
k	-	shape parameter
$f(x)$	-	probability density function
$F(x)$	-	cumulative distribution function
$x(F)$	-	quantile function
x_1, x_2, x_3, x_4, x_5		catchment charateristics
F	-	nonexceedance probability
RMSE	-	root mean square error
MAE -		mean absolute error
AD	-	Anderson Darling
GEV	-	generalized extreme value distribution
GLO	-	generalized logistic distribution
GPA	-	generalized pareto distribution
P3	-	Pearson 3 distribution
LN3		three parameter lognormal distributions
LR		linear regression
WR		wavelet regression

WGMDH	wavelet group method of data handling
GMDH	group method of data handling
DID	Department of Irrigation and Drainage
$\alpha_0 A_1^{\alpha_1} A_1^{\alpha_2} \cdots A_2^{\alpha_n} \varepsilon_0$	power function
$\alpha_1, \alpha_2, \ldots, \alpha_n$	model parameters
CE	Nash-Sutcliffe coefficient of efficiency
r^2	correlation coefficient
DWT	discrete wavelet transform
FFA	flood frequency analysis
MLM	maximum likelihood method
PWM	probability weighted moments
KS	Kolmogorov Smirnov
Q_T	flood quantiles with T return period
PD	Partial Description
DWT	Discrete Wavelet Transform
$\psi(t)$	mother of wavelet
$Q(F)$	quantile function

CHAPTER 1

INTRODUCTION

1.1 Background of Study

Flood is one of the most dangerous and recurrent type of natural disasters that occurs in Peninsular Malaysia. Flood event contribute to a lot of damages to properties, infrastructures and even loss of people lives. The basic cause of river flooding is the incidence of heavy rainfalls such as monsoon season or convective, and the resultant large concentration of runoff, which exceeds river capacity. The increase of impermeable area due to rapid development in the urban areas has shortened the time of flow travel into the river.

Flood surely cannot be prevented from occurring but human beings can prepare for it. This make a reliable estimation of flood quantiles is important for flood risk assessment project (e.g., dams, spillways, road, and culverts), the safe design of the river system, and it give a closed valuation budget of flood protection project. In order to acquire accurate estimation of flood quantiles, recorded historical time series data of stream flows is required. Long term historical data used for estimation are more reliable compared to short term data and may also reduce risk. However, it often happens that the historical data at-site of interest not always available. Although at-site of interest may have some available data but the data are not enough to describe the catchment flow because of the changes in watershed characteristics such as urbanization (Pandey and Nguyen, 1999). The UK Flood Estimation Handbook (FEH) notes that "many flood estimation problems arise at ungauged sites which there are no flood peak data" (Reed and Robson, 1999).

Mamun et al. (2012) stated that river located in Malaysia is gauged only at a strategic location and other river is usually ungauged. This could become a problem to the developer when development projects are located at ungauged catchments. Typically some site characteristics for the ungauged sites are known. Thus, regionalization is carried out to make the estimation of flow statistics at ungauged sites using physiographic characteristics. Regionalization technique includes fitting a probability distribution to series of flow and then linking the relationship to catchment characteristics (Dawson et al., 2006).

The variables affecting the flood quantile estimation include catchment characteristics (size, slope, shape and storage characteristics of the catchment), storm characteristics (intensity and duration of rainfall events), geomorphologic characteristics (topology, land use patterns, vegetation and soil types that affect the infiltration) and climatic characteristics (temperature, humidity and wind characteristics) (Hosking and Wallis 1997; Jain and Kumar 2007). In relating flood quantile at site of interest to catchment characteristics a power form equations are mostly used (e.g.,Thomas and Benson 1970; Fennessey and Vogel 1990; Mosley and Mckerchar 1993; Pandey and Nguyen, 1999; Seckin, 2011; Mamun, 2012).

At ungauged sites linear regression (LR) model is always reliable to make estimates of flow statistics or flood quantiles (see e.g. Vogel and Kroll, 1990; Shu & Ouarda, 2008; Pandey & Nguyen, 1999). Mohamoud (2008) used step-wise linear regression to identify dominant landscape and climate descriptor from 29 catchments and then developed flow duration curves that managed to forecast flow in nearby ungauged catchments. Mamun et al. (2012) used linear regression of various return periods in ten flood region in Peninsular Malaysia. The performances of LR models in estimating the flood quantiles for ungauged sites have been assessed in Pandey and Nguyen (1999) by applying jackknife procedure in simulating the ungauged sites. Several studies were also carried out by comparing the ability of LR methods with artificial intelligent (AI) based models such as artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) in predicting hydrologic events at ungauged sites by Kashani et al. (2007), Shu and Ouarda (2008) and Seckin (2011).

Group Method of Data Handling (GMDH) has shown a significant improvement by doing a combination with other method. Zadeh et al. (2002) combined GMDH model with singular value decomposition and it has shown that the combined method prediction is better than GMDH itself. Samsudin et al. (2010) proposed combined GMDH with least square support vector machine and the result showed a significant improvement on prediction.

Nowadays, wavelet transform analysis has gained its popularity because it can produce an encouraging outcome in multi-resolution analysis, variations, periodicities, and trends in time series. The wavelet transforms has the ability to decompose a signal into different level of decompositions which allows the required information to be extracted from data. Usually the extracted data gained from wavelet transformation become the input to other model. The result shows a significant improvement in predictions ability of the model applied. Thus, the ability wavelet transform has become a major reason in improving the ability of model applied predictions. The terms combinations are the popular trend nowadays. The reason is the hybridization or combination method improved the performance of traditional model. Kisi (2009) had proposed the combination of the wavelet transform and linear regression since the hybrid model is much easier to interpret for monthly stream flow forecasting.

At the moment, there are a lot of researchers implemented the time series model to estimate flood quantile at ungauged site. Practically, linear regression is the most common method to apply in ungauged site (Shu and Ourda, 2008). GMDH is one of the time series models that have proven that it has good performance in time series forecasting. Therefore, GMDH is applied. By combining GMDH with discrete wavelet transform (DWT), it can improve the performance of GMDH. The jackknife procedure is implemented to simulate ungauged site.

1.2 Background of Problem

Hydrological records of stream flow and rainfall are important for the design, planning, and operation of various water resource projects. However, it often happens that the record length of the available stream flow data at sites of interest is much shorter (partially ungauged) and even worse there may not be any stream flow record (ungauged) at these sites of interest. Typically at any catchment, there are the existences of physiographic, meteorological and hydrological characteristics. There are five variables implemented in this study which are catchment area, elevation, longest drainage path and annual mean total rainfall. Thus, regionalization is carried out to estimates the flow statistics at ungauged site. Patton and Baker (1976) stated that to identify which catchment characteristics that have meaningful statistical relationship with stream flow is a major challenge. In 1987, Department of Irrigation and Drainage (DID 1987) found that generalized extreme value (GEV) is suitable for flood patterns in Malaysia. This finding was over twenty years ago and it need to reconsider again which distribution is actually suitable to represent flood patterns at each catchment in Peninsular Malaysia. Flood frequency analysis is needed to choose the best fitted distributions for each catchment. Five distributions are applied at all catchments which are generalized extreme value (GEV), generalized pareto (GPA), generalized logistic (GLO), pearson 3 (P3) and lognormal (LN3).

Nowadays a lot of time series models are implemented in ungauged site and they prove the estimation of flood quantile is sometimes better than the conventional method which is the linear regression. In simulating the ungauged site problem jackknife procedure is applied. One of the time series models, GMDH model has shown its capability in time series forecasting. GMDH had been applied in many areas such as economy, ecology, medical diagnostics, signal processing, and control systems systems (Oh and Pedrycz, 2002; Nariman-Zadeh et al., 2002; Kondo and Ueno, 2006; Onwubolu, 2009). Although GMDH was a useful statistical tool used in many fields but within hydrology field it is rarely applied especially as a tool to estimate flood quantile at ungauged sites. Discrete wavelet transform (DWT) had been widely used to improve forecasting performance for time series model (Zhang and Dong, 2001; Partal and Cigizoglu, 2008; Elanien and Salama, 2009; Jalal and Kisi, 2010; Kisi and Cimen, 2011; Choi et al., 2011; Davanipoor et al., 2012). The DWT has various level of decomposition level. There are still no methods or techniques to determine which resolution level or decomposition level that is suitable for a specific data. GMDH also show a significant improvement by combining with genetic algorithm and fuzzy logic (Oh et al., 2005; Nariman-Zadeh et al., 2002). This study investigates the accuracy of combination of discrete wavelet transform (DWT) and GMDH model in the estimation flood quantile at ungauged sites. The combination of DWT and GMDH is to improve the estimation of GMDH itself.

1.3 Objectives of Study

In view of the above mentioned problems, this study is intended to propose WGMDH for estimating flood quantile for ungauged sites (no data available) at Peninsular Malaysia. The specific objectives of the study are as follows:

i. Identifying the significant physiographic, meteorological and hydrological characteristics at catchment area that should be used as input variables for flood model.

ii. Selection of a suitable distribution (GPA, GEV, GLO, P3 and LN3) at each station and the best distribution used for various quantile estimation.

iii. To proposed the potential application of GMDH model for flood frequency analysis at ungauged sites

iv. To proposed the potential application of Wavelet Group Method of Data Handling (WGMDH) model for flood frequency analysis at ungauged sites.

v. To proposed the effect of different level decomposition of DWT towards WGMDH and WR model estimations.

vi. To compare the performance between WGMDH model and LR model, Wavelet Regression (WR) model and GMDH model in terms of RMSE, MAE, CE and r^2.

1.4 Scope of Study

In this study, the data were obtained from Department of Irrigation and Drainage, Ministry of Natural Resources and Environment, Malaysia. There were seventy gauged stations selected including all the stations located at Peninsular Malaysia. They are located within latitude 1° N-5° N and longitudes of 100° N-104° N. The stations include wide variety of basins region ranging between 16.3 km2 to 19,000 km2. The period of the flow series for different sites varies from 11 -50 years starting from 1959 – 2009. The gauged stations are needed to simulate the ungauged site. The characteristics of catchment implemented in this study are the catchment area, elevation, longest drainage path, river slope and mean total annual rainfall.

Applying flood frequency analysis, only five distribution are used that is generalized extreme value, generalized pareto, generalized logistic, three parameter pearson and three parameter lognormal. The parameters of these five distributions are estimated using EasyFit software. The best distribution was chosen based on Anderson Darling test and root mean square error (RMSE). The most fitted distribution used to estimate flood quantile for T=10 year, T=50 year and T=100 year.

The DWT, Daubechies wavelet was chose as mother of wavelet and DWT decomposed using Mallat algorithm. In this study two, three, four and five level decomposition of DWT were applied. The DWT is combining with GMDH to produce WGMDH model. LR, WR and GMDH model are used to compare the performance of WGMDH. In simulating ungauged site, jackknife procedure was implemented. There are four numerical indices to evaluate the performance of estimation of flood quantile each model which are the root mean square error (RMSE), mean absolute error (MAE), Nash-Sutcliffe coefficient (CE) and correlation coefficient (r^2) .

1.5 Significance of the Study

This research is to expect that the proposed model WGMDH model is better than GMDH model because WGMDH is an improvement of GMDH model. Thus, WGMDH is applied in estimating flood quantile at ungauged sites. Although GMDH and WGMDH models have never been used to estimate flood quantile at ungauged site, they are expected that the estimation of WGMDH model is better than conventional method to estimate flood which is that is linear regression.

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