**UNIVERSITI PUTRA MALAYSIA**

# *AN IMPROVED STREAMFLOW MODEL WITH CLIMATE AND LAND USE FACTORS FOR HULU LANGAT BASIN*


***YASHAR FALAMARZI***

# AN IMPROVED STREAMFLOW MODEL WITH CLIMATE AND LAND USE FACTORS FOR HULU LANGAT BASIN

By

**YASHAR FALAMARZI**

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

**November 2014**

**DEDICATED**

TO

My Mother

A strong and gentle soul who taught me to trust in Allah, believe in hard work and that so much could be done with little

My Father

For earning an honest living for us and for supporting and encouraging me to believe in myself

My Parents-in-law

For being my guardians, their support and encouragement

My Wife

Without whom none of my success would be possible

And finally my lovely Sibling

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

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**November 2014**

**Chairman: Professor Ir. Lee Teang Shui, PhD**
**Faculty: Engineering**

Water is essential for human beings and it is vital in various fields such as agriculture, navigation, energy production, recreation and manufacturing. Rapid urbanization, population growth and economic developments could potentially put stress on the water resources by increasing the water demand. In addition, climate change and land use change could also cause variations in the quantity and quality of water resources. Therefore, assessing the impacts of these changes on water availability is essential and requisite to adapt water resources management and for planning sustainable development strategies especially in a rapid socio-economic development. The aim of this study is to investigate the impact of past and future climate change and land use change on mean monthly and annual streamflows in the Hulu Langat basin, Malaysia utilizing a new generation of physically based hydrological models. The James W. Kirchner (JWK) model is a new physically based model. Although this model does not need any upscaling it is more appropriate for cold and humid areas and it considers the basin as a single storage system. These limitations could have impacts on the applicability of the model. Thus, in the present study, to achieve the objectives, first, the James W. Kirchner (JWK) method was modified and the modified model (MJWK) was then combined with the Soil Conservation Service (SCS) effective rainfall estimation method (MJWK-SCS model) to estimate river flow. An averaging ensemble version of MJWK-SCS model was also proposed (E-MJWK-SCS). Afterwards, the MJWK, MJWK-SCS, E-MJWK-SCS, Soil and Water Assessment Tool (SWAT), Artificial Neural Network (ANN), Nonlinear AutoregRessive with eXogenous input (NARX) and wavelet-NARX models were utilized to predict mean monthly river flow from daily climatic data. The models were calibrated for the period 1985-1988 and the validation was performed for the period 2002-2005. In the calibration phase, the Wavelet-NARX, E-MJWK-SCS and SWAT models performed the best with the Nash-Sutcliff Efficiency (NSE) values of 0.85, 0.78 and 0.66, respectively. However, in the validation phase the SWAT and E-MJWK-SCS models performed the best with the NSE values of 0.74 and 0.73, respectively.

Since the E-MJWK-SCS and SWAT models performed well in both the calibration and validation phases based on NSE values, they were utilized to assess the climate change and land use change effects on mean monthly and annual streamflows. Prior

to applying these models, the uncertainty of their predictions was analyzed utilizing the Sequential Uncertainty Fitting 2 (SUFI2) algorithm. The uncertainty analysis showed that both the models had an acceptable level of uncertainty. However, the E-MJWK-SCS model showed lower quantity of uncertainty in prediction with p-factor and r-factor of 0.88 and 0.81 than the SWAT model with p-factor and r-factor of 0.69 and 0.51, respectively. The analysis of the past climate change and land use change impacts on streamflow showed that at annual scale the land use change was more effective than the climate change and it increased mean annual streamflow (11.43% and 5.68% utilizing E-MJWK-SCS and SWAT models, respectively). At monthly scale, both the land use and climate change altered streamflows.

The impact of possible future climate change and land use change on mean monthly and annual streamflows was also investigated. Firstly, the climatic variables were estimated under the A1B and A2 climate change scenarios employing the LARS-WG model and the land use map of year 2025 was generated based on the trend of land use changes in the period 1984-2002 utilizing the Land Change Modeler (LCM). Then mean monthly and annual streamflows were forecasted under different combinations of land use and climate change scenarios for the period 2025-2028. At annual scale, a rise in streamflow is expected under the land use change (4.07% and 3.88% utilizing E-MJWK-SCS and SWAT models, respectively) and the combined land use change and climate change scenarios (ranged from 1.81% to 4.54% under various scenarios). The climate changes scenarios represented a decline in mean annual streamflow (ranged from -5.78% to -0.27% for various scenarios). At monthly scale, both increases and decreases in flows were seen under all the scenarios considered (ranged from a decrease of 8.92% to an increase of 11.76% under various scenarios). The findings also showed that the droughts would be possible under the combined climate and land use changes scenarios in the dry seasons. It is concluded that not only both the E-MJWK-SCS and SWAT models are useful tools to simulate mean monthly river flow in the basin but are also suitable for investigating the impacts of climate and land use changes on mean monthly and annual streamflows.

**Keywords**: climate change, land use change, streamflow, Hulu Langat basin, Malaysia

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

**SATU MODEL ALIRAN SUNGAI DIPERBAIKI BERSAMA FAKTOR IKLIM DAN PENGGUNAAN TANAH UNTUK LEMBANGAN HULU LANGAT**

Oleh

**YASHAR FALAMARZI**

**November 2014**

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Air begitu penting untuk manusia dan juga sangat perlu dalam berbagai bidang saperti pertanian, pengangkutan air, penjanaan tenaga, kehiburan dan pembuatan. Perperbandaran pesat, pertumbuhan jumlah penduduk dan perkembangan ekonomi terus menambahan tegangan kepada sumber air dari segi tambahan permintaan air. Tambahan pula, perubahan iklim dan perubahan kegunaan tanah boleh juga menyebabkan perubahan kuantiti dan kualiti sumber air. Namun, penaksiran impak perubahan perubahan tersebut keatas adanya sumber air adalah perlu demi untuk menyesesuaikan pengurusan sumber air serta untuk strategi perancangan pembangunan sesuai khas dalam pembangunan sosioekonomi yang pesat. Tujuan kajian ini ialah untuk menyiasat kesan perubahan iklim masa lampau dan masa akan datang serta perubahan penggunaan tanah ke atas aliran sungai purata bulanan dan tahunan dalam lembangan Hulu Langat, Malaysia menggunakan satu model hidrologi generasi baru yang berasaskan fizikal, iaitu model James W. Kirchner (JWK). Walaupun model ini tidak memerlukan sebarang upscaling ia lebih sesuai untuk kawasan sejuk dan lembap serta ia menganggap lembangan sebagai satu sistem penyimpanan tunggal. Had-had ini mungkin mempunyai impak kebolehgunaan model ini. Maka, untuk mencapai objektif kajian ini, kaedah James W. Kirchner (JWK) telah diubahsuai dan model yang diubahsuai (MJWK) kemudian digabungkan dengan kaedah penganggaran air hujan berkesan Soil Conservation Service (SCS) (dipanggil model MJWK-SCS) untuk mentaksir aliran sungai. Versi kelompok purata model MJWK SCS juga dicadangkan (dipanggil model E-MJWK-SCS). Kemudian, model model MJWK, MJWK-SCS, E-MJWK-SCS, Alat Taksiran Tanah dan Air (SWAT) , Rangkaian Saraf Tiruan (ANN), Nonlinear Autoregressive with eXogenous input (NARX) dan wavelet-NARX digunakan untuk meramalkan aliran sungai bulanan purata daripada data iklim harian. Model model tersebut ditentukur untuk jangkamasa 1985-1988 dan diperpastikan untuk jangkamasa 2002-2005. Dalam fasa penentukuran, model model Wavelet-NARX, E-MJWK-SCS dan SWAT adalah yang terbaik dengan nilai Kecekapan Nash-Sutcliff (NSE) 0.85, 0.78 dan 0.66, masing masing. Akan tetapi, dalam fasa perpastian model SWAT dan E-MJWK-SCS adalah terbaik dengan keputusan nilai NSE sebanyak 0.74 dan 0.73 masing masing.

Memandang bahawa model E-MJWK-SCS dan SWAT berkelakuan baik dalam kedua dua fasa fasa penentukuran dan perpastian, ianya digunapakai untuk menaksirkan kesan perubahan iklim dan perubahan kegunaan tanah terhadap kadaralir bulanan dan tahunan purata. Sebelum mengguna model model tersebut, ketidakpastian ramalan dianalisiskan dengan algorithm SUFI2. Analisis ketidapastian menunjukkan bahawa kedua dua model mencapai paras ketidakpastian yang boleh diterima. Walau bagaimanapun, model E-MJWK-SCS menunjukkan kuantiti ketakpastian yang lebih rendah dalam ramalan dengan faktor p dan faktor r masing-masing 0.88 dan 0.81 berbanding dengan nilai faktor p dan faktor r masing-masing 0.69 dan 0.51, daripada model SWAT. Analisis impak kadaralir perubahan iklim dan perubahan kegunaan tanah yang lalu menunjukkan pada skala tahunan, impak perubahan kegunaan tanah lebih bermakna dibandingkkan kesan perubahan iklim dan ia meninggkatkan kadaralir tahunan purata. Pada sekil bulanan, kedua dua perubahan kegunaan tanah serta iklim mengubah kadaralir.

Impak perubahan iklim dan kegunaan tanah akan datang terhadap kadaralir bulanan dan tahunan purata juga dikaji. Demi mencapai tujuan ini, pertamanya, perubahan iklim ditaksirkan dibawah scenario perubahan iklim A1B and A2, menggunakan model TARS-WG dan peta kegunaan tanah untuk tahun 2025 dijanakan berdasarkan trend perubahan kegunaan tanah dalam jangkamasa 1984-2002 serta menggunakan Land Change Modeler (LCM). Kemudian kadaralir bulanan dan tahunan purata diramalkan berasaskan kombinasi berlainan scenario perubahan iklim dan kegunaan tanah bagi jangkamasa 2025-2028. Pada sekil tahunan, satu peningkatan kadaralir dijangkakan dibawah kolubinasi perubahan kegunaan tanah (4.07% dan 3.88% masing-masing, menggunakan model E-MJWK-SCS dan SWAT) dan scenario, manakala scenario perubahan iklim memberi kurang kadaralir tahuanan purata (berjulat dari 1.81% hingga 4.54% di dalam pelbagai senario). Pada sekil bulanan, perambahan dan pengurangan kadarahir boleh dilihat dalam semua senario yang dikajikan (berjulat dari 0.27% hingga 5.78% untuk pelbagai senario). Keputusan juga menunjukkan bahawa kemarau boleh berlaku dibawah scenario perubahan iklim dan kegunaan tanah pada musim kering(berjulat dari pengurangan sebanyak 8.92% kepada peningkatan sebanyak 11.76% di bawah pelbagai senario). Pada keseluruhannya, ia boleh disimpulkan bahawa bukan sahaja kedua dua model E-MJWK-SCS dan SWAT adalah alat berguna untuk menganggarkan aliram sungai dalam satu tadahan, tetapi ia juga sesuai untuk mengkaji kesam perubahan iklim dan kegunaan tanah.

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Finally, to my caring, loving, both a companion and supportive wife, Narges: my deepest gratitude. Her encouragement when the times got rough are duly noted and much appreciated.

## APPROVAL

I certify that a Thesis Examination Committee has met on 6 November 2014 to conduct the final examination of Yashar Falamarzi on his Doctor of Philosophy thesis entitled "An Improved Streamflow Model with Climate and Land Use Factors for Hulu Langat Basin" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| 95PPU | 95% Prediction Uncertainty |
| ACRU | Agricultural Catchment Research Unit |
| API | Antecedent Precipitation Index |
| ANN | Artificial Neural Network |
| ANNs | Artificial Neural Networks |
| AR | Auto-Regressive |
| ARMA | Auto-Regressive Moving Average |
| BFI | Base Flow Index |
| CA | Cellular Automata |
| CLS | Constrained Linear System |
| CWT | Continues Wavelet Transform |
| CLUEs | Conversion of Land Use and its Effects |
| CN | Curve Number |
| DOA | Department Of Agricultural |
| DEM | Digital Elevation Model |
| DWT | Discrete Wavelet Transform |
| DID | Drainage and Irrigation Department |
| ET | Evapotranspiration |
| FAO | Food and Agricultural Organization of the United Nation |
| GLUE | Generalized Likelihood Uncertainty Estimation |
| GIS | Geographic Information System |
| GCM | Global Circulation Model |
| HyMod | Hydrologic Model |
| HEC-HMS | Hydrologic modelling system |

| | |
|---|---|
| HUR | Hydrologic Unit Response |
| HBV | Hydrologiska Byråns Vattenbalansavdelning |
| IHACRES | Identification of Hydrographs And Component flow from Rainfall, Evaporation and Streamflow |
| ISA | Impervious Surface Area |
| IHDM | Institute of Hydrology Distributed Model |
| INT | Inter Monsoon |
| IPCC | Intergovernmental Panel on Climate Change |
| JWK | James W. Kirchner |
| KINEROS | Kinematic Runoff and Erosion |
| KS | Kolmogorov- Smirnov |
| LCM | Land Change Modeller |
| LEAM | Land use Evolution and impact Assessment Model |
| LULC | Land Use/Land Cover |
| MMD | Malaysian Meteorology Department |
| MK | Mann-Kendall |
| MW | Mann-Whitney |
| MAE | Mean Absolute Error |
| MJWK | Modified James W. Kirchner |
| MMK | Modified Mann-Kendall |
| MCMC | Monte Carlo Makrov Chain |
| MLR | Multi Linear Regression |
| MLP | Multi-Layer Perceptron |
| NSE | Nash Sutcliff Efficiency |
| NWS | National Weather Service |
| NRSC | Natural Resources Conservation Service |

| | |
|---|---|
| NAM | Nedbor-Afstromnings-Model |
| NARX | Nonlinear Auto-Regressive with eXogenous input |
| NEM | North East Monsoon |
| ParaSol | Parameter Solution |
| PM | Penman Monteith |
| PJ | Petaling Jaya |
| PET | Potential Evapotranspiration |
| PDF | Probability Distribution Function |
| RI | Recurrent Interval |
| REV | Reprehensive Elementary Volume (REV) |
| RMSE | Root Mean Square Error |
| SAC-MA | Sacramento Soil Moisture Accounting |
| SED | Semi-Empirical Distribution |
| SUFI2 | Sequential Uncertainty Fitting |
| SCE | Shuffled Complex Evolution |
| SSA | Singular Spectrum Analysis |
| SLEUTH | Slope Excluded Land, Urban Extent, Transportation and Hill shading |
| SWAT | Soil and Water Assessment Tool |
| SCS | Soil Conservation Service |
| SWM | South West Monsoon |
| SEA | Southeast Asia |
| Std | Standard deviation |
| SDSM | Statistical DownScaling Model |
| SPEA2 | Strength Pareto Evolutionary Algorithm 2 |
| SVM | Support Vector Machine |

| | |
|---|---|
| SHE | System Hydrologic European |
| ToPModel | ToPographic based hydrologic Model |
| TF | Transfer Function |
| UH | Unit Hydrograph |
| VIC | Variable Infiltration Capacity |
| WASMOD | Water and Snow balanced Model |
| WA | Wavelet |
| WMRA | Wavelet Multi Resolution Analysis |
| WNN | Wavelet Neural Network |

# LIST OF NOTATIONS

| | |
|---|---|
| $\phi$ | Activation function |
| $k_e$ | Actual evapotranspiration coefficient |
| $e_d$ | Actual vapour pressure |
| $\acute{w}$ | Adjusted value of weight |
| $T$ | Air temperature |
| $H_1$ | Alternative hypothesis |
| $Q_{gw}$ | Amount of return flow |
| $W_{seep}$ | Amount of water entering the vadose zone from the soil profile |
| $A$ | Area |
| $p_k$ | Autocorrelation function of the ranks of the observations |
| $a(i)$ | Average dissimilarity between point $i$ and all other points in cluster A |
| $\bar{R}$ | Average maximum rainfall intensity |
| $APD$ | Average percentage difference |
| $slp$ | Average slope |
| $\theta$ | bias |
| $CN_I$ | CN for dry conditions |
| $CN_{III}$ | CN for wet conditions |
| $R^2$ | Coefficient of determination |
| $r$ | Correlation coefficient |
| $m^3$ | Cubic kilometre |
| $CN$ | Curve number |
| $K^2$ | D'Agostino and Pearson statistic |
| $\tilde{\lambda}$ | Dilation factor |

| | |
|---|---|
| $k_p$ | Direct runoff coefficient |
| $Q$ | Discharge |
| $C$ | Empirical coefficient |
| $E_a$ | Actual Evaporation |
| $ET$ | Evapotranspiration |
| $R_a$ | Extraterrestrial radiation |
| $FC$ | Field capacity |
| $L$ | Filter length |
| $\psi$ | Function formed by MLP |
| $u$ | Independent value |
| $d$ | Index of agreement |
| $F$ | Infiltration depth |
| $I_a$ | Initial abstractions |
| $D_u$ | Input order |
| $\vec{x}$ | Input vector |
| $km$ | Kilometre |
| $Kwh$ | Kilowatt/hour |
| $b_2$ | Kurtosis coefficient |
| $r_1$ | Lag-1 serial correlation coefficient |
| $T_{max}$ | Maximum air temperature |
| $E(X_t)$ | Mean of sample data |
| $m$ | meter |
| $T_{min}$ | Minimum air temperature |
| $\hat{Q}_i$ | Modelled data |

| | |
|---|---|
| $m_k$ | Moment |
| $R_n$ | Net radiation |
| $Z(b_2)$ | Normal approximation of kurtosis |
| $Z(b_1)$ | Normal approximation of skewness |
| $Z_c$ | Normal variate of the MW test |
| $H_\circ$ | Null hypothesis |
| $n_A$ | Number of ‘A’ in Run test |
| $n_B$ | Number of ‘B’ in Run test |
| $n$ | Number of samples |
| $\vartheta$ | Output of neuron |
| $y(t)$ | Output of the network at time $t$ |
| $D_y$ | Output order |
| $h_w(x)$ | Output value computed by Perceptron |
| $Q_p$ | Peak discharge |
| $P$ | Precipitation |
| $R_{day}$ | Precipitation depth |
| $P(\quad)$ | Probability based on the data |
| $\gamma$ | Psychometric constant |
| $X$ | Sample data |
| $e_a$ | Saturation vapour pressure |
| $w_1$ $and$ $w_2$ | Shape factors |
| $b_1$ | Skewness |
| $\Delta$ | Slope of the saturation vapour pressure function |
| $a$ | Slope parameter |

| | |
|---|---|
| $G$ | Soil heat flux density |
| $SW$ | Soil water content |
| $km^2$ | Square kilometre |
| $S$ | Stored depth of water in the watershed |
| $U$ | Sum of series 'A' and 'B' in the Run test |
| $Q_{surf}$ | Surface runoff |
| $SR$ | Surface runoff depth |
| $U_2$ | the average 24-hour wind speed at 2 m height |
| $s(i)$ | The silhouette |
| $SC$ | The Silhouette Coefficient |
| $SAT$ | The water content of soil profile in the saturated condition |
| $\sqrt{\beta_1(b_2)}$ | Third standardized of kurtosis |
| $\sqrt{\beta_2(b_1)}$ | Third standardized of skewness |
| $t$ | Translation factor |
| $v_i$ | Variable $i$ |
| $\frac{n}{n_e^*}$ | Variance correction factor |
| $Var(s)$ | Variance of MK S statistic |
| $\varphi(.)$ | Wave function |
| $\vec{w}$ | Weight vector |
| $b(i)$ | $b(i)$ is the average dissimilarity between point $i$ and the points in the closest cluster to A |

# CHAPTER 1

# INTRODUCTION

## 1.1 Background

Water resources play a key role in economic and social developments all over the world (Laaboudi et al., 2012). Exclusively, streamflow, which is defined as an integrated mechanism of atmospheric and topographic processes, is undoubtedly significant in water resources planning (Demirel et al., 2009). Therefore, precise estimation of streamflow from rainfall, evaporation and other hydro-climatic variables is substantially important for water resources management and planning (Machado et al., 2011; Yilmaz et al., 2011). Since the variables, which are affecting streamflow, vary in both space and time, the formulation of the Rainfall-Runoff (RR) process is a complex task (Machado et al., 2011). The computer models, which simulate the RR process, are the best tools to investigate this complex process (Liew and Garbrecht, 2003). Thus, developing the hydrological models with more accurate predictions of streamflow is required (Guimarães Santos and Silva, 2013; Wijesekara et al., 2012).

The hydrologic cycle is complex and the interactions between the hydrological components are highly nonlinear. In addition, the measurement techniques of the hydrological variables are limited (Beven, 2005). As a consequence, it is virtually impossible to understand everything about the hydrological system by measurements. Therefore, a sort of simplifications and simulations are necessary to understand this process. These simple illustrations of the hydrologic cycle in the mathematical form are usually called hydrologic models. Vast numbers of hydrological models are available which can be divided into two main categories; lumped models and distributed models (Beven, 2005). The lumped models assume the watershed as a single unit and all parameters are averaged over the area of the basin. In the distributed models, the basin is divided into small grids and the state variable equation is solved for each grid. The main usage of the hydrological models is to estimate runoff from rainfall. The simulation of rainfall-runoff process is essential in water resources management such as flood control, design of hydraulic structures, irrigation scheduling, design of irrigation and drainage systems and hydropower generation etc. (Geetha et al., 2007). In addition, demands on water resources are increasing all over the world and so hydrological modelling is required to improve the decision making for the future (Beven, 2005).

Land use and climate play key roles in the hydrologic cycle. Land use distribution can have impacts on water resources in a variety of spatial and temporal scales (Ray et al., 2010). In addition, any change in land use could have great impacts on water resources. Land use change can lead to change in flood frequency (Brath et al., 2006), base-flow (Wang et al., 2006) and annual mean discharge (Costa et al., 2003). As an example, converting green and wetlands to urban and agricultural lands can increase runoff, which consequently could increase flooding problems. In recent decades, rapid conversions in land use activities, especially urbanization, have had great impacts on the hydrologic cycle.

In addition to land use, climate also influences the hydrological cycle. Climate variability can alter flow routing time, peak-flows and volume of flood (Prowse et al., 2006). It has been reported that the climate of the earth will become warmer in the future (Zhang et al., 2011). It is likely to have more frequent droughts and floods in a warmer climate (Gilroy and McCuen, 2012). Therefore, investigating the hydrological responses of the basin to these changes is essential for effective planning, management and sustainable development of water resources.

## 1.2 Problem Statement

A lot of efforts have been done in order to simulate the hydrologic cycle, spatially rainfall-runoff process. As a result vast numbers of hydrological models have been developed to simulate the water cycle. One class of these models is the physically based models. The core assumption of the traditional physically based hydrological models is that the measurable physical characteristics of a basin, governing equation, initial and boundary conditions can be solely used to forecast the catchment behaviour (Teuling et al., 2010). However, the measurements of these characteristics, especially those controlling subsurface flows, are done at the scales that are considerably smaller than catchment scale (Kirchner, 2009). In these models, scaling up of the governing equation at small scale has been utilized to find out the behaviour of hydrological system at the catchment scale. The limitation of these methods is that identifying the system properties at the appropriate scale is not easy a prior. In addition, the validity of the up-scaling assumption and using governing equation of the small scale to describe the basin scale physics are questionable. Therefore, it is essential to develop methods to identify governing equation at the appropriate scale (it means that there is no need to upscale the governing equation). James W. Kirchners's (JWK) model is one of the newest physically based hydrological models to simulate rainfall-runoff process in a basin. This method does not need any upscaling. However, it has some disadvantages such as: (1) it is appropriate for humid and cold areas where there is a low evapotranspiration rate and (2) It considers that the basin is a single storage system. The climate of Hulu Langat basin is hot and humid; and the rate of evapotranspiration is relatively high. Hysteresis in storage discharge relationship could also affect the efficiency of the JWK model. One way to reflect this hysteresis in storage responses is to combine the JWK model with a transfer function. Thus, in this study, this model was modified for the Hulu Langat basin. This modified James W.Kirchner's (MJWK) model is combined with the SCS-rainfall estimation as the transfer function to reflect the hysteresis in storage discharge relationship in storage responses.

Beside the physically based hydrological models, a lot of data-driven methods have been developed over the past two decades to dispel the problems of rainfall-runoff modelling (Besaw et al., 2010). Multi linear regression (MLR), varieties of autoregressive moving average (ARMA) models, artificial neural networks (ANNs) and Nonlinear AutoRegressive with eXogenous input (NARX) are the most common data-driven approaches. Neural network has been used and developed in various fields as a good non-linear predictor and it has been also utilized to predict runoff from rainfall data. Neural networks try to simulate the learning process, which is occurring in the human brain. The artificial neural networks (ANNs) with sigmoid activation functions are the most common type of neural networks. The NARX neural network, which is a recurrent neural network, has found to be more suitable for simulating nonlinear systems than other networks (Çoruh et al., 2014) and it also converges faster (Chen et al., 1990). However, ANN and NARX are both sensitive to the quality of input data. The hydro-climatic data often have noise as well as autocorrelation. A noisy signal can have a negative impact on the prediction accuracy of the ANN type models (Wu et al., 2009). Existence of strong correlation in the input data set of ANN type models can lead to introduce lagged prediction. In order to overcome these deficiencies, Wu et al. (2009) suggested preprocessing the data before applying the ANNs models. A lot of studies have been carried out to find out the most appropriate filtering method. One of these approaches is using a local and orthogonal function. Wavelets are the functions with these characteristics which can have advantages such as orthogonally, compact support, localization in time and frequency and fast algorithms (Zainuddin and Pauline, 2011). Utilizing wavelets as a preprocessing step in ANNs have shown positive influences on the performance of these models (Adamowski and Sun, 2010; Kisi, 2010; Maheswaran and Khosa, 2012; Nayak et al., 2013; Nourani et al., 2009b). Since none of the ANN, NARX and wavelet-NARX models were utilized in the Hulu Langat basin, in this study, these models were also evaluated in estimating monthly streamflow in the basin.

The Langat River Basin is an important watershed in Malaysia. Two third of water demand of the state of Selangor is provided from the Langat River Basin (Juahir et al., 2010). Since surface water, especially streamflow is the main source for providing water in the Langat River Basin, accurate estimation of streamflow is essential for water management and conservation. Rapid urbanization (from 31.47 km2 in 1984 to 296.24 km2 in 2010 (161.59%)) in the area has caused huge changes in land use activities. These land use changes have led to increase in the impervious surface area and consequently they may have impacts on river flow and water resources in the basin. In addition, climate change could also cause to see variations in streamflow (Toriman et al., 2012). According to IPCC (2007), the 100-year linear increase of surface temperature (1905-2005) is 0.74°C, while the global average sea level has risen since 1961 at a rate of 1.8 mm/yr. Furthermore, IPCC forecasted much higher increases in temperature by 2100 relative to 1980-1999. Such multiple increases in temperature and consequently sea level could have disastrous impacts on various sectors, especially hydrologic cycle of the basin. Therefore, studying the effects of these changes on the hydrologic cycle, specifically streamflow, of the basin is significant. Predicting the effects of changes, notably land use and climate changes, on streamflow is a significant issue for the hydrologic sciences (Singh et al., 2011). Using a physically based hydrological model which is calibrated on historical or estimated data is the most common approach to deal with this issue (Singh et al., 2011).

With these descriptions, in this study a modified version of the JWK physically based hydrological model, which does not need upscaling, was developed to estimate streamflow in the upper zone of the Langat River Basin. In addition, since the wavelet transform coupled with ANN type models has showed feasible results in previous researches (Adamowski and Sun, 2010; Chua and Wong, 2010; Kisi and Cimen, 2011; Nowak et al., 2011; Shiri and Kisi, 2010; Tiwari and Chatterjee, 2010; Wei et al., 2012), in this study this type of models were trained and tested for simulating the Rainfall-Runoff (RR) process for the first time in the basin. Furthermore, in order to compare the efficiency of the developed models with a well-established model, the SWAT model, which is a semi-distributed hydrological model, was also utilized to estimate monthly streamflow in the basin. Finally, the land use and climate changes impacts on streamflow were investigated.

## 1.3 Objectives

The main aim of this study is to simulate and forecast the mean monthly streamflow from daily rainfall and evapotranspiration data considering the land use and climate change effects in the Hulu Langat basin. The specific objectives of the study are as follows:

1. To simulate mean monthly streamflow using the modified James W. Kirchner's model (Kirchner, 2009) in the Hulu Langat basin.
2. To compare the performance of the modified James W. Kirchner's model with those of the SWAT, ANN, NARX and wavelet-NARX models in estimation of mean monthly streamflow.
3. To investigate the impacts of the past and future land use and climate changes on mean monthly and mean annual streamflow.

## 1.4 Scope of work and limitations

The scope of the study is to firstly introduce a new physically based hydrological model, which does not need any upscaling, to estimate monthly streamflow for the Hulu Langat basin and secondly assessing the impacts of land use and climate changes on streamflow in the study area. This study is limited to simulation of rainfall-runoff process at monthly scale in the north part of the Langat River Basin (Hulu Langat basin), Malaysia for two periods of 1985-1988 and 2002-2005. The reason for selecting these two time frames are that missing data in hydro-climatic data of the period 1984-2012 were a lot (more than 10%). These missing data could have negative impacts on the results of the analysis. Furthermore, the impact of the future climate change and land use change were assessed during 2025-2028.

## 1.5 Significance of the Study

Water resources are essential for human beings and vital in various fields such as agriculture, navigation, energy production, recreation and manufacturing. Reliable runoff estimation is required in various engineering applications such as water supply, disaster management and power production (Guimarães Santos and Silva, 2013; Nilsson et al., 2006). The mathematical models, known as RR models, could be utilized to estimate runoff from the related hydro-climatic variables such as rainfall and evaporation in both long and short terms. Thus, the RR models have turned into useful tools to investigate the hydrologic cycle at watershed scale. Streamflows forecasting at monthly scale can be utilized in various applications such as water resources assessments, discharge estimation, climate change impact studies and streamflow data augmentation (Xu and Singh, 1998).

In recent decades, land use change and climate change have been found to be substantially effective on streamflow. Land use conversion from for example forest to urban land could lead to increase flood frequency which have economic and social side effects. Similarly, climate change can increase the possibility of floods and droughts that threaten the food and water security as it is happening in some places in the world. Therefore, considering these two changes in simulation of the catchment water cycle is extremely essential to develop effective watershed modelling approach. Consequently, any proposed RR model should be able to take in to account the effect of climate and land use on the RR process. In this study, a physically based lumped RR model will be proposed to estimate monthly streamflow from rainfall and evapotranspiration in the Hulu Langat basin. The capability of this model in predicting monthly river flows will then be compared with those of the Artificial Neural Network (ANN), Nonlinear AutoRegressive with eXogenous (NARX) input and, the widely utilized model in watershed modelling studies, Soil and Water Assessment Tool (SWAT) models. The most accurate models will next be employed to assess the impacts of climate change and land use change on streamflow. The results of this study would be valuable for managers and decision makers to establish new policies as well as modifying the current policies in various hydrologic related fields such as water resources management, natural resources conservation, agricultural water management and urban development planning.

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