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REVIEW ARTICLE

Review of studies on hydrological modelling in Malaysia

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Abstract

Hydrological models are vital component and essential tools for water resources and environmental planning and management. In recent times, several studies have been conducted with a view of examining the compatibility of model results with streamflow measurements. Some modelers are of the view that even the use of complex modeling techniques does not give better assessment due to soil heterogeneity and climatic changes that plays vital roles in the behavior of streamflow. In Malaysia, several public domain hydrologic models that range from physically-based models, empirical models and conceptual models are in use. These include hydrologic modeling system (HEC-HMS), soil water assessment tool (SWAT), MIKE-SHE, artificial neural network (ANN). In view of this, a study was conducted to evaluate the hydrological models used in Malaysia, determine the coverage of the hydrological models in major river basins and to identify the methodologies used (specifically model performance and evaluation). The results of the review showed that 65% of the studies conducted used physical-based models, 37% used empirical models while 6% used conceptual models. Of the 65% of physical-based modelling studies, 60% utilized HEC-HMS an open source models, 20% used SWAT (public domain model), 9% used MIKE-SHE, MIKE 11 and MIKE 22, Infoworks RS occupied 7% while TREX and IFAS occupy 2% each. Thus, indicating preference for open access models in Malaysia. In the case of empirical models, 46% from the total of empirical researches in Malaysia used ANN, 13% used Logistic Regression (LR), while Fuzzy logic, Unit Hydrograph, Auto-regressive integrated moving average (ARIMA) model and support vector machine (SVM) contributed 8% each. Whereas the remaining proportion is occupied by Numerical weather prediction (NWP), land surface model (LSM), frequency ratio (FR), decision tree (DT) and weight of evidence (WoE). Majority of the hydrological modelling studies utilized one or more statistical measure of evaluating hydrological model performance (R, R^2, NSE, RMSE, MAE, etc.) except in some few cases where no specific method was stated. Of the 70 papers reviewed in this study, 16 did not specify the type of model evaluation criteria they used in evaluating their studies, 17 utilized only one method while 37 used two or more methods. NSE with 27% was found to be the most widely used method of evaluating model performance; R and RMSE came second with a percentage use 24% each. R^2 (20%) was recorded as the third most widely used model evaluation criteria in Malaysia, MAE came fourth with 16% while PBIAS is the least with 11%.The findings of this work will serve as a guide to modelers in identifying the type of hydrological model they need to apply to a particular catchment for a particular problem. It will equally help water resources managers and policy makers in providing them with executive summary of hydrological studies and where more input is needed to achieve sustainable development.

Keywords Hydrologic models · Review · Malaysia · GIS · HEC-HMS · SWAT

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Introduction

According to Penman (1961), hydrology is the science that deals with the aftermath of activities that follows a rainfall event. In another related definition by Ray (1975), hydrology is a branch of science that deals with global water resources occurrence, distribution and circulation as well as their physical and chemical characteristics and how they react to the environment (their relationship with biotic organisms included). Hydrology is concerned with the interconnection of water resources with the environment as they appear in each segment of the hydrologic cycle. (Devi et al. 2015). Hydrology encompasses all phases of earth's water which makes it essential to human lives as well as the environment (Chow et al. 1988).

There are several practical uses directly associated with the science of hydrology e.g. flood disaster management, planning for water supply, design and operation of hydraulic structures, pollution abatement, wastewater, irrigation, erosion and sediment control among others (McCuen 1998; Shaw et al. 2010; Khalid et al. 2016). In general, hydrology gives guidance for planning, management and control of water resources by applying engineering and geography principles that are fundamental for its study. Land use/land cover (LULC) changes due to urbanization, deforestation, industrialization, irrigation and other forms of changes have now been added to the hydrologic systems (Abdulkareem et al. 2017, 2018a). Others such as climate change and soil heterogeneity that are reported to have a direct effect on streamflow across the globe are also considered (Devi et al. 2015). As a result of these, different hydrologic models were developed to assess the effect of LULC change, soil characteristics and climate change on watersheds.

A model can be regarded as a simple illustration of real world system (Devi et al. 2015). Models are generally used for forecasting the performance and interpretation of different hydrological processes. They comprise of several parameters that describe their features. Although hydrological models are developed to examine the relationship between water, LULC, soil and climate change, rainfall and drainage area are the two most important hydrological model parameters to always consider.. This along with other watershed characteristics such as topography, geology and ground water aquifer are also given adequate consideration during model development (Alam et al. 2011; Devi et al. 2015; Khalid et al. 2016). As a result, several models were developed for simulating the hydrological behavior of a watershed for both surface and ground water modeling. Such models are categorized as either deterministic or stochastic, empirical, conceptual or physically based (Refsgaard 1996; Khalid et al. 2016).

The use of computer models in simulating catchment hydrological processes for runoff estimation has been inexistence for over five decades (Boughton 2006). Recently it has been the most widely used technique for water resources management and hydrological design work, with a variety of models available for use. Hydrological models are developed in such a way that, when inputted with good quality data they give good simulation results and the reverse is the case, as no model will give good simulation from faulty data. In a nutshell, hydrological model results depend on the quality of input data, rather than the model (Boughton 2006). They are vital component and essential tools for water resources and environmental management (Devi et al. 2015). They can be used to examine the quantity and quality of streamflow, groundwater development and protection, reservoir system operations, surface water and groundwater conjunctive use management, water use, groundwater development and protection, water distribution systems, as well as other water resources management strategies (Wurbs 1998; Singh and Woolhiser 2002). Although hydrological modelling of floods and droughts are significant for planning and management, this area is faced with scarcity of major input parameters, which limits its application to rainfall-runoff models. For instance, rainfall measurements are only carried out on selected areas, streamflow measurement is done at few locations (Bárdossy 2006).

Ever since when hydrologic models were discovered, real life experiments (manual way of mapping and updating LULC changes) are considered expensive and time consuming. As such, hydrologic models have been used as computational laboratories for testing the hypothesis of hydrological behavior of watersheds. Hydrological models are normally used for estimating basin's hydrological response to rainfall. The choice of a model depends on the watershed and the objective of the hydrological prediction in the watershed (Halwatura and Najim 2013). Hydrological models make available a simplified representation of an actual watershed system to obtain a better understanding of hydrological processes in the study area.

Currently there exist very few reviews with respect to hydrological studies in Malaysia. For instance, the review conducted by Khalid et al. (2016) focused only on physically based models (precisely SWAT model). In their findings, they reported that the model has been applied in both long-term and short-term simulation purposes and on different watersheds. Abdullah (2013) carried out a review on hydrological modelling in Malaysia but gave emphasis to 1D, 1D–2D, 2D, and 3D models. Another attempt by Jajarmizadeh et al. (2012), focus only on reviewing theoretical considerations and type of models in hydrology without much emphasis on the Malaysian perspective. Based on the recent challenges regarding climate change, LULC changes such as rapid urbanization, deforestation for logging and agricultural activities, the hydrological system of many watersheds in the country were transformed or being transformed. As such, several studies regarding the hydrological behavior concerning to climate change and LULC changes are being carried out. Therefore, there is need for a wider review that will cover the whole country, to have a clear view of the status of hydrological studies conducted in Malaysia. Such review will be useful to water resource managers, decision makers and land use planners for future planning and development especially in effective prediction of streamflow changes. In view of this, this review on hydrological studies in Malaysia attempts to evaluate the hydrological models used in Malaysia, determine the coverage of hydrological models in major river basins and to identify the methodologies used (specifically model performance and evaluation).

General and hydrological description of the study area

Malaysia is one of the southeast Asian countries located on latitude 2°30′N and longitude 112°30′E. It has an estimated population of about 30.33 million (UNPF 2015) covering an area of 329,750 km^2. It is divided into West and East Malaysia by South China Sea. West Malaysia (peninsular Malaysia) with 11 states shares a maritime border with Thailand from the north, Singapore and Indonesia from the south and southwest respectively. East Malaysia (Malaysian Borneo) has 2 states viz; Sabah and Sarawak shares a maritime border with Indonesia to the south and Philippines to the north. The country is characterized with a tropical climate receiving an average annual rainfall of over 2800 mm. Average temperature ranges between 21 and 30 °C while humidity range from 80 to 90% (Manaf et al. 2009; Kura et al. 2015).

Peninsular Malaysia is classified into different hydrological regions for water resources assessment. Geological characteristics and climatic factors that are important in water flow were considered in this classification. Lithology or rock porosity is the major geological feature selected while for the climatic factors, annual rainfall and annual evapotranspiration were merged together to formulate a climatic parameter used for delineation. From the lithological point of view, five lithological groups were identified from hydrogeological map of Malaysia (Chong and Tan 1986; Omang and Tahir 1994; Heng 2004) as shown in Fig. 1. Hydrological boundaries in Malaysia were demarcated by the boundaries of these lithological groups. Hydrological sub-boundaries were drawn from conditional surface water resources map of Peninsular Malaysia (DID 1974). Figure 2 shows the map of Malaysia indicating major catchments and sub-catchments. Average annual surface water yield (W) with regards to potential runoff isolines is presented by this map. Isolines are obtained as the difference between annual average rainfall (P) and average annual potential evapotranspiratation

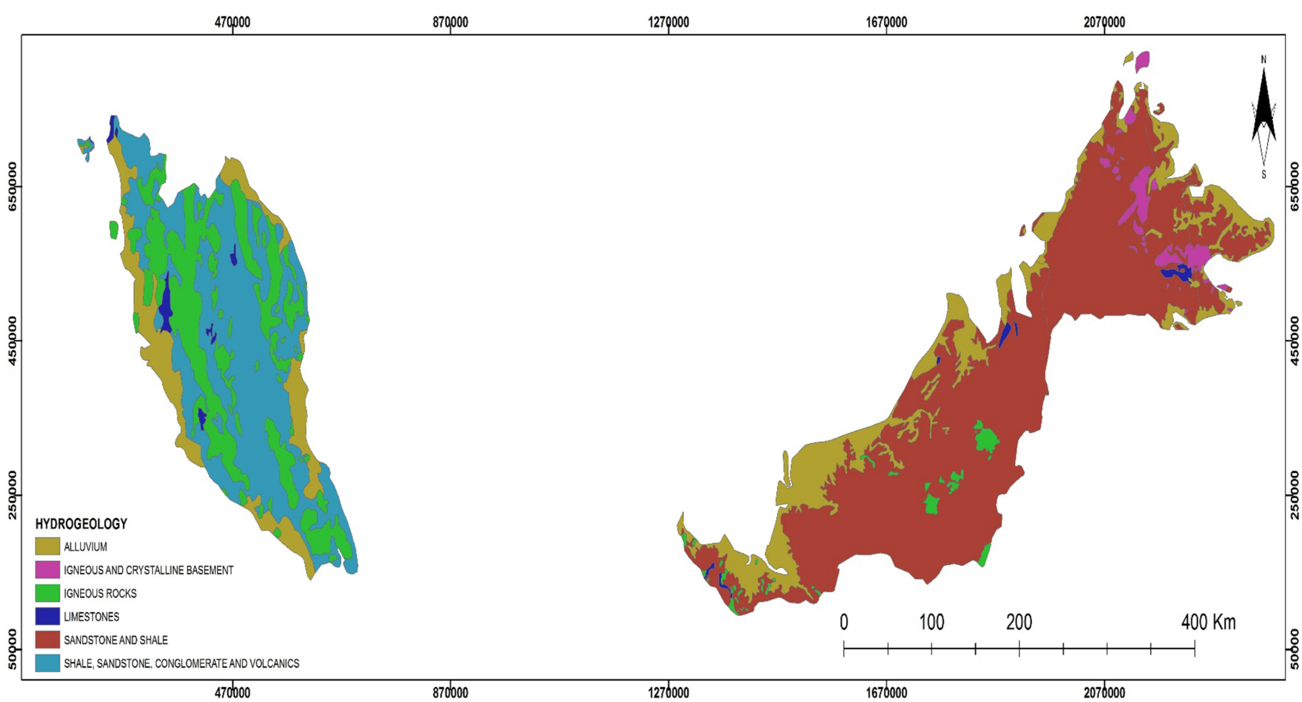

Fig. 1 Simplified hydrogeological map of Malaysia (left: Peninsular Malaysia, right: Malaysian Borneo; Sabah and Sarawak). Modified from (Chong and Tan 1986; Omang and Tahir 1994; Heng 2004)

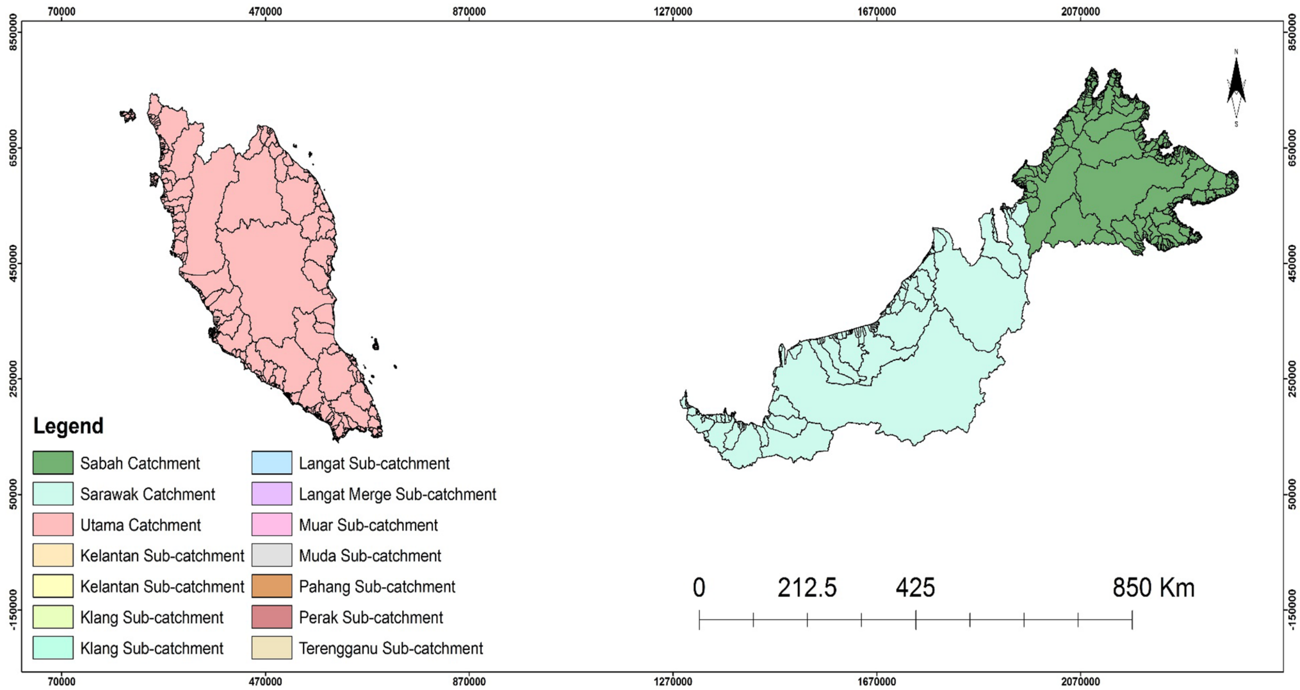

Fig. 2 Map of Malaysia showing major Catchments and Sub-catchments

(PE) as illustrated in the water balance equation $W = P - \mathrm{PE}$. Potential runoff isolines ($P - \mathrm{PE}$) are further categorized into broad groups whose boundaries were used as sub-boundaries. When lithological parameter (L) was combined with $P - \mathrm{PE}$ parameter (W), a numerical classification system with five lithological groups ($L_1 - L_5$) and four P-PE groups ($W_1 - W_4$) giving a possible combination of twenty classes. The Peninsular Malaysia was classified with the aid of this system into sixty-six hydrological classes expecting hydrological similarities. Several regions have the same quantitative classification with each other.

Classification of hydrological models

Several attempts have been made by scientists in the past to classify hydrological models (Fleming 1972; Woolhiser 1973; Singh 1995). Devi et al. (2015) reported that hydrological models can be classified based on model input parameters as well the degree to which physical techniques are applied. The classification used in this study adopted from Refsgaard (1996) as shown in Fig. 3 classified hydrological models into deterministic, stochastic and joint stochastic-deterministic. Deterministic models are further sub-divided into physically-based model, conceptual model and empirical model. This classification can be applied to watershed models as well as single component models like the groundwater models. It should however, be noted that this classification is sketchy and that fitting some model codes cannot be done exactly in the classes given by Refsgaard (1996).

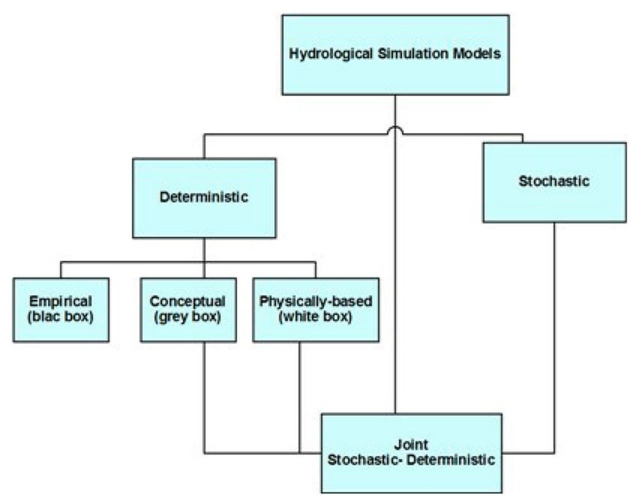

Fig. 3 Classification of hydrological models according to process description. (Modified from Refsgaard 1996)

Categories of hydrological modelling studies in Malaysia

The sub-divisions of deterministic models were used in classifying hydrological modelling studies in Malaysia. From the results (Table 1) 65% of the studies conducted used physically-based models, 37% used empirical models while 6% used conceptual models. Of the 65% of physically-based modelling studies, 60% utilized HEC-HMS an open access model, 20% used SWAT (public domain), 9% applieed MIKE-SHE, MIKE 11 and MIKE 22, Infoworks RS occupied 7% while TREX and IFAS occupy 2% each. In the case of empirical models, 46% from the total of empirical researches in Malaysia used ANN, 13% applied LR, while Fuzzy logic, UH, ARIMA and SVM contributed 8% each whereas the remaining proportion is occupied by NWP, LSM, FR, DT and WoE.

Selangor state recorded a total 21 hydrological studies from the review (Chang et al. 2017; Dlamini et al. 2017; Goh et al. 2016; Khalid et al. 2015). This could be attributed to numerous rivers in the state such as Sungai Kayu Aru River basin, Upper Bernam River basin, Klang, Langat River whose changing hydrological behaviors with response to LULC changes and climate change need to be regularly monitored. Johor and Kelantan were ranked second each with 17 hydrological researches in this review. This may be due to high incidence of flood disasters in Kelantan as reported by several authors (Tehrany et al. 2014; Kia et al. 2012; Pradhan and Youssef 2011). Sabah and Sarawak ranked third with 5 hydrological studies reviewed in this study. Pahang recorded 4 researches, Perak and Terengganu came fifth with 3 researches each. Two hydrological studies were recorded in Kedah (Table 1; Fig. 4).

Deterministic models

In deterministic models, a unit of input parameters will yield the same output. These models can be classified according to description of a watershed whether lumped or distributed. They can also be describe based on the hydrological processes in the catchment whether physically-based, empirical or conceptual. It should however, be noted that majority of physically-based models are also distributed and majority of conceptual models are lumped (Refsgaard 1996). The three main classes of deterministic models are illustrated in Fig. 3 and will be discussed below based on how they are being applied for hydrological modelling in Malaysia. Table 2 shows a summary of the general characteristics of deterministic models.

Physically-based models

Physically based-models are mathematical illustration of a real-life events. They are also referred to as mechanistic models and usually include the techniques of physical processes. These models require parameters that can be measured and are dependent upon both time and space. They have minimal hydrological and meteorological data requirement for calibration purpose but it involves the estimation several variables that represent the physical features of a catchment such as soil moisture content, initial water depth, topography, topology, etc. (Abbott et al. 1986a; Refsgaard 1996; Devi et al. 2015). Unlike conceptual models, physically-based models do not give attention to water movement in a watershed to occur between a few storage units. Rather hydrological processes involving water and energy movement are assessed from partial differential equations, e.g. Richards' equation for vadose zone flow, Boussinesq's equation for groundwater flow and Saint Venant equations for overland and channel routing. The outputs of physically-based models are more comprehensive and precise than that of other model classes. In addition, these models can generate more than half of information of a watershed that is being simulated. The principle of physically-based models can be applied for any hydrological problem and in cases where other hydrological models cannot be applied (Refsgaard 1996). Example of physically-based hydrological models commonly applied in Malaysia for hydrological are HEC-HMS (USACE-HEC 2000), SWAT (Arnold et al. 2005), MIKE SHE (Refsgaard and Storm 1995).

HEC-HMS model

The Hydrologic Engineering Center–Hydrologic Modeling System (HEC-HMS) a watershed-scale open access hydrologic model was developed by United States Army Corps of Engineers Hydrologic Engineering Center (HEC). HEC-HMS like many physically-based hydrologic models simulate most of the major hydrologic processes at a watershed scale. The model system comprises of losses, runoff transform, open-channel routing, analysis of meteorological data, rainfall-runoff simulation, and parameter estimation (USACE-HEC 2010). It uses distinct models to represent each component of the runoff process, as well as models that compute runoff volume, models of direct runoff, and models of baseflow. Every individual model run a combine basin model, meteorological model, and control specifications with run options to obtain results. The system of connectivity and physical data describing

Table 1 Summary of Hydrologic modeling studies in Malaysia

No.	Source	Category/location	Objectives	Methodology	Findings
1	Abdulkareem et al. (2018a)	Physically-based model (HEC-HMS)/Kelantan River basin	To determine relative increase or decrease in peak discharge To assess how each sub-basin contribute to peak discharge and runoff volume under different return periods	*Model performance and evaluation*	The study used two indexes (novel *fa* index and established *f* index) to rank sub-basins with regards to their contribution to the outlet. The novel *fa* index was found to rank sub-basins better than *f* index because it considers initial peak discharge per unit area and change in peak discharge per unit area occupied by each sub-basin before ranking
2	Abdulkareem et al. (2018b)	Physically-based model (HEC-HMS)/Kelantan River basin	To assess the critical scientific question of the relationship between morphometric characteristics and the hydrological factors that lead to increase in flood	*Model performance and evaluation*	The results showed that morphometric characteristics in the studied watershed influence runoff. Hence, geomorphological studies are important in understanding rainfall–runoff behavior of a river basin in addition to prediction of peak discharge carried out with hydrological models
3	Mustafa et al. (2018)	Physically-based model (HEC-HMS)/Sengkuang River, Johor	To examine the hydraulic characteristic that are liable to be flooded following rainfall and tide influence To assess optimum channel geometry	*Model performance and evaluation*	The hydrological behavior of Sungai Sengkuang was successfully simulated and the results shows that no occurrence of overflow was observed along the channel
4	Romali et al. (2018)	Physically-based model (HEC-HMS)/Sgamat River, Johor	To simulate 2011 flood peak that will be used to generate flood maps of Segamat 2011 flood	*Model performance and evaluation*: Nash–Sutcliffe coefficient of efficiency (NSE)	It was observed that the simulated peak flow are in conformity with the observed peak flow Calibration results revealed an efficiency of 0.90 while that of validation revealed 0.76
5	Adnan and Atkinson (2018)	Physically-based model (HEC-HMS)/Kelantan River basin	To establish a hydrological model for Kelantan River basin To examine changes that are responsible for changes in peak flow using 1988 and 2004 data	*Model performance and evaluation*: Coefficient of determination (R^2), NSE, percentage bias (PBIAS), mean absolute error MAE	Hydrological model of Kelantan was successfully developed Climatic factors especially rainfall and land use contribute to rainfall-runoff behavior of the watershed

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
6	Chang et al. (2017)	Physically-based model and empirical model (HEC-HMS and adaptive network-based fuzzy inference system (ANFIS))/Sungai Kayu Ara basin, Selangor	To select the optimal number of rainfall inputs to be used in developing an ANFIS model for event-based rainfall-runoff simulation	*Model performance and evaluation*: Cross-correlation analysis (CCA); and mutual-information and cross-correlation analyses (MICCA), NSE, R^2, root mean square error or (RMSE), MAE, elative peak error	The output of HEC-HMS decreases as the number of stations reduces. ANFIS can perform better than HEC-HMS for locations with low number of rainfall stations. CCA and MICCA were able to identify contributing stations which happens to be located near the outlet of contributing sub-basins
7	Dlamini et al. (2017)	Physically-based model (SWAT)/Bernam River basin, Selangor	To calibrate and validate SWAT model for streamflow simulation in a basin with data scarcity To test how well the newly improved gridded data established by Wong et al. (2011) using kriging and inverse distance interpolation techniques will be used to simulate SWAT model	*Model performance and evaluation:* R^2, NSE, PBIAS	Results of the simulation are at par with those from the improved data where R^2, NSE and PBIAS of 0.67, 0.62 and −9.4% were obtained for the calibration process while for the validation, values of 0.62, 0.61 and −4.2% were recoded respectively The new data sets can be applied in the Bernam catchment as SWAT model was observed to successfully simulate results with these data sets. Hence, the model is recommended for studying the future impacts of streamflow in the study area
8	Mah et al. (2017)	Physically-based model [HEC-HMS and Infoworks River Simulation (RS])/Sg Similajau Basin, Bintulu, Sarawak	To assess the applicability limited data from a minimally gauged catchment in analyzing the hydrological behavior of the watershed To provide guidelines for other minimally ungauged watersheds from around the world and to be used to for future control and planning of the watershed	*Model performance and evaluation:* R^2	Rainfall from nearby basins with similar climatic conditions were effectively utilized in calculating synthetic streamflow for the minimally gauged basin Synthetic streamflow measurements carried out were effectively verified by monitoring the river over a short duration
9	Ab Razak et al. (2016)	Empirical model (Auto-regressive integrated moving average (ARIMA) model), Segamat River basin, Johor	To detect trends in rainfall as well as streamflow in Segamat river using Mann–Kendall trend analysis To establish time series flood prediction modelling approach using ARIMA model	*Model performance and evaluation:* R^2, MAPE and Akaike Information Criterion (AIC)	A trend of significant increase was detected in rainfall rates at Kemelah station while a trend of significant decrease was obtained at Bandar Segamat station. The data of streamflow from Bandar Segamat however shows significantly decreasing trend ARIMA model can be applied to enhance the understanding of flood behavior, trends and their possible risk

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
10	Adenana and Noorani (2016)	Empirical model [Chaos approach, ARIMA, ANN, support vector machine (SVM)] and least square vector machine (LSSVM)/Tanjung Tualang station, Perak	To forecast river flow direction in the study area using chaos approach, ARIMA, ANN, SVM and LSSVM	*Model performance and evaluation*: Correlation coefficient (*R*), RMSE	The models used provided reasonable flow prediction
11	Asmat et al. (2016)	Physically-based model [HEC-HMS and Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability Analysis (TRIGRS)]/Kelantan River basin	To assess the effect of LULC change on Kelantan River basin	*Model performance and evaluation*	The outcome of the study revealed that direct runoff from developed areas, agricultural regions and grassland areas are more pronounced for flooding events when compared with runoff from other LULC changes in the area. Urbanization and areas of low plant density favors the increase of runoff in the monsoon season floods. While inter-flow from forest and secondary forest donates normal flow
12	Beheshti et al. (2016)	Empirical model [Artificial neural network (ANN)]/Johor River basin	To predict rainfall in the study area for the next decade with the aid of two modes of original (free from data preprocessing) and data pre-processing with singular spectrum analysis	*Model performance and evaluation*: RMSE, MAE, NSE, *R*	It was observed that hybrid learning of multilayer perception (MLP) with Centripetal accelerated particle swarm optimization (CAPSO) algorithm gives better rainfall prediction accuracy, small errors and high degree of precision than other algorithms
13	Ghorbani et al. (2016)	Physically-based model (HEC-HMS)/Kelantan River basin	To detect the effect of environmental and ecological factors of watershed development that may likely influence flood To assess flood prone areas during extreme storm events	*Model performance and evaluation*	Flood can be controlled in some sub-basins by applying technical systems which are dependent the physio-graphic features of the sub-basin and its contribution on flood peak
14	Goh et al. (2016)	Physically-based model (MIKE BASIN)/Klang River basin, Selangor	To examine probable future water scarcity in the study area with regards to climate change	*Model performance and evaluation*: water balance error (WB_{er}), *R* and NSE	Water deficit analysis carried out using 2046–2065 indicated that there will be water unavailability in majority of the months
15	Jaafar et al. (2016)	Empirical model (ANN)/Kelantan River basin	To forecast flood water level in Kelantan River basin	*Model performance and evaluation*: MSE	The model outputs were satisfactory in forecasting water level at the study area
16	Jun et al. (2016)	Empirical model (Unit hydrograph)/Kampung Kasipillay catchment, Selangor	To determine the efficiency and applicability of a flood prediction model in Kampung Kasipillay catchment	*Model performance and evaluation*: Performance error	The model effectively utilized 15 flood events in simulating hydrographs at the study area with a performance error ranging from 2.06 to 5.82%

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
17	Khalid et al. (2016a)	Physically-based model (SWAT)/Langat River basin, Selangor	To analyze uncertainty and conduct one-at-a-time sensitivity analysis of SWAT model using Sequential Uncertainty Fitting (SUFI-2) method for parameter calibration	*Model performance and evaluation*: SUFI-2	Soil Conservation Service Curve Number (SCS-CN), base flow alpha factor and groundwater delay were the most sensitive parameters
18	Khalid et al. (2016b)	Physically-based model (SWAT)/Langat River basin, Selangor	To simulate daily streamflow in the watershed	*Model performance and evaluation:* R^2, NSE, PBIAS	The model was effectively utilized in simulating daily streamflow in the basin Results of the calibration period revealed that R^2, NSE and PBIAS recorded 0.75, 0.70 and 0.15 respectively
19	Kwin et al. (2016)	Physically-based model (HEC-HMS), Empirical model (Dynamic evolving neural fuzzy inference system (DENFIS) and ARX regression model)/Sungai Kayu Ara, Selangor	To assess the applicability of NFS with online learning for modelling rainfall-runoff behavior of a small rural tropical catchment	*Model performance and evaluation*: coefficient of efficiency (CE), R^2, RMSE, MAE and relative peak error (RPE)	Results from the DENFIS are similar to those from HEC-HMS but outweigh those from ARX. Hence, this shows the likelihood of DENFIS to be adopted for rainfall-runoff modelling
20	Norzilah et al. (2016)	Physically-based model (MIKE 3 DHI)/Setiu wetland, Terengganu	To simulate hydrodynamic causes of flood events as well as ebb cycles at the inlet of the catchment	*Model performance and evaluation*: Bias, RMSE	Simulation results indicated that higher velocities obtained in the month of June 2014 may be due to Southwest monsoon into Northeast monsoon. Lower velocities obtained in November 2014 and February 2015 were due to current velocities getting more energy at the offset of Northeast monsoon season
21	Ramly and Tahir (2016)	Physically-based model (HEC-HMS)/Klang–Ampang River basin, Selangor	To simulate the recurrent occurrence of flood in Klang–Ampang River Basin	*Model performance and evaluation*: NSE	The model effectively simulated flood in the study area with a high degree of precision as illustrated by NSE value 0.86
22	Saadatkhah et al. (2016)	Physically-based model (HEC-HMS and Improved TRIGRS model)/Kelantan River basin	To determine the rate of infiltration and effect of land cover equations governing runoff volume with regards to land cover sensitivity maps	*Model performance and evaluation*	The two models used revealed that LULC changes result in rapid hydrological response towards water flow in the basin. The results also showed that urbanization and deforestation are the causes of intense water flow in the area. The results of the TRIGRS model are more reliable even though both models can be used for runoff prediction in the study area

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
23	Sulaiman et al. (2016)	Conceptual model [Topographically-based hydrological (TOPMODEL)]/Johor River basin	To simulate runoff in a medium size catchment using different resolutions from ASTER DEM (an open source DEM) as major inputs of TOPMODEL	*Model performance and evaluation*: NSE, Relative Volume Error (RV_E) and R	ASTER DEM with 30 m resolution can be efficiently utilized in streamflow simulation in regions with unavailable data compared to other DEM sources
24	Tayebiyan et al. (2016)	Empirical model (ANN)/Cameron Highlands, Pahang	To forecast streamflow across the Ringlet reservoir of Cameron Highland	*Model performance and evaluation*	The use of ANN in the study location reveals its powerful nature in rainfall runoff modelling
25	Yaseen et al. (2016)	Empirical model (ANN)/Johor River basin	To examine the efficiency of feed-forward back-propagation neural network (FFNN) and radial basis function neural network (RBFNN) in daily streamflow forecasting in the study location	*Model performance and evaluation*: MAE, RMSE, MSE, R, relative error (RE)	RBFNN model outweigh FFNN model. RBFNN can be efficiently utilized and can provide high degree of precision and validity in daily streamflow prediction
26	Hafiz et al. (2014)	Physically-based model (Integrated flood analysis system (IFAS))/Kelantan River basin	To determine the applicability of IFAS model to Kelantan River basin	*Model performance and evaluation*: Coefficient of efficiency (E_c) and peak discharge error (E_p)	The IFAS model was effectively utilized to accurately predict the trend of observed hydrograph
27	Hassan et al. (2015)	Empirical model (ANN), conceptual model [Identification of unit Hydrographs and Component flows from Rainfall, Evaporation and streamflow data (IHACRES)]/Kurau basin, Perak	To assess changes present and future changes in climate To determine the effect of climate change impact on river runoff To detect unit hydrographs and component flows from rainfall, evaporation and streamflow data	*Model performance and evaluation:* R, NSE, RMSE	ANN and IHACRES were observed to comprehensively detect the observed data ANN provides perfect trend for daily and annual runoff series compared to IHACRES
28	Juahir et al. (2015)	Empirical model (ANN)/Langat River basin, Selangor	To determine the relationship between hydrological parameters involved in flood, the factors controlling flood occurrence, optimum values for factors of flood occurrence and risk values of flood factors in the study location	*Model performance and evaluation: R*	The use of ANN can increase early warning signs for flood prevention according to the level of prediction of the flood
29	Khalid et al. (2015)	Physically-based model (SWAT)/Langat River basin, Selangor	To use Malaysian soil datasets as soil characteristics in SWAT model in place USDA Soil Taxonomy database for developing hydrological assessment framework	*Model performance and evaluation*	The Langat river basin was successfully modeled using SWAT 2009 model. The input parameters that were found to be most sensitive as determined by SUFI-2 algorithm are CN, base flow alpha factor (ALPHA_BF), and groundwater delay (GW_Delay)

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
30	Malek et al. (2015)	Physically-based model (HEC-HMS)/Muar River, Johor	To predict changes in streamflow of Muar river by integrating Regional Climate Model into a hydrodynamic model	*Model performance and evaluation*: PBIAS	The peak discharge was reduced substantially in the third section while an upsurge in discharge in second section. Changes in peak discharge is an indication of probable occurrence of flood in the area The water supply system in the area will be affected as water storage capacity was observed to have significantly reduced
31	Mohd et al. (2015)	Physically-based model (SWAT)/Kuantan watershed, Pahang	The study was aimed at assessing the output and efficiency of SWAT model in simulating streamflow based on current and future climatic conditions	*Model performance and evaluation:* R^2	SWAT can be efficiently applied for flood control and management in the study area
32	Mohtar et al. (2015)	Empirical model [Numerical weather prediction (NWP)]/Kelantan River basin	To effectively predict flood using NWP in Kelantan River basin	*Model performance and evaluation: R*	The preliminary results have indicated the ability of NWP and weather satellite images to produce a weather forecast. It is believed that there is a bright future direction to adapt NWP for flood forecasting as a tool to produce forecasts
33	Nasir et al. (2015)	Physically-based model (HEC-HMS)/Pendas river basin, Johor	To simulate peak flow for 2, 5, 10, 20, 50, and 100-year average recurring intervals (ARI) in the studied catchment	*Model performance and evaluation*	Simulated model results can be can be efficiently relied upon in peak flow prediction
34	Suparta et al. (2015)	Empirical model (ANN)/Tawau, Sabah	To develop an early warning forecasting system for space activity plan	*Model performance and evaluation*: RMSE	The convective system activity has improved during summer monsoon where maximum values of Outgoing Longwave Radiation (OLR) were observed during dry season compared to middle of July
35	Tehrany et al. (2015)	Empirical model [Support vector machine (SVM), frequency ratio (FR) and decision tree (DT)]/Kelantan River basin	To propose novel ensemble method through the combine use of SVM, FR and DT for producing spatial model in flood susceptibility assessment	*Model performance and evaluation*	The results demonstrated the effectiveness of the ensemble method as fast, precise and reasonable in flood susceptibility assessment
36	Adnan et al. (2014a)	Physically-based model (HEC-HMS)/Kelantan River basin	To determine the effects of current LULC condition on peak discharge and runoff volume To determine the LULC type that exerts the highest influence on peak discharge and runoff volume	*Model performance and evaluation*	Rainfall change has a significant impact in determining the peak discharge and runoff depth for the study area

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
37	Adnan et al. (2014b)	Empirical model (ANN)/Kuala Lumpur, Selangor	To simulate flood and to propose a new advanced neural network technique for forecasting storm 5 h prior to the event	Model performance and evaluation Best fit, Akaike's Final Prediction Error (FPE), loss function (V), RMSE	The model efficiently forecasted storm, 5 h prior to the time of occurrence
38	Ali et al. (2014)	Physically-based model (SWAT)/Langat river basin, Selangor	To assess the efficiency of GIS interface of physically-based hydrologic model in forecasting daily stream flow as well as sediment trends in the study catchment	*Model performance and evaluation:* R^2 and NSE	The model can be efficiently utilized for river discharge simulation and water quality modelling in Malaysia for future development and planning
39	Basarudin et al. (2014)	Physically-based model (HEC-HMS)/Kelantan River basin	To determine the influence of extreme rainfall on the performance of HEC-HMS model	*Model performance and evaluation*: RMSE, R	The study managed to demonstrate that rainfall change has a significant impact to determine the peak discharge and runoff depth for the study area
40	Perera and Lahat (2014)	Empirical model (Fuzzy logic approach)/Kelantan River basin	To determine the ability of fuzzy logic approach to predict flood in Kelantan River basin	*Model performance and evaluation*: MAE, Relative Root Mean Square Error (RRMSE), NSE and R	The fuzzy logic approach is efficient enough to predict flood based on its acceptable performance tested using performance indicators in Kelantan River basin, Malaysia
41	Tan et al. (2014)	Physically-based model (SWAT)/Johor River basin	To examine individual as well combined effects of LULC change and climate variability on hydrological components in Johor river basin	*Model performance and evaluation:* R^2, NSE and PBIAS	Climate change exerts more effect than LULC change on streamflow and evaporation
42	Tehrany et al. (2014)	Empirical model [SVM and weight of evidence (WoE)]/Terengganu	To produce exact flood susceptible map by boosting SVM through integrating with WoE based statistical method	*Model performance and evaluation*: Bivariate statistical analysis (BSA), R	Flood susceptibility map was effectively produced using WoE and radial basis function kernel RBF-SVM with a success rate of 96.48% and 95.67% respectively
43	Yeganeh and Sabri (2014)	Empirical model (Fuzzy logic, Multi-criteria ranking and Weighted Linear Combination (WLC) methods) Iskandar, Johor	To determine extreme variables that contribute to risk of flooding based on physiographic features of the area and develop a flood susceptibility map using GIS	*Model performance and evaluation*	The use of natural environment should be done with caution to avoid untenable plan that can influence the development of environmental, social and economic aspects Development of impervious surfaces due to LULC changes were identified as the most efficient way of influencing flood risk by humans The flood susceptibility map produced signifies that more than 50% of the study area is under the risk of being flooded

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
44	Abdullah (2013)	Physically-based model (TREX)/Lui watershed, Selangor, Semenyih watershed, Selangor and Kota Tinggi, Johor	To test the TREX model for monsoon floods simulation To examine flood susceptible areas during extreme storm events To assess the influence of rainfall duration on the extent of peak discharge which is dependent upon catchment area Assessment and provision of graphs for the relationships between peak discharge and catchment area	*Model performance and evaluation*: Relative Percentage Difference (RPD), PBIAS and NSE	The model TREX model was tested and evaluated using field measured data from several rainfall events All the catchments were not susceptible to heavy storms except in the main channel In all the catchments in the study area, the extent of peak discharge for probable maximum precipitation as well world's greatest events were recorded to be 5 and 12 times greater than 100-year rainfall event Peak discharge decreased as catchment area increase
45	Kabiri et al. (2013)	Physically-based model (HEC-HMS)/Klang watershed, Selangor	To compare results from SCS-CN and Green-Ampt model for the estimation of runoff and flood in Klang catchment on an event basis	*Model performance and evaluation*: RMSE, MAE, R^2, R and NSE	Days with heavy rainfall will occur more frequently causing a higher frequency of river flow events There was no significant difference between the SCS-CN and Green-Ampt loss method applied in the Klang watershed
46	Tahir and Hamid (2013)	Conceptual model (Tank model)/Sungai Gombak, Klang River basin, Selangor	To develop a flood forecasting model using Tank model	*Model performance and evaluation*: MAE, RMSE, NSE	Flood forecasting model was successfully developed in the Sg. Gombak and was able to provide reliable prediction at Jalan Tun Razak
47	Tehrany et al. (2013)	Empirical model [rule-based decision tree (DT), FR and logistic regression (LR)]/Kelantan River basin	To compare the ability of DT and the combine use of FR and LR in flood susceptibility mapping	*Model performance and evaluation*: FR, LR	DT is fast with no statistical assumptions giving it the ability to process data by different measurement scales DT has a tree structure making it beneficial as the most important and influential conditioning factors are established in the preliminary nodes but the degree of relevance diminishes as you move down the tree It has the capacity of choosing conditioning factors in flood modelling and can discard other factors during build up process
48	Abood et al. (2012)	Physically-based model (HEC-HMS)/Kenyir catchment and Berang catchment, Terengganu	To evaluate the extent HEC-HMS model can simulate rainfall-runoff for Kenyir and Berang catchments with two different rainfall infiltration methods	*Model performance and evaluation*: Mean square error (MSE), mean absolute percentage error (MAPE)	SCS-CN method recorded 6.5% simulation error for Berang and 8.2% for Kenyir catchment. While the Green and Ampt method recorded 9.13% and 11.11% for Berang and Kenyir respectively

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
49	Alaghmand et al. (2012)	Physically-based model (HEC-HMS, MIKE 11) Kayu Ara River basin, Selangor	To determine the reliability of HEC-GeoHMS to extract the inputs of HEC-HMS and MIKE 11 GIS to prepare input geometric data for MIKE 11	*Model performance and evaluation: R*	HEC-GeoHMS can be readily employed as a reliable and accurate tool for extraction of input geometric data for HEC-HMS hydrological model. MIKE 11 GIS is useful for the preparation geometric data input for MIKE 11 as well for viewing results from the hydraulic models
50	Kia et al. (2012)	Empirical model (ANN)/Johor	To develop a flood model with the aid of flood contributing factors using ANN techniques and GIS to model and simulate flood prone areas of Johor river basins	*Model performance and evaluation:* R^2, sum squared error (SSE), MSE and RMSE	A multilayer perceptron model was developed and combined with GIS. The new method presented applied several causes of flood disaster for modelling floods which are presented in spatial form
51	Mustafa et al. (2012)	Physically-based model (HEC-1)/Upper Bernam River basin Selangor	To assess the influence of land development using HEC-1 model in the Upper Bernam River Basin	*Model performance and evaluation*: MAE, RMSE, Theils's coefficient (*U*)	The model can be simulated for future land development plans to evaluate hydrological impacts to avoid shortage of irrigation water and control the adverse effects of floods
52	Rahim et al. (2012)	Physically-based model (MIKE-SHE)/Paya Indah Wetlands, Selangor	To simulate different hydrological components of total water balance in Paya Indah Wetlands	*Model performance and evaluation: R*, NSE	Results from the studies indicated that climate change elements govern the total water balance in the area. The model results were found to be reliable with an estimated total of less than 1% of the total precipitation. Thus, indicating a sustainable interaction among the hydrological components
53	Amini et al. (2011)	Physically-based model (HEC-HMS)/Damansara Watershed, Selangor	To quantify changes in streamflow in Damansara watershed with response to LULC changes with the aid of real storms as test conditions	*Model performance and evaluation*: Deviation of runoff peaks (D_v)	It was found that the sensitivity of the hydrologic response to LULC changes increases as the recurrence interval of rainfall events decreases, and that those impacts are more pronounced in different sub-basins
54	Mah et al. (2011)	Physically-based model (Infoworks River Simulation (RS))/ Kuching-Batu Kawa-Bau Expressway Sarawak	To assess the influence of channel bypass structures in flood control	*Model performance and evaluation: R*	The bypass channel has aided in significant reduction of flood in the area

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
55	Pradhan and Youssef (2011)	Conceptual model (Probability distributed model) Physically-based model (Kinematic wave model)/ Kelantan River basin	To produce a flood susceptibility map for the Kelantan corridor	*Model performance and evaluation*	Flood susceptibility map was produced with the combine use of probability density moisture and rainfall simulation models. The results show the flood-prone areas delineated on the map which match with areas that will be severely affected by flood (approximately 100-year flood)
56	Shamsudin et al. (2011)	Physically-based model (HEC-HMS)/Sungai Johor, Sungai Tebrau, Sungai Skudai and Sungai Segamat, Johor	To determine uncertainty in HEC-HMS model parameters for Johor catchments using Monte Carlo Simulation (MCS)	*Model performance and evaluation*: Peak weighted root mean square error, univariate-gradient search algorithm, *R*	The study was able to estimate uncertainty associated with HEC-HMS parameters through multiple trials
57	Sulaiman et al. (2011)	Empirical model (ANN)/Rantau Panjang Station, Johor Baru	To investigate the effectiveness of steepness coefficient (SC) in the sigmoid function of ANN model that is designed to test the level of precision of 1-day water level forecasts	*Model performance and evaluation*: Statistical index efficiency coefficient, NSE, RMSE	The performance of ANN data training in flood prediction was improved through the use optimal SC when compared to the utilization of optimal SC
58	Kuok et al. (2010)	Physically-based model (HEC-HMS)/Sarawak	To establish a linear relationship between storage coefficient and catchment area	*Model performance and evaluation:* R^2, peak error	A relationship between storage coefficient and catchment area was successfully established It was observed that calculated time of concentration and storage coefficient are closely related to optimized
59	Razi et al. (2010)	Physically-based model (HEC-HMS)/Kota Tinggi watershed, Johor	To estimate flood using HEC-HMS model in Kota Tinggi watershed	*Model performance and evaluation: R*	The model was able to simulate flood effectively in the study area
60	Sulaiman et al. (2010)	Empirical model (Unit hydrograph)/ Pahang River basin	To identify and rank flood source areas with regards to their contribution to the outlet	*Model performance and evaluation*	Among the 16 sub-basins of Pahang river basin, sub-basin of Sungai Pahang was ranked first in production of flood discharge while Sungai Perting sub-basin was ranked last in term of production of flood discharge
61	Wong et al. (2010)	Empirical model (land surface model (LSM))/Pahang River basin and Muda River basin, Kedah	To utilize two different methodological approaches (lumped basin model and distributed routing model) to assess the influence of sub-grid variability and spatially varied topography in runoff generation	*Model performance and evaluation*: PBIAS, MAE, R^2, NSE	Uncertainty exists in the relationship between atmospheric forcing and runoff hydrology even though simulated runoff results were similar to observed results

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
62	Alansi et al. (2009)	Physically-based model (SWAT)/ Bernam basin, Selangor	To develop a methodology for SWAT model calibration and validation for enhance flow simulation and prediction To assess the optimal prediction cycles of the catchment	*Model performance and evaluation:* R^2, NSE, MAE, RMSE, *U*	The SWAT model was successfully applied for the simulation and prediction of flow in the study area The model can be used for studying the effect of LULC changes on flow
63	Ayub et al. (2009)	Physically-based model (AVSWAT-X)/ Sungai Langat, Selangor	To forecast daily stream flow and suspended solids using AVSWAT-X	*Model performance and evaluation:* *R*, average error	The model successfully simulated stream flow and suspended solids in the area
64	Hasan et al. (2009)	Physically-based model (HEC-HMS)/Sungai Kurau basin, Perak	To simulate the hydrologic condition of Sungai Kurau Basin To examine the influence of LULC change on the hydrological behavior of the watershed	*Model performance and evaluation*	The model results indicated a reasonable fit between observed and simulated data, hence HEC-HMS can be utilized for forecasting hydrologic behavior in the studied catchment
65	Pradhan (2009)	Empirical model (Logistic regression)/Kelantan River basin	To produce flood susceptible map of flood prone areas in Kelantan River basin with the aid of a statistical model and GIS	*Model performance and evaluation*	It was observed from the results that 1:25,000 can be used to achieve flood prone areas, a scale compared to some common flood hazard map scales. Flood pone areas delineated commensurate to areas that are likely to be affected by floods
66	Pradhan et al. (2009)	Empirical model (Logistic regression)/Kelantan River basin	To map out maximum flood prone area in Kelantan River basin with the aid of multiple regression model using GIS techniques and remote sensing	*Model performance and evaluation*: Flood susceptibility index	The results indicated that map out flood prone areas can be mapped out on a scale of 1:25,000 is similar to what is obtained in some common medium scaled flood hazard map. Flood areas (susceptible maps). Flood prone areas delineated (otherwise known as susceptibility areas) coincide with areas that are likely to be affected by significant flooding (roughly 100-year flood)
67	Ros et al. (2008)	Physically-based model (HEC-HMS)/Kenyir catchment, Terranganu	To determine the procedure for obtaining the best probable maximum flood (PMF) hydrograph in the study area with regards to dam safety study	*Model performance and evaluation*	The results indicated that the capacity of the dam to resist spillway discharge is suitable enough to sustain PMF during cases of extreme storm events
68	Mah et al. (2007)	Physically-based model (Infoworks River Simulation (RS))/ Sungai Sarawak Kanan	To reconstruct historical flood events of flood susceptible areas at Sungai Sarawak Kanan for producing hydrographs that will clarify flood activities in Bau town and surrounding areas	*Model performance and evaluation: R*	Infoworks RS successfully simulated results at flood depths and flood watermarks within the range observed by Department of Irrigation and Drainage Sarawak

Table 1 (continued)

No.	Source	Category/location	Objectives	Methodology	Findings
69	Nor et al. (2007)	Empirical model (Radial base function (RBF), ANN) and Physically based (HEC-HMS)/ Sungai Bekok Johor, and Sungai Ketil Kedah	To model rainfall-runoff relationship in Sungai Bekok Catchment Johor and Sungai Ketil catchment Kedah	*Model performance and evaluation:* *R*, RRMSE, RMSE, MAPE	The RBF method can be used simulate streamflow hydrograph accurately
70	Yusop et al. (2007)	Physically-based model (HEC-HMS)/Skudai River, Johor	To determine runoff features and outcome of hydrograph modelling from an oil palm catchment	*Model performance and evaluation:* Efficiency index (EI), *R*	Peak flow and storm flow volume were moderately correlated with rainfall. The hydrographs were satisfactorily modeled using the HEC-HMS. The efficiency indexes of the calibration and validation exercises are 0.81 and 0.82, respectively

a watershed are stored in the basin model (Verma et al. 2010). HEC-HMS model adopts a concept of semi-distributed modeling by using sub-catchments and channel routing components.

Several researches have been conducted using HEC-HMS model in the river basins of Malaysia for evaluating the hydrologic response of the various catchments (Abdulkareem et al. 2018a, b; Chang et al. 2017; Asmat et al. 2016; Malek et al. 2015; Basarudin et al. 2014; Kabiri et al. 2013). Majority of the hydrological studies reviewed in this study gave attention to long-term streamflow changes in river basins, effect of LULC changes on streamflow and direct runoff as well as the impact of climate change on the hydrological behavior of watersheds (Table 1).

Abdulkareem et al. (2018a) utilized HEC-HMS to determine relative increase or decrease in peak discharge and to assess how each sub-basin contribute to peak discharge and runoff volume under different return periods. The study used two indexes (novel *fa* index and established *f* index) to rank sub-basins with regards to their contribution to the outlet. They concluded that the novel *fa* index is found to rank sub-basins better than *f* index because it considers initial peak discharge per unit area and change in peak discharge per unit area occupied by each sub-basin before ranking. Asmat et al. (2016) applied HEC-HMS model to assess the effect of LULC change in Kelantan, a tropical complex catchment that is under the influence LULC change due to deforestation for logging activities, agriculture and urbanization. They were able to show that direct runoff from developed areas, agricultural regions and grassland areas are more pronounced for flooding events when compared with runoff from other LULC changes in the area. While urbanized areas and areas of low plant density favors the increase of runoff in the monsoon season floods. HEC-HMS model was also applied to Kelantan river basin by Ghorbani et al. (2016). According to their results, flood can be controlled in some sub-basins by applying technical systems, which are dependent on the physiographic features of the sub-basin and its contribution on flood peak. In another study, HEC-HMS model was applied to Muar river, Johor, to detect changes in streamflow of the river (Malek et al. 2015). There results showed changes in peak discharge, which is an indication of probable occurrence of flood in the area. They were also able to detect that the water supply system in the area will be affected as water storage capacity was observed to have significantly reduced (Table 1).

Kabiri et al. (2013) used two different infiltration methods SCS-CN and Green-Ampt method in HEC-HMS for the estimation of runoff and flood in Klang catchment on an event basis. They were able to find out that days with heavy rainfall will occur more frequently causing a higher frequency of river flow events. The results also showed that, there was no significant difference between

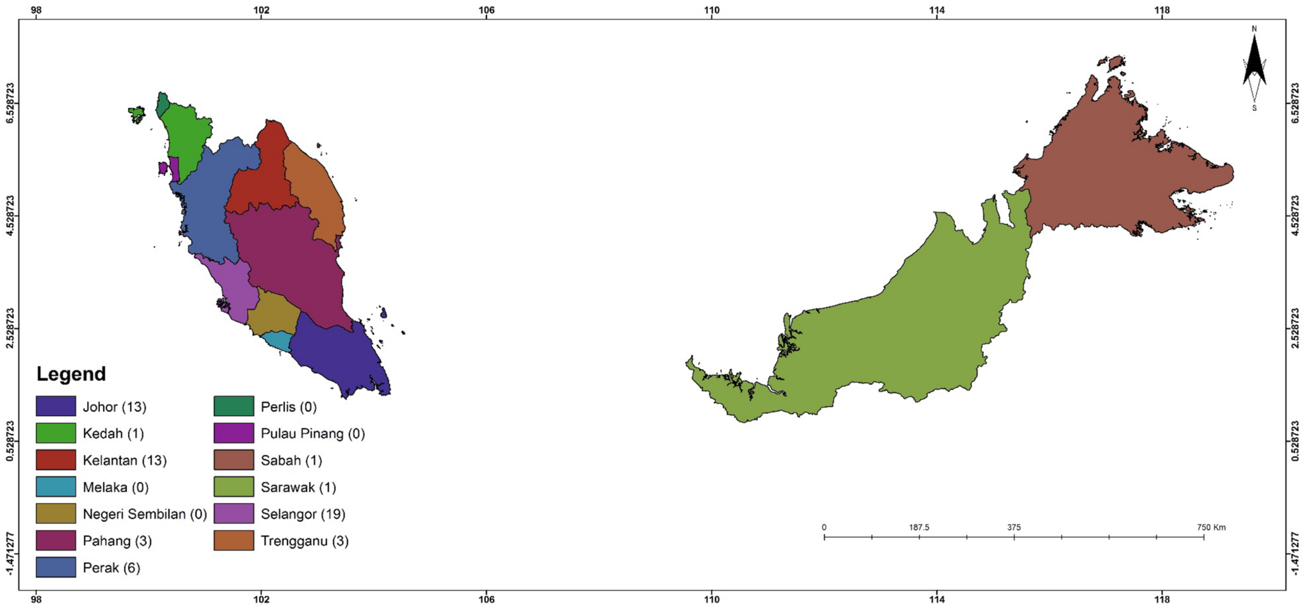

Fig. 4 Map of Malaysia showing spatial distribution of number of hydrological studies across the state

Table 2 Characteristics of Deterministic models

Physically based model	Conceptual model	Empirical model
White box model or mechanistic	Grey box model or parametric	Black box model or metric
HEC-HMS, MIKESHE, SWAT	TOPMODEL	ANN, unit hydrograph
Spatial distribution driven, assessment of parameters outlining physiographic feature	Involve reservoir modelling comprise semi-empirical equations that are physically based	Mathematical equations with values derived from time series
Initial model data required as well as watershed morphological features	Parameters are extracted from field data and calibration	Features and processes of the system are minimally considered
Complex model and not easy to use. Require skills and computational capability	Simple and easy to use in computer code	High degree of forecasting ability, low explanatory depth
Challenges with scale related problems	Large data sets required (hydrological and meteorological data)	Differ from one catchment to the other
Valid for several conditions	Curve fitting as part of the calibration process giving difficulties in physical interpretation	Valid within the boundary of a certain domain

the SCS-CN and Green-Ampt loss method applied in the Klang watershed. Abood et al. (2012) also compared SCS-CN and Green-Ampt methods in HEC-HMS in two different catchments (Kenyir and Berang catchments). They also reported no significant difference exist between the two infiltration methods in the two catchments. In another study, uncertainty in HEC-HMS model parameters for Johor catchments using Monte Carlo Simulation (MCS) was determined (Shamsudin et al. 2011). The results of the uncertainty analyses were given in a range of 1.25– 4.99 mm for initial loss, with an average of 153.55 mm/h. While constant loss rate was reported to have a range of 0.98–299.87 mm/h with an average of 153.55 mm/h. The study was able to estimate uncertainty associated with HEC-HMS parameters through multiple trials. A dam safety study was integrated with HEC-HMS modelling in Kenyir catchment, Terranganu with the aim of determining the procedure for obtaining the best probable maximum flood (PMF) hydrograph (Ros et al. 2008). The results indicated that the capacity of the dam to resist spillway discharge is suitable enough to sustain PMF during cases of extreme storm events. Yusop et al. (2007) utilized HEC-HMS in an oil palm dominated catchment to determine runoff features and outcome of hydrograph modelling. Their simulation showed that peak flow and storm flow volume were moderately correlated with rainfall and the hydrographs were satisfactorily modeled using the HEC-HMS. The efficiency indexes of the calibration and validation exercises are 0.81 and 0.82, respectively (Table 1).

SWAT

Soil water assessment tool (SWAT), is a public domain physically-based model developed to examine and predict the circulation of water and sediment as well as agricultural production with nutrients (Arnold et al. 2005). It has an excellent capability of simulating long-term experiments to facilitate real catchment response (Devi et al. 2015; Khalid et al. 2016). SWAT usually delineate a watershed into smaller sub-basins, which are further separated into hydrologic response units (HRU), LULC, vegetation and soil features. The major input parameters used by the model are daily rainfall, minimum and maximum air temperature, solar radiation, relative air humidity and wind speed. The model has been effectively utilized in Malaysia and from around the world (Devi et al. 2015). Some of the researches conducted in Malaysia using SWAT model include; Dlamini et al. (2017), Khalid et al. (2016a), Khalid et al. (2016b), Mohd et al. (2015), Ali et al. (2014), Tan et al. (2014), Alansi et al. (2009). Most of these studies were conducted with their attention focusing on basin hydrological response, that include river discharge, sediment and nutrient flux as well as effect of LULC change on river discharge on surface runoff and the impact of climate change on sediment.

Dlamini et al. (2017) calibrated and validated SWAT model for streamflow simulation in Bernam river basin, Selangor with data scarcity. They also tested how well the newly improved gridded data established by Wong et al. (2011) using kriging and inverse distance interpolation techniques will be used to simulate SWAT model. They showed that results of the simulation are at par with those from the improved data where R^2, NSE and PBIAS of 0.67, 0.62 and −9.4% were obtained for the calibration process while for the validation, values of 0.62, 0.61 and −4.2% were recoded respectively. They also found that the new data sets could be applied in the Bernam catchment, as SWAT model was observed to successfully simulate results with these data sets. In another research, Khalid et al. (2016a) analyzed uncertainty and conducted one-at-a-time sensitivity analysis of SWAT model using sequential uncertainty fitting (SUFI-2) method for parameter calibration in Langat river basin, Selangor. The results showed that soil conservation service curve number (SCS-CN), base flow alpha factor and groundwater delay were the most sensitive parameters. Furthermore, Khalid et al. (2015), were able to calibrate SWAT model using Malaysian soil datasets as soil characteristics in place of USDA Soil Taxonomy database for developing hydrological assessment framework at Langat river basin, Selangor. Results of the simulation revealed that, SWAT could be efficiently applied for flood control and management in the study area. Mohd et al. (2015) worked with SWAT model by coupling it with statistical climate downscaling tools at Kuantan watershed, Pahang. They found that the model could be efficiently applied for flood control and management in the study area (Table 1).

Tan et al. (2014) examined individual as well combined effects of LULC change and climate variability on hydrological components in Johor river basin. They showed that a combination of climate and LULC change effect result in the increase of annual streamflow by 4.40% and that of evaporation by 1.20%. While the individual effect of climate change elevated streamflow by 4.40% and that of LULC change by 0.06% while for evaporation, climate causes an upsurge of 2.20% and LULC change reduced by −0.20% (Table 1). In another study, the optimal prediction cycles of the catchment were assessed in Bernam basin, Selangor an irrigated basin for rice granary (Alansi et al. 2009). The study used historical record of 27 years' data (1981–2007), data sets from 1981 to 2004 were utilized for calibration while data sets from 2005 to 2007 were used for model validation and flow prediction. A 50% reduction in the monthly irrigation water was observed in months when flow is low, this underscore the importance of introducing structured best management practices (BMPs) like ponds to the study location. This will enhance land development plan to manage and control future changes in LULC on flow quantity.

SWAT was applied by Ayub et al. (2009) for hydrological evaluation of Langat River Basin using 1997, 2001, and 2003 historical data to compare the model results. Although the model successfully simulated streamflow and suspended solids in the area. The 2 months (June and July 1997) data used for calibration are not satisfactory enough to describe the hydrological performance of the streamflow in the study area based on long time changes while using a daily time bound hydrological model. The recommended time for describing a watershed appropriately is the use of at least 20 years of nonstop daily historical data (Khalid et al. 2016).

MIKE SHE

Systeme Hydrologique European (MIKE SHE) is a public domain physically-based model that requires large sets of physical parameters for its calibration (Refsgaard and Storm 1995). It was established based on SHE modeling criteria (Abbott et al. 1986a, b) and it is simple and easy to use. Several processes in the hydrological cycle are being considered by the model e.g. rainfall, evapotranspiration, streamflow, interception, saturated and unsaturated ground water flow. The model can simulate the interaction of both overland and channel water movement as well as their individual flow. Simulation of nutrients, pesticides and sediments and several other water quality problems can as well be carried out in large catchments (Devi et al. 2015).

There are several studies in Malaysia that applied MIKE SHE and MIKE related versions (Table 1). For example Goh et al. (2016) used MIKE BASIN a map-based decision support tool to examine probable future water scarcity in Klang river basin, Selangor with regards to climate change. Simulation results from dam level were not alike with observed results for the reservoir model verification. This may be due to data scarcity especially rainfall at the upstream of the dam. Therefore, 18 Global Circulation Models (2046–2065) downscaled projected future rainfall data were utilized for climate change scenario assessment. There results showed that water deficit analysis carried out using 2046–2065 indicated that there will be water unavailability in majority of the months.

Norzilah et al. (2016) used MIKE 3 (uses a technology similar to that of MIKE 21) at Setiu wetland, Terengganu to simulate hydrodynamic causes of flood events as well as ebb cycles at the inlet of the catchment. The results of the simulation indicated that higher velocities obtained in the month of June 2014 might be due to Southwest monsoon into Northeast monsoon. Lower velocities obtained in November 2014 and February 2015 were due to current velocities getting more energy at the offset of Northeast monsoon season. In another research where different hydrological components of total water balance were simulated using MIKE-SHE at Paya Indah Wetlands (Rahim et al. 2012). There have being reported worries on the uncertainty of hydrological behavior of the wetlands to climate change and forest management (Lu et al. 2006). Results from the studies indicated that climate change elements govern the total water balance in the area. The model results were found to be reliable with an estimated total of $>1\%$ of the total precipitation. Thus, indicating a sustainable interaction among the hydrological components.

Conceptual models

Conceptual models otherwise known as lumped models are also commonly applied in hydrological modelling. They function with dissimilar but mutually interconnected storages that illustrate physical features in a watershed. Conceptual models operate using a system that accounts for stored moisture contents on a continuous basis. Hydrological behavior description cannot be built upon equations that are meant to be valid for each soil unit, because all model parameters represent an average value of the entire watershed. Thus, the equations will have a physical base even though they are semi-empirical in nature. As such, calibration also becomes a component of assessing model parameters as field data alone cannot be sufficiently used. The availability of hydrological time series data large enough for modelling permits the use of conceptual models for rainfall-runoff simulation. In Malaysia, few researches exist in literature that applied conceptual models to measured hydrological data for streamflow prediction as shown in Table 1.

Sulaiman et al. (2016) applied TOPMODEL (Topographically-based hydrological) in a medium size catchment in Johor river basin for the simulation of runoff using different resolutions from ASTER DEM (an open source DEM) as major inputs of TOPMODEL. The TOPMODEL is a conceptual model designed to capitalize on information that is connected to runoff. It can be applied to a single unit or a multiple unit of sub-basins with the aid of elevation data (usually in grid) for the drainage basin area. The model can also be referred to as variable contributing area conceptual model as its parameters can be measured theoretically. The results showed that ASTER DEM with 30 m resolution is reasonable in producing topographic index, which is crucial in TOPMODEL and can be efficiently utilized in streamflow simulation in regions with unavailable data compared to other DEM sources. DEM resolutions used in this study ranged from 30 to 300 m were remarkably observed to influence the topographic index distribution. Additionally, varying the resolution of the DEM exerts a strong influence on the performance of the model.

In a research conducted by Hassan et al. (2015) to determine the effect of climate change impact on river runoff and to detect unit hydrographs and component flows from rainfall, evaporation and streamflow data. The researchers used a conceptual model; IHACRES and an empirical model; ANN at Kurau basin, Perak to achieve these objectives. Although the study did not consider the physical features of the catchment such as topography, soil permeability. The models were able to comprehensively detect the observed data. While ANN provides better trend for daily and annual runoff series compared to IHACRES. Tahir and Hamid (2013) used tank model consisting of four tanks that are similar to actual storage in Sungai Gombak, Klang River basin, Selangor. The hydrological model was developed for flood forecasting in the area. The flood forecasting model was successfully developed in the Sg. Gombak and was able to provide reliable prediction at Jalan Tun Razak. Flood susceptibility map was produced for the Kelantan corridor by Pradhan and Youssef (2011) with the combine use of a conceptual model (probability distributed model) and a physically-based model (kinematic wave model). The study illustrates multiple parameter method for defining flood susceptible areas in the study location carried out in a GIS environment with the aid of multi-criteria decision-making systems. Flood susceptibility map was produced with the combine use of probability density moisture and rainfall simulation models. The results show the flood-prone areas delineated on the map match the areas that will be severely affected by flood (approximately 100-year flood).

Empirical models

Empirical or black box models as they are often called, involved the use of mathematical equations that have been evaluated from concurrent input and output time series and not from physiographic features of a watershed. These models are categorized into three based on their source viz; hydro informatics based, empirical hydrological methods and statistically based methods. The hydro informatics based model is a new class of 'transfer function models' that is currently in use. They are of two types, a group based on neural network, e.g. ANN while the other is based on evolutionary algorithms, e.g. SVM. Empirical hydrological models are the most popular among black box models, e.g. the unit hydrograph model whose principles are mostly applied by most hydrological models (Sherman 1932; Nash 1959). Nowadays most comprehensive models use empirical hydrological models as part of their component. For instance, the unit hydrograph is mostly utilized for river flow routing and linear reservoir to signify groundwater system in conceptual models. Statistically based method used in hydrology were fully developed with the aid of basic statistical theories. They are mathematically more technical than other classes of empirical model, e.g. ARIMA models (Box and Jenkins 1970), The Constrained Linear Systems (CLS) model (Todini and Wallis 1977).

Unit hydrograph

Unit hydrograph is the hydrograph obtained from one unit excess rainfall that occurs homogenously on a catchment uniformly at a given period. Unit hydrograph has little number of parameters (usually 1–3 but less than 4) which include hydraulic and hydrologic information of the watershed. Physiographic characteristics such as drainage basin area are generally accepted without doubt while other watershed variables are usually estimated (Rabuñal et al. 2007). Unit hydrograph experiments are usually based on two major principles invariance; a hydrograph resulting from runoff in a watershed because of excess rainfall or the total amount of rainfall after infiltration and other losses occur. Superposition; is the hydrograph produced from excess rainfall pattern generated by superimposing unit hydrograph because of distinct quantity of excess rainfall that occurred in each unit (Dooge 1959).

From the review (Table 1), little number of studies were observed that utilized the unit hydrograph for hydrological modelling. Some of them include; the study by Jun et al. (2016) in Kampung Kasipillay catchment, Selangor conducted with the aim of determining the efficiency and applicability of a flood prediction model in Kampung Kasipillay catchment. The results showed that the model effectively utilized 15 flood events in simulating hydrographs at the study area with a performance error ranging from 2.06 to 5.82%. Sulaiman et al. (2010) integrated the unit hydrograph with flood response approach (Saghafian et al. 2008; Saghafian and Khosroshahi 2005) to identify and rank flood source areas with regards to their contribution to the outlet at Pahang river basin. The results indicated that among the 16 sub-basins of Pahang river basin, sub-basin Sungai Pahang was ranked first in production of flood discharge while Sungai Perting sub-basin was ranked last in terms of production of flood discharge (Table 1).

ANN

ANN applies generalizations of human cognition or neural biology to process information (Lippmann 1987; Haykin 1999). Commonly used types of ANN include the one with several layers with some neurons on each and interconnected with feed forward connections in other words, withdrawal of one neutron cannot go to the entry of another neutron of the same or succeeding layer and trained with the backpropagation algorithm (Johansson et al. 1991). In Malaysia, the use of ANN in the field of hydrology has recorded tremendous success despite reluctance by some scientist from around the world to utilize this emerging field of hydrology. The black-box nature of ANNs is one of the reasons why some researches from around the globe are unwilling to utilize these models, even though they can be easily be interpreted with some readily available techniques. ANNs has been extensively utilized in Malaysia to model rainfall-runoff relationship in catchments, river flow forecasting, assessment of present and future climatic change, detection of early warning signs for flood prevention among others as summarized in Table 1.

Adenan and Noorani (2016) integrated Chaos approach, ANN, SVM, and LSSVM to forecast river flow direction in Tanjung Tualang station, Perak. The results showed that all the models used provided reasonable flow prediction. In addition, they were able to find out that river flow is deterministic and can easily to be forecasted in the area. They recommended chaos approach as the ideal method for analysis and river flow forecasting for providing information that will be useful to water resources planners. In a different study, Beheshti et al. (2016) predicted rainfall in Johor river basin for the next decade with the aid of two modes of original (free from data preprocessing) and data preprocessing with singular spectrum analysis. They used Centripetal accelerated particle swarm optimization (CAPSO) and

Gravitational search algorithm (GSA) as free from data preprocessing while Imperialist competitive algorithm (ICA) was utilized as data preprocessing with singular spectrum analysis. It was observed from the results that hybrid learning of multilayer perception (MLP) with CAPSO algorithm gives better rainfall prediction accuracy, small errors and high degree of precision than other algorithms. The use CAPSO has advantages over other algorithms that include; it does not require tuning of any algorithmetic parameter and it illustrates a good performance with testing data. Kwin et al. (2016) integrated a physically-based model (HEC-HMS) and dynamic evolving neural fuzzy inference system (DENFIS) and ARX regression model to assess the applicability of NFS with online learning for modelling rainfall-runoff behavior of a small rural tropical catchment. Results from the DENFIS are similar to those from HEC-HMS but outweigh those from ARX. Hence, this shows the likelihood of DENFIS to be adopted for rainfall-runoff modelling.

The efficiency of feed-forward back-propagation neural network (FFNN) and radial basis function neural network (RBFNN) was tested in daily streamflow forecasting in Johor river basin (Yaseen et al. 2016). The results pointed out that RBFNN model outweigh FFNN model. RBFNN can be efficiently utilized and can provide high degree of precision and validity in daily streamflow prediction. Tehrany et al. (2015) carried out a study in Kelantan river basin aimed at proposing novel ensemble method through the combine use of SVM, FR and DT for producing spatial model in flood susceptibility assessment. They were able to prove that the individual use of statistical and other machine learning methods is not sufficient for flood susceptibility assessment. The results demonstrated the effectiveness of the ensemble methods as fast, precise and reasonable in flood susceptibility assessment. Fuzzy logic was applied at Iskandar, Johor to determine extreme variables that contribute to risk of flooding based on physiographic features of the area and develop a flood susceptibility map using GIS (Yeganeh and Sabri 2014). From the study, it was found out that the use of natural environment should be done with caution to avoid untenable plan that can influence the development of environmental, social and economic aspects. Development of impervious surfaces because of LULC changes were identified as the most efficient way of influencing flood risk by humans. The flood susceptibility map produced signifies that more than 50% of the study area is under the risk of being flooded.

Model performance and evaluation

The use of modeling tools in water resources management is on the rise which is aimed at predicting the possible future changes in climate, land use change as well as land and crop management practices on the quantity and quality of land and water resources (Moriasi and Wilson 2012). Yet, the ability of these models to make predictions accurately is still needed to be verified using proper model validation techniques (Bathurst et al. 2004). Although, the choice of appropriate validation technique to be used for a hydrologic model is still a topic of research on its own. It should however be noted that no general procedure exists for the validation of models in the literature. In view of this, numerous modelers are of different views as to how validation should be carried out and reported for facilitating the peer-review process and the ability to bear legal scrutiny (Santhi et al. 2001; Engel and Flanagan 2006; Jakeman et al. 2006; Moriasi et al. 2007; Moriasi and Wilson 2012).

Agreement between observed and simulated values are evaluated either using graphical and statistical methods during hydrological model calibration and validation. Graphical method is the oldest and easiest method to use. It can be used by comparing observed and simulated time to peak, peak discharge, rising and falling limb (Green and Stephenson 1986; Legates and McCabe 1999). The use of graphical method is sometimes difficult especially when unequal but similar observed and simulated values are involved (Green and Stephenson 1986). Statistical method uses numerical values to test the level of agreement between observe and simulated time to peak, peak discharge, and volume of flow. Statistical measures are used to describe the validity of a model for a particular application and this may guide the modelers to choose the most appropriate type of model for the application in question (Bellocchi et al. 2010). For any hydrologic model to be applied successfully, calibration and validation processes are crucial. This is normally dependent upon the technical capability of the hydrological model, technical skills of the operator as well as the quality of input data. For most, if not all, hydrologic models calibration is an interactive procedure for parameter evaluation and improvement. It plays a vital role in hydrologic modeling by reducing uncertainties in model predictions. In reality, model validation is an extension of the calibration process. Normally in hydrology, calibration and validation are carried out by comparing and finding the relationship between simulated and observed values.

In this review, majority of the hydrological modelling studies utilized one or more statistical method of evaluating model performance except in some few cases where model evaluation criteria was not clearly stated (Table 1). Of the 70 papers reviewed in this study, 16 did not specify the type of model evaluation technique they used in validating their studies, 17 used only one method while 37 used two or more methods. The use of NSE along with other methods as a model evaluation criterion is the highest with a total percentage use of 27% while R and RMSE came second with a percentage use 24% each. R^2 (20%) was recorded as the third most widely used model evaluation criteria in Malaysia; MAE is fourth with 16% while PBIAS is the least method use with 11%.

Jun et al. (2016) used performance error only, Ramly and Tahir (2016) employed R only, Malek et al. (2015) applied only PBIAS. In some studies, two or more statistical measures were applied e.g. Adenan and Noorani (2016) evaluated their models with R and RMSE for evaluating their hydrological model. WB_{er}, R and NSE were employed by Goh et al. (2016) in testing the performance of their model. Kwin et al. (2016) applied CE, R^2, RMSE, MAE and RPE for the validation of HEC-HMS, DENFIS and ARX regression model. Other studies did not clearly state the type of model performance and evaluation used, e.g. Abdulkareem et al. (2018a), Asmat et al. (2016), Ghorbani et al. (2016), Khalid et al. (2015), Nasir et al. (2015), Adnan et al. (2014a), Sulaiman et al. (2010) etc. This lack of clear evaluation criteria by some studies may be due to absence of general procedure for validation of models in the literature. As numerous modelers are of different views as to how validation should be carried out and reported for facilitating the peer-review process and the ability to bear legal scrutiny (Santhi et al. 2001; Engel and Flanagan 2006; Jakeman et al. 2006; Moriasi et al. 2007; Moriasi and Wilson 2012). In addition, the use of visual comparison (Saadatkhah et al. 2016) between simulated and observed data as well as judgement based on experience of the modeler are also considered significant by hydrologists for evaluating model reliability and performance. Among the statistical methods commonly utilized in Malaysia for hydrological model performance and evaluation, R, R^2, NSE, RMSE, MAE and PBIAS were discussed in this review as they are utilized in by different researchers.

Correlation coefficient (*R*)

R is sometimes mistaken with R^2. They are both used in evaluating the performance of hydrological models. The Pearson correlation is the most commonly used measure of statistical association. It provides numerical estimate of the statistical co-variation between measured and simulated data (Addiscott and Whitmore 1987). The procedure is presented in Eq. (1);

$$R = \frac{\sum_{i=1}^{N}(Q_{Obs}-\bar{Q}_{Obs})(Q_{sim}-\bar{Q}_{sim})}{\sqrt{\sum_{i=1}^{N}(Q_{Obs}-\bar{Q}_{Obs})^2(Q_{sim}-\bar{Q}_{sim})^2}} \quad (1)$$

where Q_{Sim} is the simulated discharge at time $t=i$, Q_{Obs} is the observed discharge at time $t=i$, $\bar{Q}_{sim}$ is the average simulated discharge $\bar{Q}_{Obs}$is the average observed discharge; N is the number of observations. Some scientists are of the view that correlation coefficient should not be used solely as a measure of performance (Fox 1981; Willmott 1982; Abdulkareem et al. 2018c, d). As its degree of assessing performance does not rely on the precision of estimates. This is because correlation between two unequal measurements can be high while a low correlation value may be obtained from measurements with small differences. As such, the use of nonparametric correlation such as concordance, Spearman and Kendall's coefficients are also advocated for model evaluation purposes (Press et al. 1992; Dhanoa et al. 1999; Agresti 2002). In Malaysia, several hydrological studies were conducted that utilized R as a measure for testing the validity of their hydrological models. Example of such researches include; Adenan and Noorani (2016) while working on Chaos approach, ARIMA, ANN, support vector SVM and LSSVM at Tanjung Tualang station, Perak. Beheshti et al. (2016) on ANN in Johor river basin. Goh et al. (2016) on a physically-based model (MIKE BASIN) in Klang river basin, Selangor. Correlation coefficient was applied to a validate two hydrological models, one empirical (ANN) and one conceptual (IHACRES) in Kurau basin, Perak (Hassan et al. 2015).

Coefficient of determination (*R*²)

This can be described as the square of correlation coefficient (Krause et al. 2005). The equation representing R^2 is presented in the following equation;

$$R^2 = \frac{\sum_{i=1}^{N}(Q_{Obs}-\bar{Q}_{Obs})(Q_{sim}-\bar{Q}_{sim})}{\sqrt{\sum_{i=1}^{N}(Q_{Obs}-\bar{Q}_{Obs})(Q_{sim}-\bar{Q}_{sim})}} \quad (2)$$

R^2 values range from 0 to 1, which illustrates how the distributed observed variables are described by the simulation. Simulated values equal to 1 represent a perfect distribution between observed and simulated model values, while values equal to 0 signifies no correlation. One major disadvantage of R^2 is that, there will be ambiguity in the results if the model underestimate or overestimate the results (Krause et al. 2005). Although this can be easily sorted out comparing visually the observed and simulated results (Nejadhashemi et al. 2011).

Just like R, several hydrological studies conducted in Malaysia utilized R^2 as a statistical measure for model validation (Table 1). Ab Razak et al. (2016) applied R^2 along with MAPE and ACAIC in validating ARIMA model in Segamat river basin, Johor. Mohd et al. (2015) while working in Kuantan watershed, Pahang utilized R^2 as the only statistical measure in validating a physically-based model (SWAT). R^2 was used in Langat river basin, Selangor to validate SWAT model for a study aimed at assessing the efficiency of GIS interface of the model in forecasting daily stream flow and sediment trends

(Ali et al. 2014). Kabiri et al. (2013) used both R^2 and R in evaluating HEC-HMS model at a semi-urban catchment. Kuok et al. (2010) utilized R2 along with peak error in calibrating and validating HEC-HMS model they used in developing a relationship between storage coefficient and catchment area.

Nash–Sutcliffe efficiency (NSE)

Nash–Sutcliffe efficiency (Nash and Sutcliffe 1970) is the commonest and highly reliable method for evaluating the analytical power of hydrological models. It is represented by Eq. 3. NSE values ranges between 0 and 1. A perfect fit is denoted by the value 1 while 0 denotes a poor fit. According to Andersen et al. (2001), NSE values between 0.50 and 0.95 represent good simulation result. It is worth mentioning that a subset of these statistics has been and is being used in the studies on model evaluation with the use of NSE as the commonest tool in most studies (McCuen et al. 2006).

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Q_{iObs} - Q_{iSim})^2}{\sum_{i=1}^{N}(Q_{iObs} - \bar{Q}_{iObs})^2} \tag{3}$$

The reliable nature of NSE in evaluating hydrological models makes it a very common tool in Malaysia for assessing hydrological models depending on whether the model in question is physically-based, empirical or conceptual (Table 1). e.g. Romaly et al. (2018) used NSE on HEC-HMS (physically-based model) to evaluate a study conducted with the aim of simulating 2011 flood peak that will be used to generate flood maps of Segamat 2011 flood. Beheshti et al. (2016) used NSE on ANN (an empirical model) to predict rainfall in Johor river basin for the next decade. A physically-based model (HEC-HMS) was validated with NSE by Ramly and Tahir (2016) while working in Klang-Ampang River basin, Selangor. Sulaiman et al. (2016) evaluated the performance of a conceptual model (TOPMODEL) to simulate runoff on a medium size catchment using different resolutions from ASTER DEM in Johor river basin. In another research that integrated an empirical model (ANN) and a conceptual model (IHACRES) in Kurau basin, Perak, NSE was utilized for the validating both models (Hassan et al. 2015). Perera and Lahat (2014) simulated and validated a Fuzzy logic approach (empirical model) with the NSE for determining the ability of the model to predict flood in Kelantan river basin.

Root mean square error (RMSE)

In order to have a positive evaluation result, careful selection of variables for RMSE was recommended by Moriasi et al. (2007). This is a prerequisite given by Eq. 4, that measures the level of fitness between the model simulated data and the observed data. The values normally used are peak discharge, time to peak and total volume. Other parameters can also be used depending on the model in question and the desired objective.

$$RMSE = \left(\frac{\sum_{i=1}^{N}(Q_{iObs} - Q_{iSim})^2}{N} \right)^{\frac{1}{2}} \tag{4}$$

The use of RMSE cut across both physically-based, conceptual and empirical models in Malaysia as highlighted in Table 1 (e.g. Norzilah et al. 2016; Yaseen et al. 2016; Hassan et al. 2015; Adnan et al. 2014b; Tahir and Hamid 2013, etc.).

Mean absolute error (MAE)

MAE given by Eq. 5, is used in determining the global goodness of fit of simulated error (the difference between the observed data and the model predicted output). MAE values of *0* indicate a perfect fit.

$$MAE = \frac{\sum_{i}^{N}\left|Q_{iObs} - Q_{iSim}\right|}{N} \tag{5}$$

Mean absolute error is a type of statistical measure utilized by hydrologists for hydrological validation. Table 1 shows some of the researches that applied MAE for evaluating their hydrological models e.g. Adnan and Atkinson (2018) applied MAE along with other model evaluation criteria to examine changes that are responsible for variations in peak flow using 1988 and 2004 data. MAE was also applied as one of the statistical measures evaluating a research involving 3 different models; physically-based model (HEC-HMS), empirical model DENFIS and ARX regression model at Sungai Kayu Ara, Selangor (Kwin et al. 2016). Mustafa et al. (2012) used MAE to validate a physically-based model (HEC-1) at Upper Bernam River basin Selangor. LSM model was evaluated with MAE in Pahang River basin and Muda River basin for a study aimed at assessing the influence of sub-grid variability and spatially varied topography in runoff generation (Wong et al. 2010). Alansi et al. (2009) applied MAE for evaluating a SWAT model in Bernam basin, Selangor.

Percent BIAS (PBIAS)

Gupta et al. (1999) reported that PBIAS is a type of statistical error analysis that quantifies the likelihood of simulated model values to overestimate or underestimate the observed data. PBIAS can be calculated using the following equation;

$$PBIAS = \left(\frac{\sum_{i=1}^{N}(Q_{iObs} - Q_{iSim})^2}{\sum_{i=1}^{N} Q_{iObs}} \right) \times 100 \tag{6}$$

Values of PBIAS can either be positive or negative. Positive value indicated that simulated values have underestimated observed values (peak discharge, time to peak or volume of flow). While a positive PBIAS value is an indication of overestimation of observed values by the simulated values. PBIAS values equal to zero indicated that the model perfectly simulated the results given rise to the same values of both observed and simulated values. Application of PBIAS for evaluating hydrological model performance in Malaysia is not as extensive as that of the measures of performance. As only a handful of researches were observed to utilize this criteria (Dlamini et al. 2017; Malek et al. 2015; Tan et al. 2014; Abdullah 2013; Wong et al. 2010).

Conclusion

A review of hydrological modelling studies in Malaysia was conducted in this study. The objectives, hydrological model utilized in each studies and findings were identified, summarized and presented in a tabular form. The major hydrological models used in Malaysia were discussed along with their advantages and major set-backs. From the review, it was found that, most hydrological studies focused on simulating streamflow in one river basin or the other. The results showed that 65% of the studies conducted used physically-based models, 37% used empirical models while 6% used conceptual models. Of the 65% of physically-based modelling studies, 60% utilized HEC-HMS an open source models, 20% used SWAT (public domain model), 9% applied MIKE-SHE, MIKE 11 and MIKE 22, while Infoworks RS occupied 7% whereas TREX and IFAS occupy 2% each. Thus, indicating preference for open access models in Malaysia. In the case of empirical models, 46% from the total of empirical researches applied ANN, 13% used LR, while Fuzzy logic, UH, ARIMA, SVM contributed 8% each whereas the remaining proportion is occupied by NWP, LSM, FR, DT and WoE.

Majority of the hydrological modelling studies utilized one statistical method or the other for evaluating hydrological model performance except in some few cases where model evaluation criteria was not clearly stated. Of the 70 papers reviewed in this study, 16 did not specify the type of model evaluation technique they used in validating their studies, 17 used only one method while 37 used two or more methods. The use of NSE along with other methods as a model evaluation criterion is the highest with a total percentage use of 27% while R and RMSE are second with a percentage use 24% each. R^2 (20%) was recorded as the third most widely used model evaluation criteria in Malaysia, MAE came fourth with 16% while PBIAS is the least with 11%.

Selangor state recorded a total 21 hydrological studies from the review (e.g. Chang et al. 2017; Dlamini et al. 2017; Goh et al. 2016; Khalid et al. 2015). This could be attributed to numerous rivers in the state such as Sungai Kayu Aru River basin, Upper Bernam River basin, Klang, Langat River who's changing hydrological behaviors with response to LULC changes and climate change need to be regularly monitored. Johor and Kelantan were ranked second each with 17 hydrological researches in this review. This may be due to high incidence of flood disasters in Kelantan as reported by several authors (Tehrany et al. 2014; Kia et al. 2012; Pradhan and Youssef 2011). Sabah and Sarawak ranked third with 5 hydrological studies reviewed in this study. Pahang recorded 4 researches, Perak and Terengganu came fifth with 3 researches each. Two hydrological studies were recorded in Kedah.

In conclusion, for any modeler to conduct a hydrological modelling study, it will be necessary for them to identify the problems and objectives of the intended research as well as resources available. This will help them in choosing the best model and evaluation techniques for their project to overcome the limitations attached to each. In addition, the need for an integrated modeling approach (using two or more models for a project) is strongly advocated by this study. This will help modelers to compare results from different model types to make a better prediction of streamflow changes that will be useful to water resources planners and decision makers.

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