The Pharma Innovation Journal 2018; 7(4): 1161-1164

www.ThePharmaJournal.com

The Pharma Innovation

ISSN (E): 2277- 7695
ISSN (P): 2349-8242
NAAS Rating: 5.03
TPI 2018; 7(4): 1161-1164

www.thepharmajournal.com
Received: 30-02-2018
Accepted: 31-03-2018

Ayushi Trivedi
M. Tech Student, Department of Soil and Water Engineering, J.N.K.V.V, Jabalpur, Madhya Pradesh, India

SK Pyasi
Professor, Department of Soil and Water Engineering, J.N.K.V.V, Jabalpur, Madhya Pradesh, India

RV Galkate
Scientist E, Central India Hydrology Regional Centre, WALMI Campus, Bhopal, Madhya Pradesh, India

Correspondence
Ayushi Trivedi
M. Tech Student, Department of Soil and Water Engineering, J.N.K.V.V, Jabalpur, Madhya Pradesh, India

A review on modelling of rainfall – runoff process

Ayushi Trivedi, SK Pyasi and RV Galkate

Abstract
Water is one of the most important natural resources and a key element in the socio-economic development of a state and country. Water influences every sphere of the environment supporting life on earth. Its varying availability in time and space is a matter of concern to the mankind since fresh water is not an ever-present resource. A rainfall- runoff model is a mathematical model describing the rainfall - runoff relations of a catchment area, drainage basin or watershed. A rainfall runoff model can be really helpful in the case of calculating discharge from a basin. The transformation of rainfall into runoff over a catchment is known to be very complex hydrological phenomenon, as this process is highly nonlinear, time-varying and spatially distributed. Over the years researchers have developed many models to simulate this process. Based on the problem statement and on the complexities involved, these models are categorized as empirical, black-box, conceptual or physically-based distributed models. The proper planning and management of the water resources in a location becomes a real big trouble for the hydrologists if discharge data is not available. Hence, engineers and hydrologists from all over the world have inclined towards the computer software for the estimation of runoff in any catchment or basin for handling any civil engineering project. These software models are more accurate and less time consuming than the physical method for the collection of data. They also have an advantage of extending the result and therefore future prediction is also possible. Many researchers are focusing their studies on these issues and trying to find out solution. Here, a brief account of research work done by some of such scientists, which indicated the use of rainfall runoff model is reviewed.

Keywords: RRL AWBM model, evapotranspiration, CROPWAT 8.0 model, HBV model, SMAR model, calibration, validation

Introduction

Rainfall - Runoff Modelling

Linde *et al*. (2008) [16] conducted a study and the hydrological models HBV and VIC were compared for the Rhine basin by testing their performance in simulating discharge. Overall, the semi-distributed conceptual HBV model performed much better than the distributed land surface model VIC (E=0.62, r2=0.65 vs. E=0.31, r2=0.54 at Lobith). It is argued here that even for a well-documented river basin such as the Rhine, more complex modelling does not automatically lead to better results. Moreover, it is concluded that meteorological forcing data has a considerable influence on model performance, measurements is emphasized.

Bhola (2010) [2] used the SCS-CN and the soil information, rainfall, storm duration, soil texture, type & amount of vegetation cover and conservation practices are considered while a new dimension has been added to the modeling approach through the adoption of the ANN technique as these models possess desirable attributes of universal approximation, and the ability to learn from examples. The performance comparison of both the models is made with coefficient of determination (R^2) which is coming to be 0.82 in case of SCS-CN method and 0.89 in case of ANN. Further a comparison is made of both the models i.e. ANN and SCS-CN for the runoff of river Kosi in year 2009.

Gobena (2010) [8] conducted a study and in this study, a daily rainfall- runoff modeling which is very helpful to further strengthen assessment, planning and management of water resource in the basin was conducted for selected three catchments of Upper Awash Sub Basin using two models namely AWBM and SMAR models among five lumped conceptual models nested in Rainfall-Runoff library. Automatic calibration and verification of the models were performed using Genetic Algorithm optimization method together with Nash Sutcliffe criteria and runoff difference as primary and secondary objectives respectively. A comparison of observed and simulated flow as well as comparison of performance of the two models were conducted. Both AWBM and SMAR models predict the flows fairly well with overall Nash Sutcliffe criteria of 0.6 to 0.85 for both calibration and verification periods.

Kumar (2011) [15] developed an distributed approach to simulate the rainfall runoff process of a catchment. The catchment area had been divided in to the numbers of divisions equal to the numbers of rain gauge station. The rainfall in a particular rain gauge is considered as uniformly distributed over the entire sub catchments. Spatially distributed catchment characteristics have been obtained from the 90 m resolution SRTM digital elevation data. A lump model was also developed using average rainfall of the catchment. The infiltration capacity of the basin depends on the land use and soil property. Horton's and Green-Ampt equations are most commonly used equations for estimation infiltration of a basin. Curve Number (CN) method is also a widely used method for estimating infiltration characteristics of the watershed, based on the land use property and soil property. Therefore the estimation of infiltration parameters or curve number of the basin is made initially. An inverse model is formulated and solved for estimating the curve numbers for the lump and distributed models.

Tramblay *et al*. (2011) [19] analysed how rainfall-runoff modelling using an event-based model can be sensitive to the use of spatial rainfall compared to mean areal rainfall over the watershed. This comparison was based not only on the model's efficiency in reproducing the flood events but also through the estimation of the initial conditions by the model, using different rainfall inputs. Results show that spatial rainfall increases the efficiency of the model. The advantage of using spatial rainfall is marked for some of the largest flood events. In addition, the relationship between the model's initial condition and the external predictor of soil moisture provided by the SIM model is better when using spatial rainfall, in particular when using spatial radar data with R^2 values increasing from 0.61 to 0.72.

Vinithra (2013) [20] made an attempt to estimate the surface runoff for Krishnagiri district, Tamil Nadu using SCS- CN method. Hydrological soil group (HSG), land use / land cover Map, Soil and multi spectral remote sensing data are used for the analysis. Runoff is computed for different areas barren land, agriculture, industrial, forest. Based on these derived information soil classification falls under group C. The estimated amount of average annual surface runoff is 76.53 mm, which is corresponds to 54% of annual average rainfall of Krishnagiri district.

Nayak (2013) [17] demonstrated the potential use of wavelet neural network (WNN) for river flow modeling by developing a rainfall-runoff model for Malaprabha basin in India. Daily data of rainfall, discharge, and evaporation for 21 years (from 1980 to 2000) have been used for modeling. In the modeling original model, inputs have been decomposed by wavelets and decomposed sub-series were taken as input to ANN. Model parameters are calibrated using 17 years of data and rest of the data are used for model validation. Statistical approach has been used to find out the model input. Optimum architectures of the WNN models are selected according to the obtained evaluation criteria in terms of Nash–Sutcliffe efficiency coefficient and root mean squared error. Result of this study has been compared by developing standard neural network model and NAM model. The results of this study indicate that the WNN model performs better compared to an ANN and NAM model in estimating the hydrograph characteristics such as flow duration curve effectively.

Choudhari (2014) [6] conducted a study and HEC-HMS model was used to simulate rainfall-runoff process in Balijore Nala Watershed of Odisha, India. To compute runoff volume, peak runoff rate, base flow and flow routing methods SCS curve number, SCS unit hydrograph, Exponential recession and Muskingum routing methods are chosen respectively. Rainfall Runoff simulation is conducted using 24 random rainstorm events covering four year (2010 –2013) data. Out of these, 12 events are selected for model calibration and the remaining 12 for model validation. For calibration of model the statistical tests of error functions like mean absolute relative error (MARE) and root mean square error (RMSE) between the observed and simulated data are conducted. The calibrated model with optimized parameter is used for model validation. The model validation was found to be satisfactory with low values of statistical error functions.

Kumar (2016) [13] studied the influence of back propagation algorithm and their efficiencies which affect the input dimensions on rainfall runoff model. The capability of the Artificial Neural Network with different input dimensions have been attempted and demonstrated with a case study on Sarada River Basin. The developed ANN models were able to map relationship between input and output data sets used. The developed model on rainfall and runoff pattern have been calibrated and validated. The significant input variables for training of ANN models were selected based on statistical parameters viz. cross-correlation, autocorrelation, and partial autocorrelation function. Various combinations were attempted and six combinations were selected based on the statistics of these functions. It was found those models considering rainfall lag rainfall and lag discharge as inputs were performing better than those considering rainfall alone. It was found that the neural network model developed is performing well.

RRL AWBM Model

Sharifi (1994) [18] developed a AWBM model for the small catchments of New England in Australia. The AWBM model was used in the rainfall runoff modelling. The results obtained were acceptable and the working on AWBM was convenient.

Boughton (2004) [3] estimated the hydrological sensitivity, measured as the percentage change in mean annual runoff, of two lumped parameter rainfall-runoff models, SIMHYD and AWBM and an empirical model, Zhang01, to change rainfall and potential evaporation. These changes are estimated for 22 Australian catchments covering a range of climates, from cool temperate to tropical and moist to arid. The results show that the models display different sensitivities to both rainfall and potential evaporation changes. The SIMHYD, AWBM and Zhang 01 models show mean sensitivities of 2.4%, 2.5% and 2.1% change in mean annual flow for every 1% change in mean annual rainfall, respectively.

Jones (2005) [11] investigated the sensitivity of runoff to rainfall and potential evapotranspiration (PET), as modelled by two commonly used rainfall-runoff models (AWBM and SIMHYD). Data from 22 unimpaired catchments throughout Australia are used. The results indicate that a simple linear relationship can be used to estimate the percentage change in mean annual runoff for given percentage changes in mean annual rainfall and PET. The modelled runoff is about three to five times more sensitive to rainfall than to PET. Both models show very similar runoff sensitivity to rainfall, with percentage change in runoff of about two to three times the percentage change in rainfall. The runoff is more sensitive to PET in AWBM, with a one per cent increase in PET reflected as about 0.8 per cent reduction in runoff in AWBM compared to about 0.5 per cent reduction in runoff in SIMHYD. The

runoff sensitivity to rainfall is higher in low rainfall and runoff regions.

Jones (2006) [12] worked on finding the hydrological sensitivity, changes in annual runoff by two models SIMHYD and AWBM. The location was in Australia and 22 australian catchments ware taken for the study. The results showed different sensitivities to both rainfall and potential evaporation changes. The SIMHYD showed mean sensitivity of 2.4% and AWBM showed mean sensitivity of 2.5% when mean annual rainfall is changed by 1%.

Boughton (2007) [4] used a 64-year data set of daily rainfall and runoff, and average monthly potential evapotranspiration (PET) was split into subsets of 2, 5, 10, 20 and 30 years. Each subset was used to calibrate the AWBM daily rainfall-runoff model. Each subset calibration was then used to estimate runoff from the 64 years of rainfall and PET data. The ratios of calculated to actual total runoff were used to determine probabilities of error from the different lengths of data used for calibration. There was little difference in results from the 2 and 5 year subsets with 10% chance of error in estimating long term runoff in the range of -21% to +31%.

Boughton (2009) [5] investigated that the result of applying the method to a group of gauged catchments is the production of a single set of parameter values for the AWBM that can be used with any catchment in the group, or used to estimate runoff on ungauged catchments in the same locality. The method is demonstrated on 121 catchments, comprising groups in five States of Australia from the tropics to temperate zones and over a wide range of catchment sizes and runoff characteristics. With adjustments to input rainfall of less than 20%, the average annual runoff from any catchment in a group can be reproduced by a single set of parameter values to any required degree of precision. The ability of a single set of parameter values to estimate average annual runoff from a group of catchments with only small adjustments of input rainfall raises doubts about the ability to determine the effects of catchment characteristics on runoff with current rainfall-runoff data sets.

Jamal (2011) [10] described the comparative results for one conceptual and five ANN models for daily RR modeling. The daily rainfall, streamflow, and evapotranspiration data from Jardine River catchment, Australia are used to carried out study. The conceptual model used is Australian Water Balance Model (AWBM) which is one of the most widely used RR model in Australia. It was found that the ANN models are superior to the conventional conceptual models due to their ability to handle the non-linearity and dynamic nature of the natural physical processes in a more efficient manner.

Kumar (2013) [14] developed two hydrological models named the SCS CN model and AWBM model in Tadepalli, Andhra Pradesh. The location coordinates were 16.4667°N latitudes and 80.6000°E longitudes. The total catchment area was 61.5 sq km. The rainfall data of 5 years were used in the study. Along with SCS CN, GIS was used for obtaining the composite curve number and getting the land use/ land cover pattern. The value of co-relation r2 =0.76 was obtained between observed and computed runoff.

Kumar (2016) [13] conducted a study and the raster data is processed in ERDAS and geo-referenced and then LU/LC map, drainage map, contour map, DEM (digital elevation model) is generated in GIS. Estimated runoff using SCS-CN & RRL is computed with runoff, simulated and actual rainfall data in years 2008, 2009, 2010, 2011, 2012. In general good co-relation (r2 =0.76) has been bound between observed and computed runoff.

Yu (2014) [21] evaluated their ability to model non-stationary daily flows, to quantify the effect of land disturbance, and to assess their performance in catchments outside Australia, two models were applied to two small watersheds, the Fernow watershed No. 6 in West Virginia, USA, for the period 1959–2009, and the River Rimbaud watershed in the French Alps for the period 1968–2006. Both watersheds have experienced well documented disturbances as a result of clearing and fire, respectively. On balance, the AWBM worked marginally better than SimHyd for these two catchments, and neither model worked satisfactorily for the Fernow watershed where forest clearing, application of herbicide and changes in species composition had occurred.

Haque (2014) [9] used the AWBM model for quantitative assessment of uncertainty. Both gauged and ungauged catchments were taken in the study. The main result obtained from this research work was that AWBM modeling outputs could vary from −1.3% to 70% with two different input rainfall data. The performance of the AWBM model was found to be dominated mainly by the selection of appropriate rainfall data followed by the selection of an appropriate calibration data length and optimization algorithm. Different optimizers were employed in the AWBM model but the effects were minimal. He concluded that this methodology can be useful to other catchments in Australia and other countries.

Balvanshi (2015) [1] developed a Rainfall Runoff model using AWBM for runoff estimation. Bina basin was chosen in this study with catchment area of 1180 sq. km. The coefficient of determination for the model calibration and validation were 0.909 and 0.835 respectively. The model was also tested on Nash–Sutcliffe Efficiency Index (EI) and the calibration and validation values obtained were 0.824 and 0.618 respectively.

Yu (2015) [22] conducted a study and two daily models (AWBM and SimHyd) were initially calibrated for each of three distinct phases in relation to the well documented land disturbance. At daily and monthly time scales, both models performed satisfactorily with the Nash–Sutcliffe coefficient of efficiency (NSE) varying from 0.77 to 0.92. When aggregated to the annual time scale, both models underestimated the flow by about 22% with a reduced NSE at about 0.71. Exploratory data analysis was undertaken to relate daily peak hourly rainfall intensity to the discrepancy between the observed and modelled daily runoff amount. Preliminary results show that the effect of peak hourly rainfall intensity on runoff prediction is insignificant, and model performance is unlikely to improve when peak daily precipitation is included.

Chouhan (2016) [7] describes the use of RRL AWBM (Rainfall Runoff Library Australian Water Balance Method Model) to investigate its performance, efficiency and suitability in Shipra river basin situated in Madhya Pradesh, India. The AWBM is a catchment water balance model that relates runoff to rainfall with daily or hourly data. AWBM model was calibrated and validated using daily weighted precipitation, daily evapotranspiration and daily observed runoff time series of 11 years period from 1996 to 2006. The model was calibrated for the six years period from 1996 to 2001 and validated for five years period from 2002 to 2006. The reliability and performance of AWBM model was evaluated based on Accuracy criteria such as Coefficient of determination (R2), Nash–Sutcliffe Efficiency Index (E), Root Mean Square Error (RMSE), and correlation coefficient

(r). The coefficient of determination R^2 value for calibration and validation period is 0.656 and 0.496 respectively which indicating good agreement between the observed and simulated runoff. The Nash–Sutcliffe Efficiency (E) for calibration and validation is 65.40% and 48.40% respectively. The model was found suitable for Shipra basin in simulating hydrological response of the basin to the rainfall and predicting daily runoff with good degree of accuracy.

Conclusion

The studies gone through in this paper highlighted the various application of free domain model and also discussed various aspects to evaluate the irrigation project their planning and remedial measures. The model could also be used to simulate the runoff in other sub basin of similar characteristics. There were suggestion made to tackle the issues and efficient utilization of water resources. Prediction runoff for future planning for any catchment area or drainage basin for development of water resources is a challenge for present scenario. It also reveals from these studies that development, testing and application of various rainfall runoff models is only the solution for quantification of available water and may be the solution to get efficient water utilization and to improve water productivity in the command areas.

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