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Rainfall-runoff Modelling of Amochu Basin in Bhutan using HEC-HMS Model with Remote Sensing and GIS-based Parameterization

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Abstract

Modelling surface runoff of a basin is important for integrated water resource management, planning developmental activities, flood mapping and zoning, safeguarding human lives and building resilient flood protection structures downstream. The low-lying plain of Amochu basin is no exception to flood and natural disaster. Recurrent floods have led to loss of life and property. HEC-GeoHMS and HEC-HMS models were applied to generate and simulate river runoff from daily precipitation fusing in with other basin parameters. The input parameters for rainfall-runoff modelling were carried out effectively by using GIS and Remote Sensing techniques. application of Remote. The simulation analysis of rainfall-runoff model combines soil conservation service-curve number (SCS-CN) for loss calculation, SCS Unit Hydrograph for transformation and Muskingum methods were implemented for routing of flow. The streamflow stimulated using HEC-HMS model were analysed and compared with the existing observed streamflow data. The model efficacy was evaluated using Nash-Sutcliffe Efficiency Coefficient (NSE) and Root Mean Square Standard Deviation (RMSE). For the annual time series (January-December), the average values of NSE were 0.68 and 0.64 for calibration and verification, correspondingly. For the seasonal time series (June-September), the model achieved average NSE value of 0.66 and 0.65 during calibration and verification, respectively. The association of streamflow from model simulation verified satisfactory agreement with the detected streamflow values during both calibration (R^2=0.6) and validation (R^2=0.6). The average area weighted Curve Number (CN) derived from 11 sub-basins of Amochu was 75.7

Keywords: Precipitation: Rainfall-runoff: HEC-HMS: Remote sensing: Modelling: NSE.

Introduction

Nature does not contribute precipitation at a constant or at predictable rate to Mother Earth, precipitation varies temporally and spatially due to large number of reasons. Streamflow, the natural outcome of precipitation, the central component of human requirements for survival, hygiene, agriculture, water supply, recreation, socio economic development and for natural environmental sustenance (Maria and Vargas, 2015). The rising population along with the economic developments have placed greater dependency on natural resources which ultimately leads to its excessive depletion. The change in precipitation pattern, land use and land cover, maximizing the land use parcel are some growing problems leading to recurrent flood in the low-lying areas. Around 1.4 billion people were impacted due to floods since the last decade of the 20th century with close to 100.000 fatalities reported (Kuenzer et al., 2013). The United Nations report showed that flood killed more people than any other type of disaster and caused most damage (Nguyen Thanh Long, 2001).

Remote Sensing and GIS are the most effective tools in rainfall-runoff modelling, flood hazard mapping, disaster risk assessment and management. The Rainfall-runoff modelling outcomes are applicable in three main categories including Flood Forecasting system, design of water management structures and pollution diffusion models (Jeníček, 2006). For an effective and result oriented model, input parameters influencing the outcome are Watershed characteristics such as slope, shape and size, cover of soil and duration of rainfall have a directly influence the peak flow and volume of runoff from any area (Chandler and Walker, 1998). The modifications in Land use and Land cover (LCLU) knowingly effect the runoff characteristics of a drainage basin, thus affecting the surface and groundwater resources. Based on the findings of Dos Santos et al. (2018), in the Xingu River Basin, the conversion of around 57% of forested areas into pasture caused an increase of about 6.5% in annual streamflow, as well as these alterations also triggered the hydrological processes like evapotranspiration, percolation, and surface runoff.

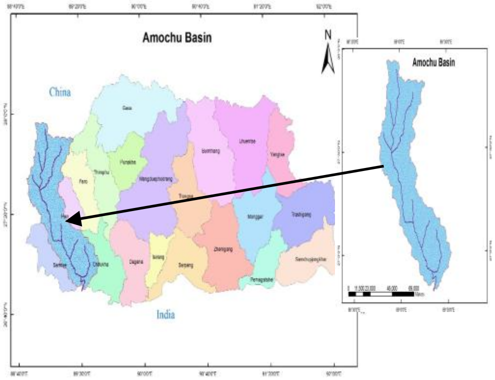


Fig. 1 Amochu Basin the study area in south-west Bhutan

The spatial variability of soil moisture plays a critical role in runoff formation across the region which is important for deep understanding the simulation process of hydrological models (Brocca et al., 2010).

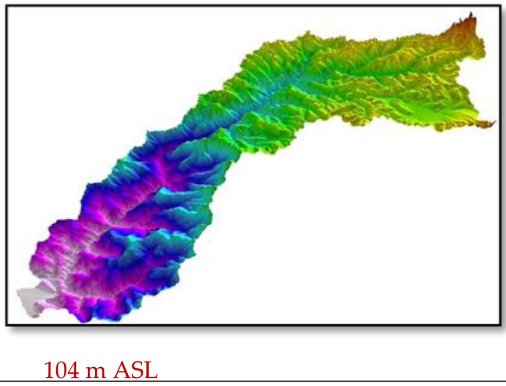
The hydrologic soil groups, land use and treatment classes integrates to form soil-cover complexes, for which a CN value is determined (Abraham et al., 2020). The increases value of CN signifies greater runoff potential, and thus precise classification of hydrologic soil groups is obligatory for obtaining dependable runoff estimates (Hydrology Training module, 2018). Out of many methods, Soil Conservation Services and Curve Number (SCS–CN) technique is considered as one of the most primitive and modest method for rainfall runoff modelling (Mishra and Jain, 2004). The SCS curve number imitates the infiltration capacity of soils in connection with land use/land cover (LU/LC) and antecedent soil moisture condition (AMC) (Amutha and Porchelvan, 2009). HEC-HMS model, developed by the U.S Army Corps of Engineers is a semi-distributed hydrologic model that simulates the hydrologic response of a watershed for various hydrometeorological input (Scharffenber et al., 2010).

The HEC HMS model allows the simulation of discrete storm events as well as continuous precipitation input at different time resolutions (Zhang et al., 2013). Yusop et al. (2007) reported through his studies that rainfall and runoff data from two-storm events were employed to calibrate and validate the HEC-HMS model. In context to hydrological model performance, Moriasi et al. (2007) classified model as very good (>0.75), good (0.65-0.75), satisfactory (0.5-0.65), and unsatisfactory (<0.5) based on NSE statistics. Meanwhile, Santhi et al. (2001) believed that NSE>0.5 was satisfactory, while Singh et al. (2005) concluded NSE>0.65 should be considered as satisfactory.

Materials and Methods

Study Area

The Amochu represents as one of the key river basins of Bhutan. The Basin lies in the western region of the country, and extends covering three districts of Bhutan viz Samtse, Chhukha and Haa. As illustrated in Figure 1, The river originates in China and continues its course through Bhutan to downstream into India. The basin covers an area of 3,810.84 km² with elevation gradually rising from 104 m a.s.l to 7,277 m towards the Tibetan Plateau in the north. The percentage rise of elevation from the basin outlet point to the highest point of the watershed is 5.48% shown in Figure 2. The basin extent to 88º 45'0"E to 89º20'0"E and 26º50'0"N to 27º55'0"N. Typically, the basin is elongated in shape with longitudinal length (north-south) of 125.72km. The form factor is 0.24 and is considered low. The river flows through deep valleys and gorges from high mountainous regions to flat plains.



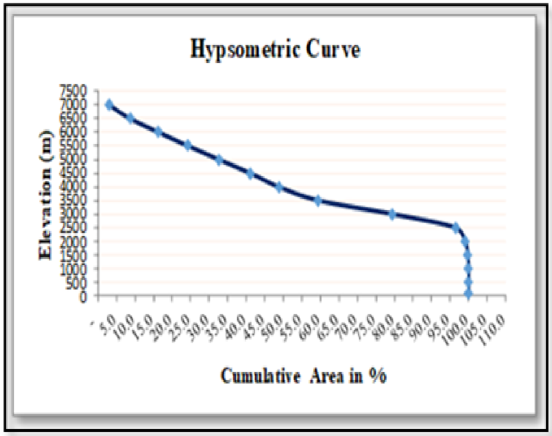


Fig.2(a) 3D view and (b) Hypsometric graph of Amochu Basin

The plain area accounts to 3.02% of the total areas, while the elevation ranging from 4000m-4500m and 4500m-5000m cover 19.9% and 17.1% of total area, respectively. The hypsometric graph shows the distribution of elevations across the catchment area. According to Alhamed and Ahmad (2017) the Hypsometric analysis refers to the relationship between horizontal cross-sectional drainage basin area and elevation.

Climatic Conditions

The southern foothill of the river basin experiences heavy rainfall during the monsoon season followed by dry spell during the winter. The highest daily rainfall recorded annually at the station in Phuentsholing and Sipsoo was 284.4mm and 296.3 mm respectively whilst the Namjayling higher region received lower rainfall with an annual daily maximum of 99mm.

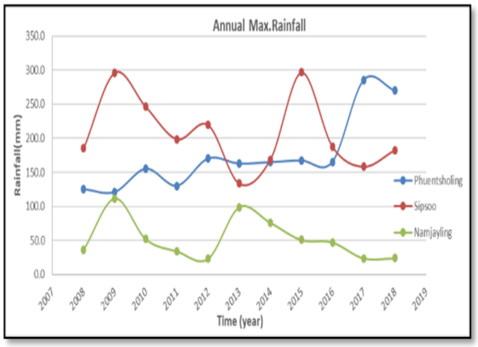


Fig. 3 Annual daily maximum rainfall of three different Gauging stations

The temperature within the basin varies largely due to variability in elevation. In the foothill plain, the average annual temperature ranges from 17ºC to 32ºC. While in the high hilly region the temperature ranges approximately between 9ºC to 18ºC and dipping to -14.5 ºC during the winter.

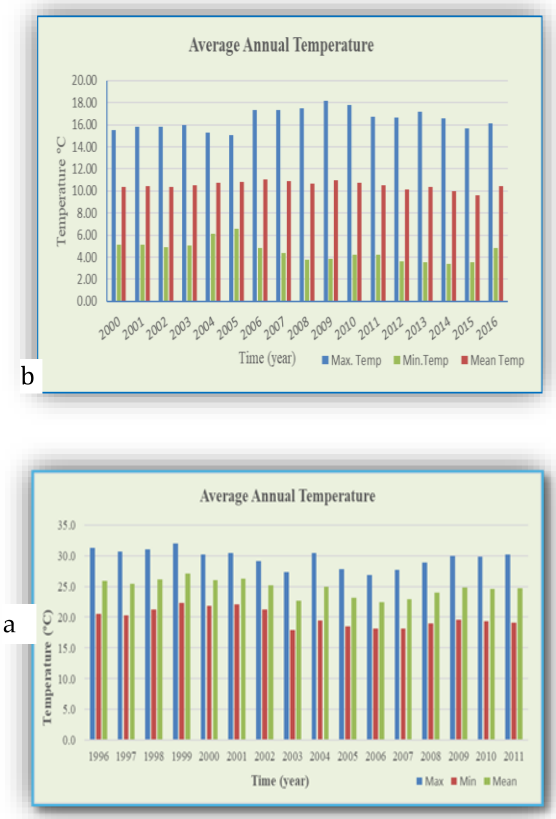
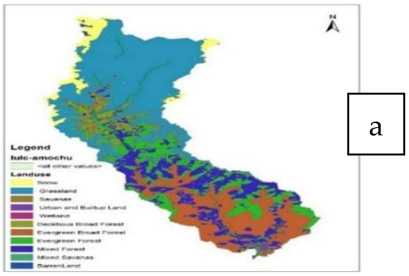


Fig. 4 Average annual temperature (a) Phuentsholing (b) Namgayling, Haa

Soil and Land use and Soil

Subtropical evergreen broad leaf forest in dominant in lower altitude (150 to 2000m), needle shaped leaf in the temperate region and Alpine zone is characterized scrub vegetation or barren. Farming or agriculture activities are visible in the subtropical and temperate region of the basin as shown in Figure 5(a). The four standard soil classes A, B, C and D as illustrated in Figure 5(b) represents soils with low, moderately low, moderately high, and high runoff potential, respectively. Other groups consist of dual ratings such as B/D and C/D. In such conditions, the runoff potential will depend on the drainage of soil depth conditions.



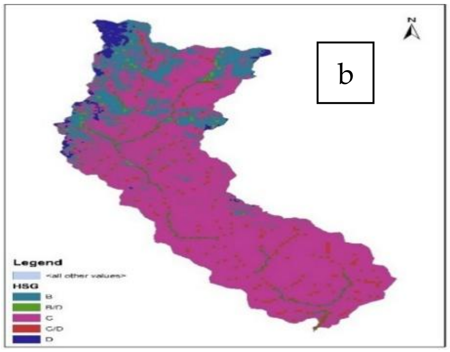


Fig. 5 The basin (a) LULC map and (b) Soil map

Table 1 Different Data and its Source

S.No	Data Details	Source	Remarks
1	Rainfall, Discharge & Temperature	NCHM, Royal Govt. of Bhutan	Daily resolution, Year: 2008-2017
2	LULC	MODIS	500m resolution
3	DEM	Alos Palsar	30m resolution
4	Soil Map	Earth Data; HYSOGs	250m resolution

Creation of Database

The HEC-HMS model requires long term metrological dataset primarily the precipitation dataset in hydrological modelling. Applying Theissen Polygon method, the average rainfall from three nearby class-A rainfall stations (one within the basin, other two from the nearby basin) were computed. The time series rainfall data and available runoff data from nearby gauging station were plotted as preliminary check to evaluate the trend and response of discharge to rainfall. Topography, land use-land cover, and soil composition plays a crucial role for describing the are land systems and are also very indispensable for the hydrological model setup (Arnol et al., 1998).

The input element of the model involves components of the land that consist of DEM, land use and soil type (Ghoraba, 2015). The HEC-HMS model is framed in order to simulate the rainfall runoff process of dendritic watershed systems (HEC-HMS User Manual, 2016). The setting up of basin model, watershed delineation, stream network generation, sub-basin creation to extraction of hydrologic parameters were preprocessed in HEC-GeoHMS tool as shown in Figure 6 (a) & (b).

The HEC-GeoHMS input file is imported to hydrologic simulation engine HEC-HMS tool for hydrological simulations. Applying the SCS Curve Number method and SCS unit hydrograph method, the precipitation in turn converts to runoff/discharge. In SCS framework, the ratio of actual retention to maximum retention is considered equal to the ratio of actual runoff to potential maximum runoff (Mishra et al., 2006). Land use, soil type and antecedent rainfall are considered to determine runoff potential.

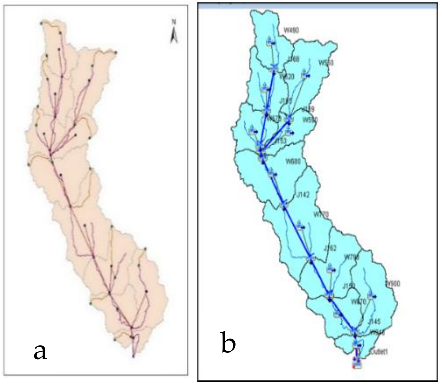


Fig. 2 HEC HMS Basin Model

$$\frac{F}{S} = \frac{Q}{P - Ia} \quad .....(1)$$

Where, *F* =Actual retention (mm), *S* = Potential maximum retention (mm), *Q* = Accumulated runoff depth (mm), *P* = Accumulated rainfall depth (mm), *Ia* = Initial abstraction (mm).

Curve Number (CN) is dimensionless and is a function of Land use, Soil hydrologic group and antecedent moisture content (AMC) in the soil. The CN value varies from 0-100 (Victor et al., 1996). The weighted CN for the watershed was calculated by applying the equation as mentioned below.

$$\mathrm{CN} = \frac{\sum \mathrm{CNi\ x\ Ai}}{\sum \mathrm{Ai}} \quad ...(2)$$

The maximum retention storage S is derived from CN by applying the following relationship mentioned in Equation 3.

$$\mathrm{S} = \frac{25400}{\mathrm{CN}} - 254 \quad ...(3)$$

Obtaining the retention storage, the runoff depth from rainfall series is estimated using the SCS runoff equation in HEC-HMS Model

$$\mathrm{Q} = \frac{(P - Ia)2}{\mathrm{CN}} \quad ...(4)$$

The performance evaluation of rainfall-runoff model is important to ensure its efficiency and predictability. After HEC-HMS model trials, the model was calibrated with precipitation and observed streamflow datasets from the year 2008 to 2010. The parameters obtained from calibration of model were applied to validate the model using datasets from 2011,2016 and 2017. The observed streamflow and simulated flow are plotted in Figure 10 and 11.

Model Efficiency

Model calibration and verification are very significant evaluation processes of the input parameters to the model and model itself in terms of its applicability and determining its outcomes. In order to assess the performance of the HEC-HMS model was examined by using Nash-Sutcliffe Efficiency (NSE, Nash and Sutcliffe, 1970). The equation below shows the computational approach. The NSE values lie between −∞ and 1 where, NSE = 1 specifies a perfect fit, while a NSE ⩽ 0 recommends that the mean of the observed values is a better predictor than the evaluated model itself (Gupta and Kling, 2011).

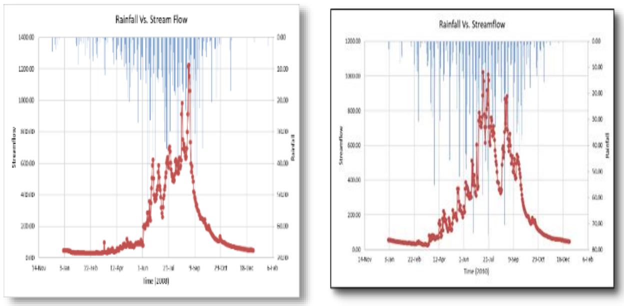
$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{N}(Oi-Pi)^2}{\sum_{i=1}^{N}(Oi-Pa)^2} \qquad \ldots(5)$$

where, Oi =Observed discharge value, Pi= Simulated discharge value, Oa= Mean of observed discharge value, N = Sample size (N), Ia = Initial abstraction (mm). According to Moriasi et al. (2007) the performanceof the model is very good, good, satisfactory, and unsatisfactory if the NSE is larger than 0.75, between 0.65 and 0.75, between 0.5 and 0.65 and less than 0.5, respectively.

Results and Discussion

Observed Rainfall and Discharge

The quantum of surface runoff generated from precipitation is affected by many transitional factors. Visual examination of daily time series rainfall plotted against observed streamflow does not quantitatively show proportional response to precipitation. The convolutions in hydrographs do not adequately display timely response of streamflow to precipitation shown in Figure 7.



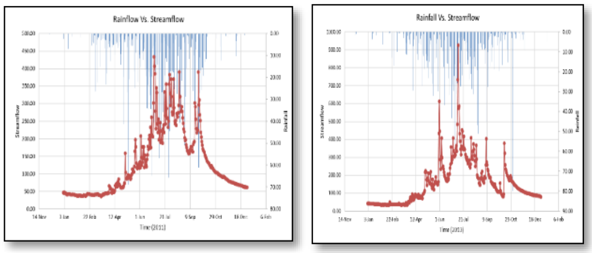


Fig. 3 Observed rainfall and streamflow hydrograph plot for the year 2008, 2010, 2011 and 2013

Simulated and Observed Streamflow

The predicted and actual stream flow over the calibration periods 2008, 2009 and 2010 are compared in Figure 8 and 9. The evaluation of model during model calibration exhibited good performance with NSE values 0.72, 0.68 and 0.63 from three consecutive annual (Jan. through Dec.) predicted and observed streamflow data. And during seasonal (June through Sept.) time series when the basin experiences heavy to very heavy rainfall the NES values from predicted and observed streamflow were 0.72, 0.67 and 0.60.

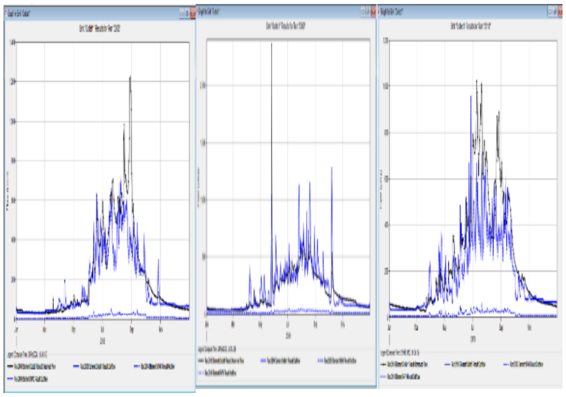


Fig. 4 Simulated and observed streamflow (calibration) Jan.-Dec., year 2008, 2009, 2010

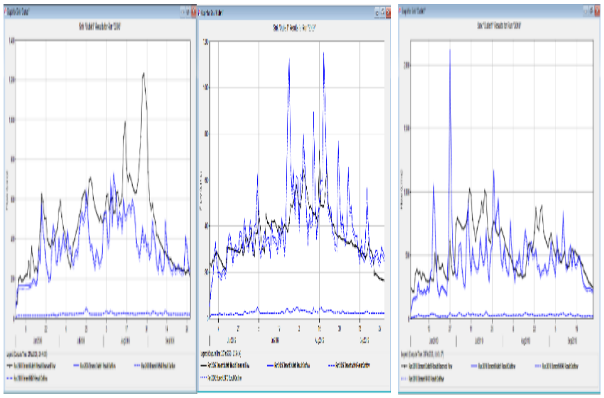


Fig. 5 Simulated and observed streamflow (calibration) June-Sept., year 2008, 2009, 2010

Similarly, the predicted and actual stream flow over the model validation periods 2011, 2016 and 2017 are compared in Figure 10 and 11. The model simulation performance during validation showed good and satisfactory outcome with NES values of 0.77, 0.59 and 0.56 for annual (Jan. through Dec.) time series and NES values of 0.78, 0.64 and 0.52 for seasonal (June through Sept.) time series.

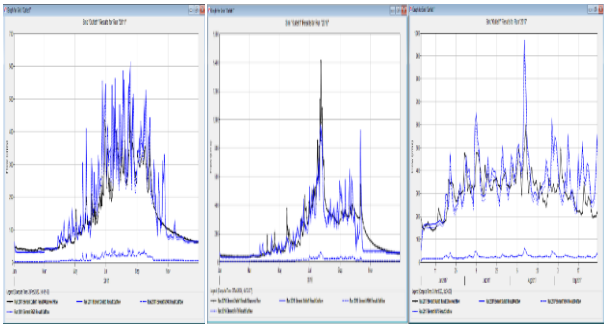


Fig. 6 Simulated and observed streamflow (Validation) Jan.-Dec. for 2011,2016 &2017

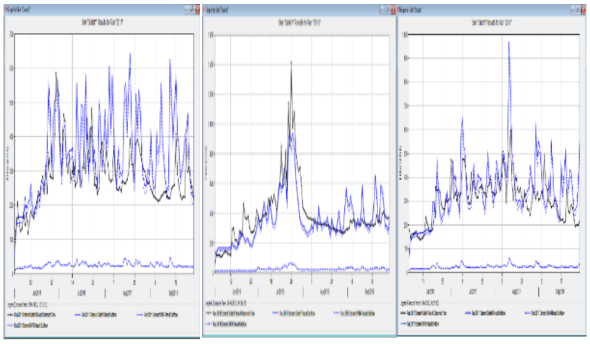


Fig. 7 Simulated and observed streamflow (Validation) Jan.-Dec. for 2011,2016 &2017

Table 2 NSE and RMSE from Calibration and Validation of HEC HMS Model

Sl. No	Annual/ Seasonal	Year	Calibration		Year	Validation	
			NSE	RMSE		NSE	RMSE
1	Jan.-Dec	2008	0.72	0.50	2011	0.56	0.70
2	Jan.-Dec	2009	0.68	0.70	2016	0.77	0.50
3	Jan.-Dec	2010	0.63	0.60	2018	0.59	0.60
4	June-Sept.	2008	0.72	0.50	2011	0.52	0.70
5	June-Sept.	2009	0.67	0.70	2016	0.78	0.50
6	June-Sept.	2010	0.6	0.70	2018	0.64	0.60

On account of spatial variability of soil groups, land use across the basin, the curve number is determined in reference to standard AMC II values. The curve number is further optimized during the calibration of model for each sub catchment. The curve number varied from 70.16-81.4 in 11 different sub-catchments. The basin CN is area-weighted average value of CN 75.7. The study on 450 number of basins in Nepal showed Curve Number ranging from 70-80 (Binaya et al, 2008). The table below shows the Curve Number of each sub-basin.

Table 3 Curve Number of sub-basin and weighted CN

Sub-basin	Area	CN
W490	274.52	81.30
W520	294.62	80.65
W560	413.52	81.40
W570	251.03	77.77
W590	260.49	79.75
W680	480.9	70.16
W770	655.59	72.96
W790	428.28	71.25
W870	280.01	71.25
W900	413.09	71.25
W940	112.77	75.07
Total	3864.82	
Area-weighted CN		75.70

Discussion

Data Gaps and Inconsistencies in Rainfall and Streamflow

Significant data gaps were observed in precipitation and streamflow data including anomalies and outliers. Rainfall data on large scale were missing from 2012,2013,2014, 2015 and 2017. Data from 2012/13/14/15 had lots of missing observations of streamflow. The visual check from rainfall data when plotted against the observed streamflow data, significant gaps in observed streamflow hydrographs (Figure-7) response to subsequent episodes of rainfall were observed. The research outcomes are significantly dependent on the length and continuity of time series data. Larger and comprehensive data makes statistical analysis more reliable. While data gaps and inconsistencies lead to bias parameter estimation and weaking of predictive capability of models.

Hydroclimatic Condition of Basin

As the basin spans all three climatic zones of Bhutan, shows a significant variation in the hydro-climatic conditions and hydrological patterns, the pattern of precipitation and streamflow across the catchment area. The basin is elongated in shape (Figure 1) with Form Factor of 0.24. The overland flow begins its journey at an elevation of 7277m above sea level (asl) passes through various landforms, modifying the hydrological responses prior to reaching the basin outlet at an elevation of 104m asl. Similarly, the land use pattern, the soil moisture, and humidity greatly influence the surface runoff contributing to streamflow. It is important to have more automatic hydrometric and rain gauging stations within the catchment. And having to avail accurate and better data resolution ground data would improve the efficiency and accuracy of the model results and forecasting capability.

Baseflow

The Base flow values considered in this study are monthly constant baseflow method based on the literature reviews. The referred baseflow values applied in the model were further considered as calibration parameter. While it is important to take up site-specific studies in determining the baseflow as the baseflow value may vary between watersheds and sub watersheds due to its geographical landforms, soil groups and landcover and antecedent moisture content.

Different Forms of Precipitation

The higher region of the watershed experiences snowfall contributing to surface runoff and streamflow. To account for better streamflow estimation, it is important to undertake studies and consider snow as precipitation input to generate runoff in hydrological modelling.

Conclusions

The primary objective of this research was to prepare a wholistic HEC-HMS hydrological simulation model for the watershed comprising of high topography variability (104m~7277m), large variation in climatic conditions, and limited hydro-metrological data. And all these are cross cutting issues across all major watershed of Bhutan. The hydro-metrological and surface characteristic data limitations greatly reduce the predictability capability of models affecting modelling process and accuracy. Considering the impact of flooding on basin flood plain, the model simulation streamflow for the time period (June ~ September) is significant to this research work. The average NSE values of 0.66 and 0.65 during calibration and verification can be considered satisfactory model performance. The results exemplify the scope to improve sensitivity and accuracy of the model with better hydro-metrological and surface characteristic data for longer period of time. The area weighted average CN number 75.7 can be applied to similar watersheds of Bhutan with similar climatic conditions, land use-landcover, soil characteristics and watershed surface configurations.

Statements and declarations

Data Availability Statement

Raw data supporting this study are available from the corresponding author upon request.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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