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Urban Rainfall-Runoff Modeling Using HEC-HMS and Artificial Neural Networks: A Case Study

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Abstract
Urban flooding nowadays becomes common throughout the world. The main reason for these floods is rapid urban development and climate change. During the monsoon, the flows in the urban drains will be high and the main reason for these high flows is the existence of a combined network system (i.e. drainage and stormwater). Further, the flow in the city (under study) drainage network was very high and some areas of the network exceeds more than discharge carrying capacity. Hence, this may result in overflow from the manholes and create an overland flood problem. Rainfall-Runoff modeling in these situations in the urban catchment will be essential and required to understand the flow pattern that helps in flood management. Therefore, the current study chose Hydrologic Modeling System (HEC-HMS) and Artificial Neural Network (ANN) for rainfall-runoff modeling at an hourly period for the Kukataplly (zone-12) watershed of Hyderabad city, Telangana State in India. This zone-12 watershed was one of the most affected hydraulic zones of Greater Hyderabad Municipal Corporation (GHMC) during the monsoon period in the past 21 years. The present study focuses on a comparative study between HEC-HMS and ANN has been carried out to comprehend the flood scenario in the study area. Finally, the performance of the model is checked with statistical indices such as Nash-Sutcliff Efficiency (NSE), and Coefficient of Determination (R^2). HEC-HMS yielded good results (NSE = 0.74 and $R^2 = 0.76$) when it has taken care of the maximum possible nonlinear complex data to be analysed.

Keywords- Rainfall-runoff modeling, HEC-HMS, Artificial neural networks.

1. Introduction

Among all the natural disasters, urban floods are frequently occurring and they affect most people globally (UNISDR, 2015). The main reason for urban flooding is the existence of commercial and industrial settlements in urban areas (Rangari et al., 2020). According to the WMO report (2009), the proportion of the population living in urban areas has risen from 36% to 54% between 1961 and 2014 due to the increased demand for land. Uncontrolled urbanization causes changes to the natural watersheds, which leads to a higher impervious percentage and decreases infiltration, resulting in a high rainfall-to-runoff conversion rate. Subsequently, urban catchments experience higher peak flows and flood volumes compared to rural areas (Suriya and Mudgal, 2012).

Stormwater systems in urban areas play an important role, which conveys rainfall received from urban areas to outlet points such as lakes or rivers. However, due to the less space and rising land values, managing stormwater in urban locations has become a major concern (Ahmed et al., 2013). Unfortunately, due to inadequate maintenance and uncontrolled urbanization, most of the stormwater drains in urban areas cannot handle excess runoff during extreme rainfall events. Consequently, these short-duration rainfall events become more frequent, occurring with high intensity (Awakimjan, 2015).

The impact of climate change alters the streamflow quantity and flow peak (Pathak et al., 2018). Runoff measurement in a watershed can assist in resolving many watershed management issues. The frequent and significant flooding in a watershed is mainly due to an exceedance in runoff volumes routed to the channels than that of stream carrying capacity (Jobe et al., 2018). Hence, it is important to assess the flood magnitude and intensity for the management of floods (Nyaupane et al., 2018) caused by urbanization and climate change, which increase the runoff peak (Thakali et al., 2018). The change in the climate can cause significant variations in peak flow (Kalra et al., 2017). For example, if peak flows are predicted in urban areas, early flood warnings can aid in enhancing flood preparedness in advance. For that, it needs flow measuring devices in urban areas. For the measurement of flows, there are different conventional and advanced techniques available. One of the oldest techniques followed all over the world by hydrographers is the stage-discharge relationship also called a rating curve (Turnipseed and Sauer, 2010). The rating curve of a stream channel mainly depends on its hydraulic particulars, and floodplain and will change from time to time at a particular section of that stream. There are certain changes in the hydraulic particulars (i.e., width, depth) of a stream channel, this can be due to the deposition of sand or garbage transported from different parts of localities, man-made changes such as dumping of the waste directly into the channel. These changes might require accurate subtractions from the discharge measurements. Hence, it requires a full reevaluation of the rating curve. Another way of flow discharge measurements was carried out using non-contact sensor-based ultrasonic level transmitters (Arattano and March, 2008). The functioning of this sensor equipment is based on a non-contact principle that involves measuring the duration taken by an ultrasonic pulse to travel from the equipment's sensor to the liquid's surface and back.

The behavior of watersheds in hydrological response is estimated using hydrologic modeling for a specific depth of rainfall (Halwatura and Najim, 2013) and this process is defined as a simplified representation of the actual problem (Wheater et al., 2007). Many studies have used hydrological modeling in different fields such as streamflow prediction in the ungauged basin (Swain and Patra, 2017), assessment of climate change and urbanization effects (Nandakumar and Mein, 1997; Alfy, 2016), prediction and estimating the flood magnitude (Zhijia et al., 2008; Yazdi et al., 2014) for the resources management. To simulate the runoff generated over a catchment there are different types of models available (Viessmann et al., 1989) and these models are further divided based on the complexities associated, with empirical or black box, conceptual, and physically based distributed models (ex. HEC-HMS, Soil & Water Assessment Tool). Every model has its own set of benefits and drawbacks and many circumstances, in reality, need to use the basic system of theoretic models, black box models (e.g., ANN).

HEC-HMS (Hydrologic Engineering Center- Hydrologic Modeling System) model that could be applied for many hydrological simulations and can also be applied to study and analyze urban flooding, flood frequency, flood warning system planning, reservoir spillway capacity estimations, stream restorations, etc. (U.S. Army Corps of Engineers, 2008). The other hydrologic and hydraulic models such as HEC-RAS (Hydrological Engineering Centre-River Analysis System), and SCS-CN (Soil Conservation Service-Curve Number) are freeware and generate understandable outputs easily. In addition to these computational models, the other black box type such as the ANN rainfall-runoff model process in the trial version of Alyuda Neurointelligence was performed. The result reveals from both the methods viz., HEC-HMS and ANN can be used for rainfall-runoff modeling depending on the available data (Baghel et al., 2021). The current study has been applied by ANNs to cross-validate the focused methodology as the ANNs are powerful techniques used for the relation between rainfall and runoff modeling. The results obtained from the ANN model will support decision-making in the field of water resources planning and management. Additionally, they help urban planners and managers in implementing the necessary measures to deal with poor prediction in an emergency and quick decision-making.

Keeping the real-world scenario in view the current study challenges to model the rainfall-runoff relationship over a large size watershed such as zone-12 (a sub-catchment of *Hyderabad urban* watershed) of 16 hydraulic zones of *Greater Hyderabad Municipal Corporation (GHMC)* of the Telangana State in India. The study watershed drainage network covers majorly the *Kukatpally* area and collects all the drainage flows from its surrounding areas through the small channels and joins to *Kukatpally* major channel. Finally, the channel disposes into the *Hussainsagar Lake* having a designed storage capacity nearly equivalent to three thousand million cubic feet where the lake receives frequent excess inflows during the monsoon and gets released into the *Musi River*, a tributary of the *Krishna* River basin in India. The results obtained from two different models (i.e., HEC-HMS, ANN) have been used to check performance statistics including NSE (Nash-Sutcliffe Efficiency) (Nash and Sutcliffe, 1970), RMSE (Root Mean Square Error), and R^2 (Coefficient of Determination). In this paper, based on the statistical efficiency, a suitable method is proposed for rainfall-runoff modeling even with limited data availability for the watershed.

The rest of the manuscript is organized as follows. Section 2 gives in detail of the study area and its description. Section 3 presents data sources, collection, and thorough methodology of comparison of HEC-HMS and ANN models for rainfall-runoff modeling for the zone-12 watershed. Section 4 presents land use/land cover classification, changes in land use/land cover over sub-watersheds, and performance evaluation of HEC-HMS and ANN models. Finally, Section 5 concludes the work and provides the direction for future research.

2. Study Area

Hyderabad city goes under a semi-arid region by Köppen-Geiger atmosphere order is Bsh (Peel et al., 2007). The city is located at a latitude of 17.3850° *N* and a longitude of 78.4867° *E* at an elevation of 542 m. The normal yearly precipitation was observed at 796 *mm* for each year from 1971 to 1990. Further, it has expanded to 840 *mm* every year (Agilian and Umamahesh, 2016). In Hyderabad, there is minute precipitation consistently and has the least in January, with a normal of 4 *mm* and 175 *mm* in September, which is the most noticeable month. The temperatures arrive at 45*ºC* throughout the mid-year season and with the beginning of storms during June the temperature drops and changes between 26*ºC* to 38*ºC*. 74% of yearly precipitation is contributed distinctly by the southwest rainstorm and 14% of precipitation is contributed by the northeast monsoon. The effect of environmental change has announced that the vulnerabilities in rainfall and short-duration rainfall are the primary purposes behind flooding in Hyderabad city since 2001.

The Municipal Corporation of Hyderabad (MCH), which used to cover an area of 170 km^2, has now transformed into the Greater Hyderabad Municipal Corporation (GHMC) which encompasses a wider area of 650 km^2. All the activities within the city were managed by GHMC, including sanitation, safe drinking water supply, heritage protection, aesthetic infrastructure, feeding to the poor people, and a stormwater drainage system. To study and manage the stormwater system in this area, it has been divided into 16 stormwater zones (GHMC 2007). For the present study, the *Kukatpally* zone (zone-12) located between 17°34'35.44" *N* and 17°24'34.03" *N* latitude and 78°22' 51.34" *E* and 78°28' 40.39" *E* longitude was considered. This region had an average elevation of 489.5 *m* and encompassed an area of 173.68 km^2. Among 16 hydraulic zones, zone-12 is one of the fastest growing and most affected by floods during the monsoon in the city. The longest main channel length in this zone travels about 19.97 *km* and finally joins into the *Hussain Sagar Lake* which is the most outlet for all tributaries. For the first time in the city to monitor the flow or gauge in the *Kukatpally* major channel, an ultrasonic level transmitter sensor was installed by the Department of Civil Engineering, Osmania University upstream of *Hussain Sagar Lake* (Figure 1). The flow is observed continuously at hourly intervals and the data has transmitted to the end-user through the data logger via email communication.

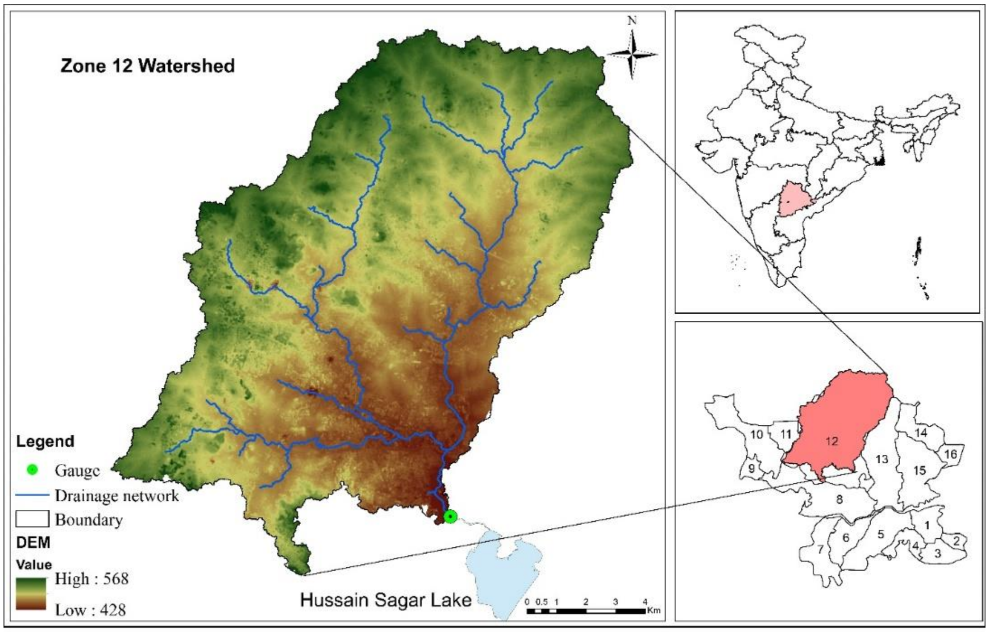


Figure 1. Study area map.

3. Materials and Methods

3.1 Data Sources

Hyderabad city is having only one rain gauge station at Begumpet maintained by India Meteorological Department (IMD). The hourly rainfall data for the monsoon period (September to October 2020) purchased from IMD has been considered (Figure 3). The zone-12 watershed majorly has one flow gauge station installed in September 2020. Hence, the 2020 year monsoon period has been used for the simulation period. The Cartosat Digital Elevation Model (Carto-DEM) of 10 *m* resolution was procured from the National Remote Sensing Centre-Indian Space Research Organization (NRSC-ISRO) (Figure 1). The spatial information for the model such as the land use map was extracted using IRS-Resouresat 2 LISS IV satellite imagery of 5.4 *m* resolution for the year 2017. The soil data has been collected from the Telangana State Remote Sensing Applications Centre (TRAC) (Figure 2) was assigned to the sub-watersheds based on hydrological soil group classification. The discharge data for the selected period (September to October 2020) to calibrate the model is collected from the ultrasonic level transmitter sensor located at the final disposal outlet upstream of *Hussainsagr Lake* at the Begumpet location. The input data and their respective sources used for the model are given in Table 1. A detailed outline of the methodology is represented in Figure 6.

Table 1. Input data products, period, and its official sources.

S. No.	Data product	Period	Source	Weblink
1.	Cartosat DEM (10 *m*)	-	NRSC, Balanagar, Hyderabad	https://bhoonidhi.nrsc.gov.in/bhoonidhi/index.html
2.	IMD hourly rainfall (*mm*)	Sep to Oct 2020	IMD Begumpet, Hyderabad	https://dsp.imdpune.gov.in/
3.	Land use/Land cover (5.4 *m*)	2017	NRSC, Balanagar, Hyderabad	https://bhoonidhi.nrsc.gov.in/bhoonidhi/index.html
4.	Soil type (1:50,000)	2010	TRAC, Hyderabad	Official request
5.	Hourly discharge (m^3/s)	Sep to Oct 2020	Ultrasonic level transmitter, Osmania University	http://datacloud.aeronsystems.com/admin/adminviewstation.php?deviceldforcustomgraph=5ef0686173c54a7815000029

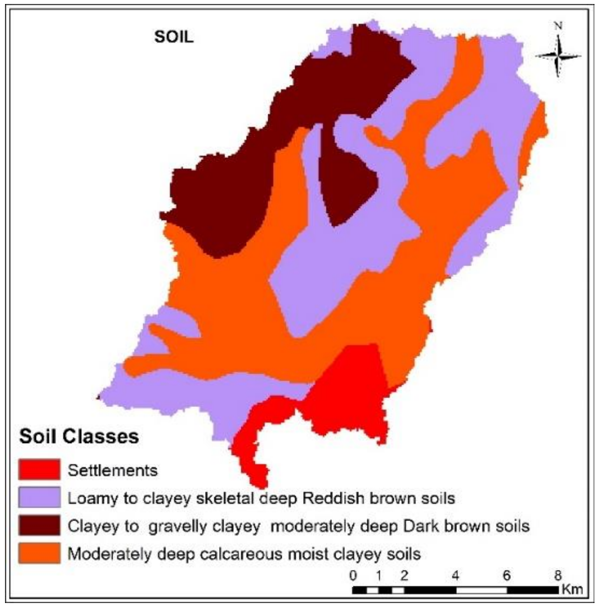


Figure 2. zone-12 watershed soil map.

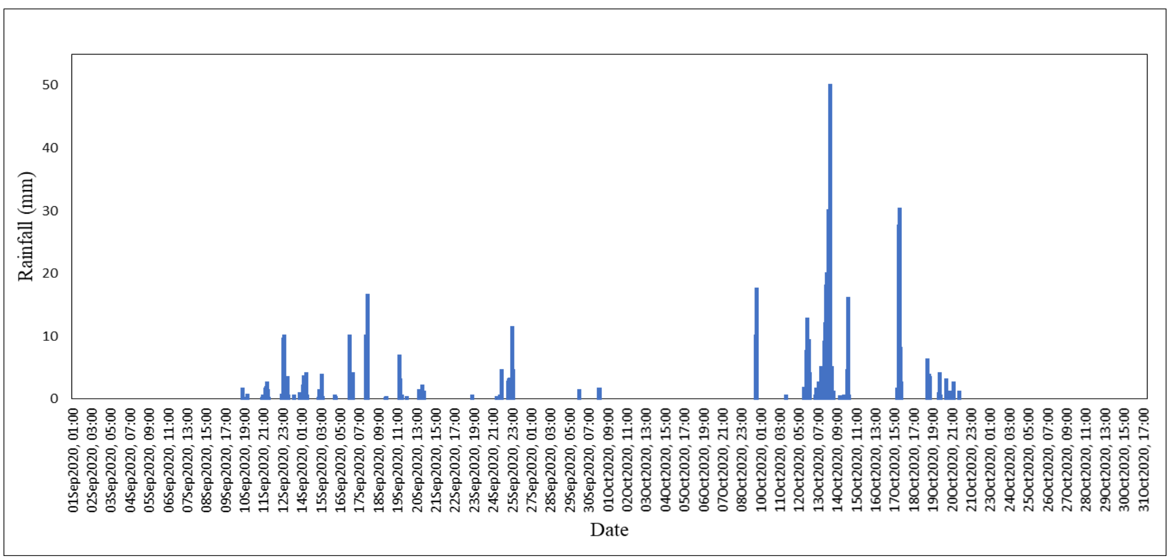


Figure 3. Hourly rainfall variation for zone-12 watershed.

3.2 Ultrasonic Level Transmitter Sensor Setup for Real-Time Flow Monitoring

The type of drainage system in the city is an almost open channel and old. In the case of such a system till today there was no flow gauging station available in the city. Hence, a new initiative has been filed by Osmania University to measure the flow continuously in the *Kukatpally* major channel of the zone-12 watershed. The flow collected from other parts of areas in this zone finally joins into the *Hussain Sagar Lake*, which was the biggest lake located center of the city. The setup of the sensor in the field and its flow measurement process is shown in Figure 4.

***Sensor Setup and Principle*:** The setup consists of *L* shape frame for sensor mounting, General Pocket Radio Services (GPRS) data logger with a subscriber identity module (SIM) card, an Uninterruptable Power Supply (UPS), Surge Protection, a power supply module, cable and earthing, and database center for storing the data received from the sensor. All the setups were erected at the location in zone-12 watershed outlet next ultimate disposal of *Hussain Sagar Lake*. An ultrasonic open channel flow meter is used to measure the real-time water level in the canal by transmitting ultrasonic waves into the water. These measured flow levels store the data in the GPRS data logger. Further, the water level recorded in the sensor was used to measure the flow using the Mannings formula. Datalogger continuously logs the flow data to the local server using SIM data. Real-time data can be viewed in the web portal (aeronsystems.com) and mobile app (Aeron Splash) along with historical trend data (24 hr) emailed to registered users every day at 08:00 am.

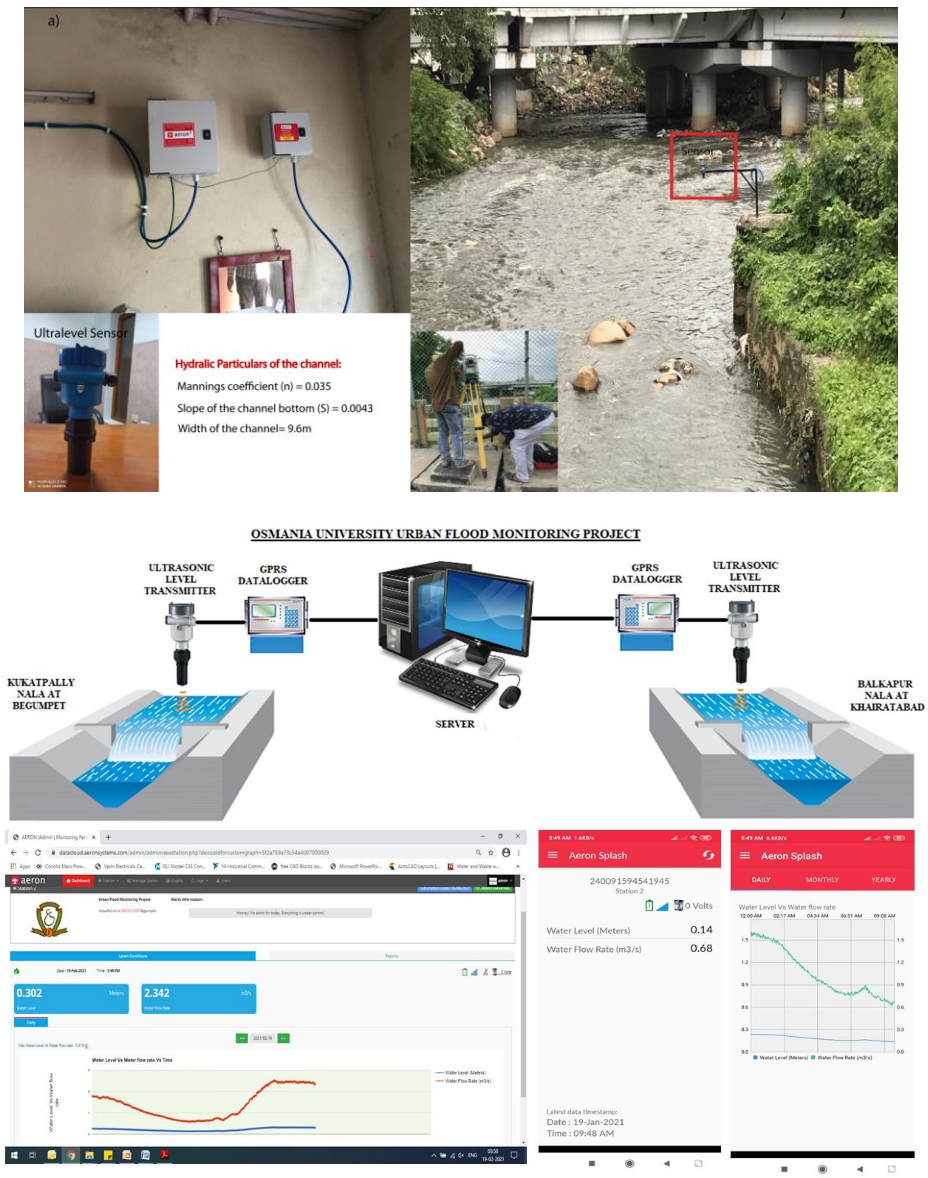


Figure 4. Real-time flow monitoring for zone-12 watershed a) investigated sensor site location b) schematic setup of ultrasonic level transmitter.

3.2.1 Flow Measurement in Open Channel

An empirical equation most often used to measure the flow in the open channel is Manning's formula and it has been used in this study. Combined with the continuity equation ($Q= VA$), it is expressed as:

$$Q = \frac{KAR^{2/3}S^{1/2}}{n} \tag{1}$$

where, Q is the measured discharge (m^3/s), A is the cross-sectional area of the flow (m^2), R is the hydraulic radius (m), S is the slope of the channel at the point of measurement, n is roughness and K is constant.

The parameters such as width, slope, and roughness coefficient involved in Manning's formula were measured using the total station survey along the channel. The measured channel hydraulic particulars and their roughness coefficient value (George et al., 1989) were selected based on the channel condition type at the site location is represented in Table 2.

Table 2. Open channel description.

Width (m)	9.6
Slope (meter/meter)	0.0043
Roughness coefficient	0.035

3.2.2 Flow Observation during September and October 2020 Monsoon

A new initiative has been taken by Osmania University, Hyderabad first time for monitoring the flow in the channel. The movement of water through the channel is influenced by many factors in this zone at the sensor-observed outlet. In this zone, the channels were interconnected with major lakes viz., IDL Lake, Kukatpally Lake, Yellamma Lake, Yellamma Lake, Chinnamaisamma Lake, Kamuni Lake, Mullakathuva Lake, Kamuni Lake, Timmidi Lake. These lakes nowadays become impervious and it does not allow infiltration into the ground. During the monsoon, it becomes reaches the full tank level (FTL), and thus it creates overland flooding downstream and also upstream (backwater from the lakes). Such a situation becomes common for a decade and continues during the monsoon due to the climate change impact. Hence, to know the actual carrying capacity in the channel during the monsoon and summer seasons an ultrasonic-level transmitter is installed upstream of *Hussain Sagar Lake* at Begumpet (Figure 5).

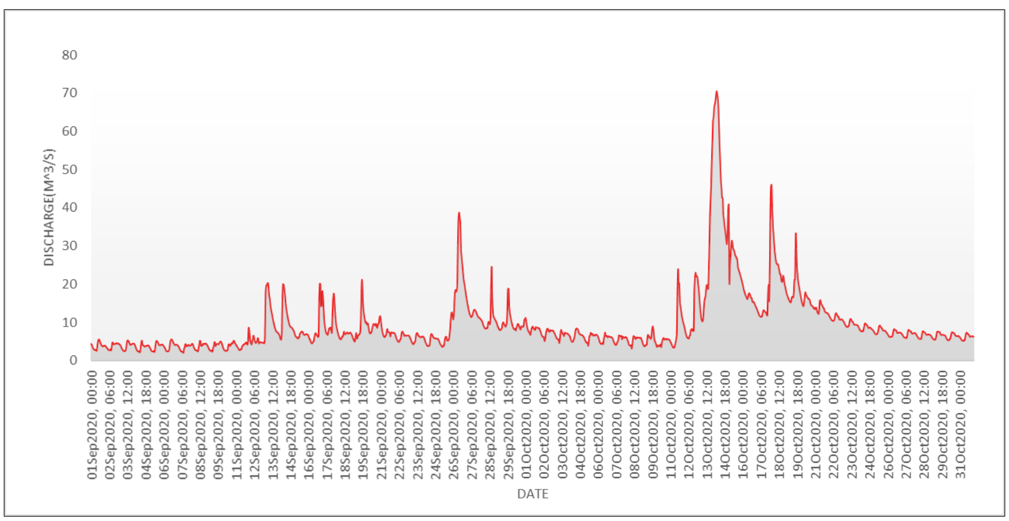


Figure 5(a)

Figure 5(b)

Figure 5. Flow Measurements a) observed hydrograph during the September and October 2020 b) gauge measuring location.

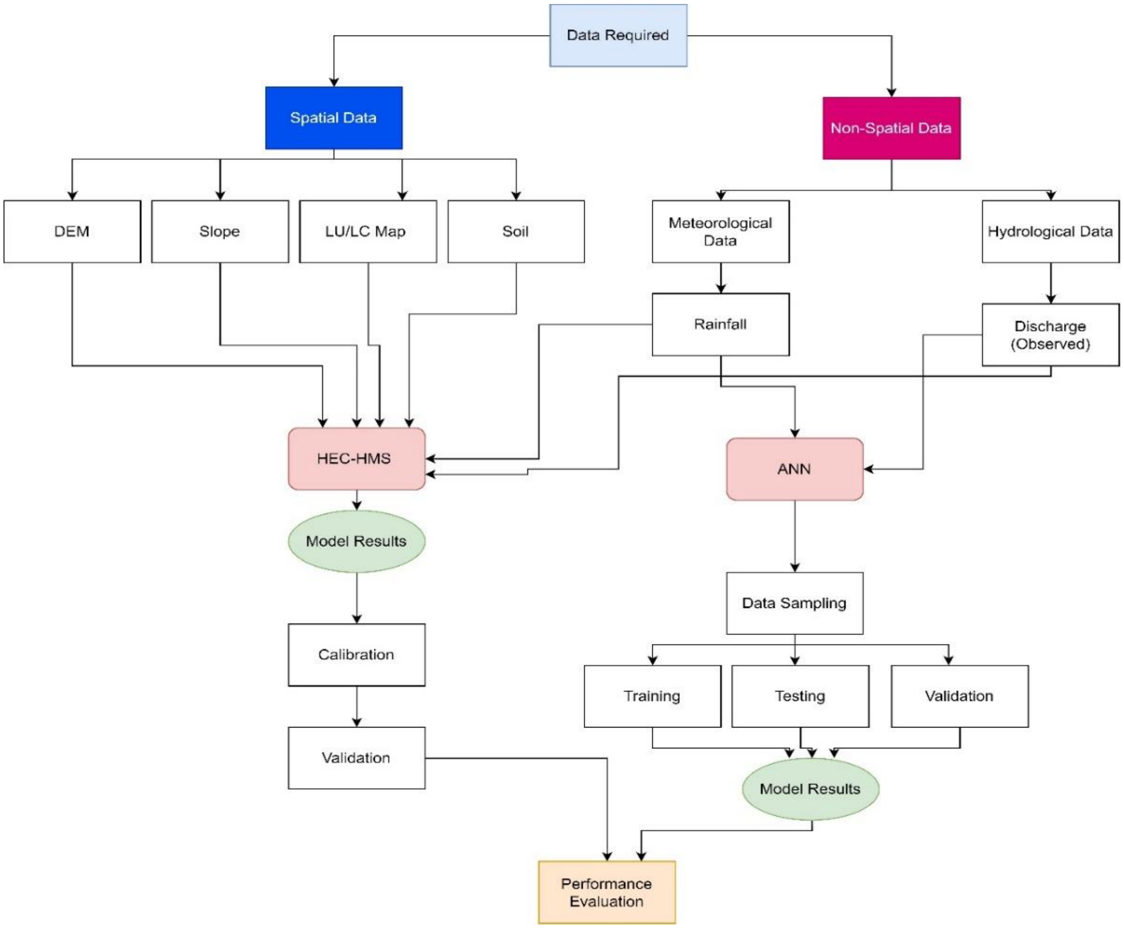


Figure 6. A schematic diagram of the proposed methodology.

During the latest 2020 monsoon, this zone received a short-duration intense rainfall of 57.5 mm at 23.00 *hr* at Madhapur station on 13th October (as per the TSDPS report). On 14th October this zone recorded the highest flow rate of 71.13 m^3/s (Figure 5) while during the non-monsoon it recorded normal flow obtained from residential and commercial areas through the drainage network. The mean dry weather flow observed during the unseasonal was 1.72 m^3/s (Jan to March) and its value varies during the morning, afternoon, and evening hours (Figure 5). After the end of the monsoon again its flow rate follows the same trend (Jan to March).

3.3 Hydrological Engineering Center-Hydrological Modelling System (HEC-HMS)

The HEC-HMS model, developed by the US Army Corps of Engineers, is a semi-distributed (i.e., physically and conceptual) model. The model is specifically created to simulate a dendritic watershed-type system and can serve multiple purposes such as urban flooding simulation, analyzing flood frequency, planning flood warning systems, assessing reservoir spillway capacity, and stream restoration. The model consists of several modules that perform distinct functions such as loss estimation, open channel routing, runoff alteration, and analysis of meteorological data. Additionally, there are separate modules that can be used for estimating different components of the runoff process (i.e., runoff volume, direct runoff, and base flow). These individual modules can be used independently for their respective purposes (Saleh et al., 2011; Choudhari et al., 2014). The HEC-HMS model consists of five major components including basin models, meteorological models, control specifications, input data, and outputs. The estimation of rainfall-runoff from simulation can be performed in the basin model given input from the meteorological model. The control specifications describe the period and time step of the simulation run. And the input data components, such as time-series data, set of data, and gridded data are often required as a parameter or boundary conditions in the basin and meteorological models. Finally, the model output data are presented through the graphical user interface (Bajwa and Tim, 2002).

To verify the model performance under different watershed conditions, the simulated hydrograph is compared with the observed flow data. The HEC-HMS model comprises different loss methods specifically designed for event-based modeling and continuous runoff simulation. The grid-based and soil moisture type loss methods are two types that require a large number of input parameters, whereas the deficit and constant loss methods are simpler. Conversely, the transformation methods offered by the HEC-HMS model are complex and require a significant number of input values, making it challenging to apply them to ungauged watersheds where these parameters may not be available. Various researchers have successfully applied the Soil Conservation Service (SCS) unit hydrograph, Snyder unit hydrograph, and Clark unit hydrograph for rainfall-runoff simulation (Straub et al., 2000; Fang et al., 2005; Cunderlik and Simonovic, 2007; Yilma and Moges, 2007; Banitt, 2010; Halwatura and Najim, 2013). The SCS method has certain advantages, including its ability to perform well in different environments, it requires only a few variables such as lag time, land use, and slope, which makes calculation easier, and its ability to produce results that are as good as those of more complex models (Lastra et al., 2008).

The study involves the application of a semi-distributed model for the zone-12 watershed of the GHMC, covering the two-month monsoon period from September to October 2020. The model's calibration and validation are based on the sensor data obtained from the upstream final disposal point leading into the Hussain Sagar Lake. The zone-12 watershed is further divided into eighteen sub-watersheds, and the basin area's hourly rainfall data is utilized. To derive the physical properties of the watershed at the sub-watershed level, such as channel length, basin drainage area, and slope, CartoDEM is employed in conjunction with HEC-HMS 4.6 version (as illustrated in Figure 7). The HEC-HMS's basin component is utilized to provide the watershed's physical properties, which calculate the runoffs through the loss, transform, and baseflow estimations. The study utilizes the curve number as the loss method, Clark unit hydrograph as the transform method, recession as the baseflow method, and Muskingum as the routing method.

Figure 7. Schematic representation of zone-12 watershed delineated from CartoDEM using HEC-HMS 4.6 version.

Meteorological data is inserted into the model through the meteorological component. There are different meteorological components in the model viz., precipitation component, snowmelt, and evapotranspiration details. The model consists of eight precipitation approaches namely, frequency storm, gauge weights, gridded precipitation, HMR52 storm, hypothetical storm, inverse distance, specified hyetograph, and standard project storm. Any of them can be selected for modeling. In this study, the specified hyetograph method was performed for runoff simulation. This specified hyetograph method is based on a recent flood event that occurred in October 2020. HEC-HMS has another component such as control specifications are one of the main components of a project and are primarily used to control simulation runs.

HEC-HMS has several modeling parameters. From these parameters, time of concentration, percentage (%) imperviousness, initial discharge, curve number, recession constant, and Muskingum constants (K and X) are found to be very important. The curve number, percentage (%) imperviousness, initial discharge, and time of concentrations of each sub-basin value are calculated and used as initial conditions. The other important parameter range values that can be used in the calibration of runoff quantity are represented in Table 3. The model was run for two months (September to October 2020) for calibration. The model was validated for November 2020 month with the observed flow measured at the outlet upstream of *Hussain Sagar Lake*. The auto-calibration is carried out using the optimization trail manager. HEC-HMS has two different approaches for model optimization: deterministic, and stochastic. In this study, the deterministic approach was used and which begins with initial parameter estimates and adjusts them so that the simulated results match the observed flow.

Table 3. Parameter range values applied for zone-12 watershed.

S. No.	Parameters	Values/Range
1.	Muskingum (*K*)	0 to 120
2.	Muskingum (*X*)	0 to 0.5
3.	Curve number (*CN*)	30 to 100
4.	Recession constant	0.2
5.	Ratio to peak	0.1

The HEC-HMS model performance is assessed using statistical indicators such as the NSE, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The statistical performance equations used are given correspondingly in equations (2)-(4) as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_i' - Q_i)^2}{\sum_{i=1}^{n} (Q_i - Q_{\text{avg}})} \tag{2}$$

where, Q_{avg} is the average of the observed data (m^3/s) for the relevant being evaluated; Q_i is the observed discharge (m^3/s); n is the number of observations, and Q_i' is the simulated discharge (m^3/s). NSE values can vary from -∞ to 1. In general, the model is more accurate if NS is closer to 1. The NS is sensitive to extreme values and may produce sub-optimal results when the data set holds large outliers in it.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i} - X_{\text{model},i})^2}{n}} \tag{3}$$

where, X_{obs} shows the observed values; X_{model} indicates modeled values at the time *i*, and RMSE is a measure of the difference between the predicted and actual discharges. It is ranged between 0 and 1. The best value to obtain for the RMSE is 0 as all the points lie exactly on a line with a positive slope of 1.

$$\text{MAE} = \frac{\sum_{i-1}^{n} (S_i - O_i)}{N} \tag{4}$$

where, N indicates the number of records, S_i demonstrates the simulated values, and O_i shows the observed values. MAE represents the mean absolute difference between the predicted and observed flow values. MAE values can range from 0 to ∞, lower MAE values signify better model estimation.

3.4 Artificial Neural Networks (ANN)

ANNs are mathematical models simplified from a highly complex phenomenon fundamentally derived from biological neuron systems as the biological neural networks can learn high-level complexity and nonlinearity and results in sophisticated solutions required. Several applications have dealt with ANNs in hydrology using three and four-layered methodologies. Figure 8 shows the information process that input is fed through the input later towards the output later where the output of the objective problem is received and the soft computing process will be happening to be solved in the hidden layers. Usually, the number of neurons and layers in between input and output layers is decided by the trial-and-error method. Relative connection for each link is assigned by a synaptic weight between node to node which represents the strength of the nodes.

$$y_i = f(\textstyle\sum_{i=1}^{m} W_i X_i + b_i) \tag{5}$$

where, X_i is the input received at node *j*, W_i is the input connection pathway weight, *m* is the total number of inputs to node *j*, and *bj* is the node threshold. Function *f* is called an activation function which determines the response of a node to the total input signal that is received.

The most commonly applied continuous activation function which is differentiable everywhere is the sigmoid transfer function that can map the nonlinear process.

$$f(x) = \frac{1}{1+e^{-x}} \tag{6}$$

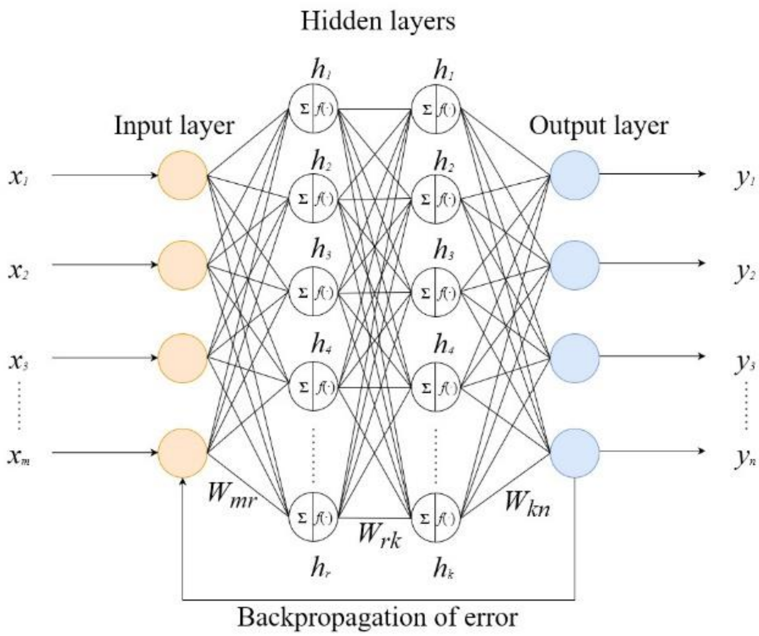


Figure 8. Four-layered feed-forward artificial neural network configuration.

where, *f*(*x*) is the sigmoid function, *e* is the Euler number. The ANN tool is particularly flexible as it often develops the unknown relationship between the input and output data through a process of training, without a prior idea of the catchment properties. It has a set of processing elements and weights connected to the nodes. The ANN model is designated as a nonlinear mathematical setup, and it has the capability in representing the random complex nonlinear practice. This model always relates the input and output by using an appropriate learning condition through the suitable arrangement of the neural networks and nonlinearity in the processing elements. It is being extensively used throughout the world because it has the potential advantages of universal prediction, can learn from different samples, and can process an enormous quantity of data quickly.

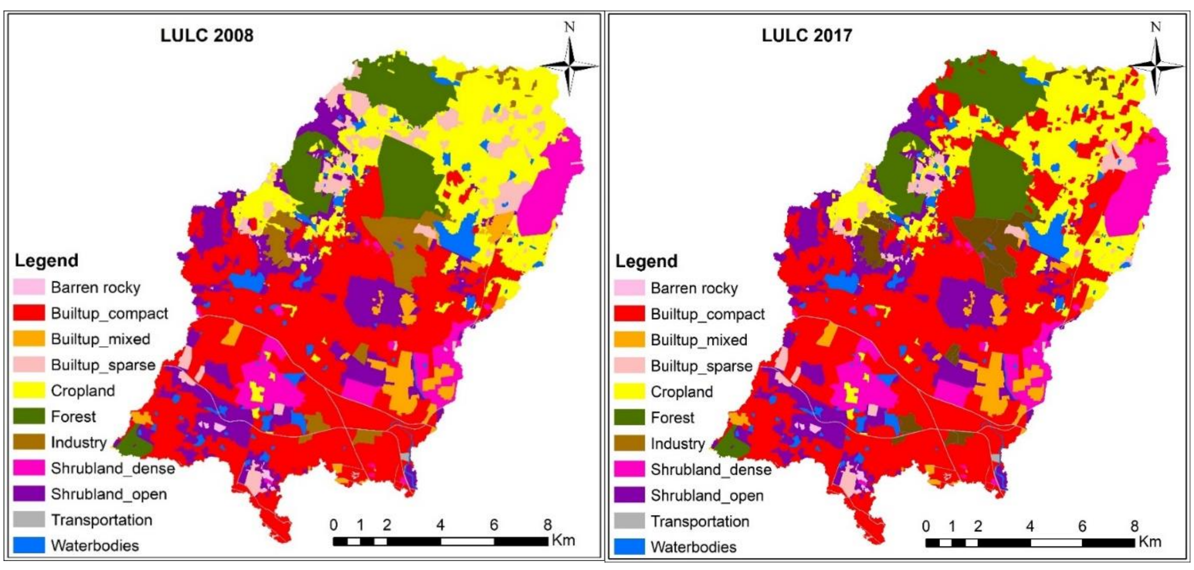
In the present study, feed-forward Batch backpropagation ANN models have been used for the simulation of discharge. The current algorithm works on the principle that it compares the target with the generated output when each input pattern of the training data set passes through the network and the error is propagated back to the input layer to adjust connecting strengths until there is the least or insignificant difference between target and generated output is obtained.

The Rainfall-Runoff data sets were first normalized in the range between 0 to 1 for a maximum value of the time series using the sigmoid activation function to reduce the saturation effect. The current study used the Batch backpropagation algorithm with a constant learning rate (η) of 0.15 in the model development, and momentum rate (α) in the range of 0.6 to 0.9. Similarly, the number of input nodes in the input layer was taken equal to the number of input variables and was initially tried from an equal number of input nodes to double that of input nodes (Hipel and Feng, 1994). However, corresponding to one output, only one node was taken in the output layer.

4. Results and Discussions

4.1 Land use/Land cover (LULC) Classification

The kind of land classification and soil type provide the curve number, it is one of the important parameters needed for the hydrological models. In this study, the SCS approach was considered in rainfall-runoff modeling. The SCS method considers various significant factors in runoff estimation such as soils, and watershed characteristics (i.e., slope, elevation, shape, and land use) over the study area (Jensen, J.R 1996; USDA, 1972). For the estimation of curve number, and percentage of imperviousness LULC map classification is necessary. Hence, in this study, we used Resourcesat-2 LISS IV imagery (5.8m) for LULC classification. The LULC classification has been carried out by feature extraction and pixel-based methods using Imagine Objective module on the ERDAS Imagine platform. The resulting LULC maps extracted from the Resourcesat-2 LISS IV imagery for zone-12 are shown in Figure 9. The rate of change of LULC between the years 2008 and 2017 is predicted as the percentage deviation of each class divided by the number of years. The rate of change of built-up compact was increased to 0.56% and conversely, built-up mixed, built-up sparse, cropland was decreased to 0.05%, 0.31%, and 0.20% respectively (Table 4). From Table 4, it is observed that the built-up compact is only increasing and that it is spreading spatially towards the periphery of the basin boundary. In the core city actually, there was no scope for growth in built-up but along the channel, there were encroachments, and due to these reduced the flow path significantly.



a) b)

Figure 9. Land use/Land cover map for a) 2008 b) 2017.

The percentage of imperviousness and perviousness calculated for the years 2008 and 2017 (Figure 10) have been calculated and assigned for the sub-watershed in the HEC-HMS model. Figure 10 reveals that the maximum percentage of imperviousness and perviousness is observed as 6.57%, and 13.67% for sub-watershed 16 and 6 in the year 2008 respectively. In the same way, the latest LULC for the year 2017 was considered to study the urban sprawl for zone 12 and the causes for it. It is indicated from the LULC maps of 2008 and 2017 there was no change in the maximum percentage of imperviousness and perviousness (Figure 10), but there was a migration towards the peripheries of zone 12. The main reason for this migration is there was no chance of additional built-up space existing in the central area of zone-12.

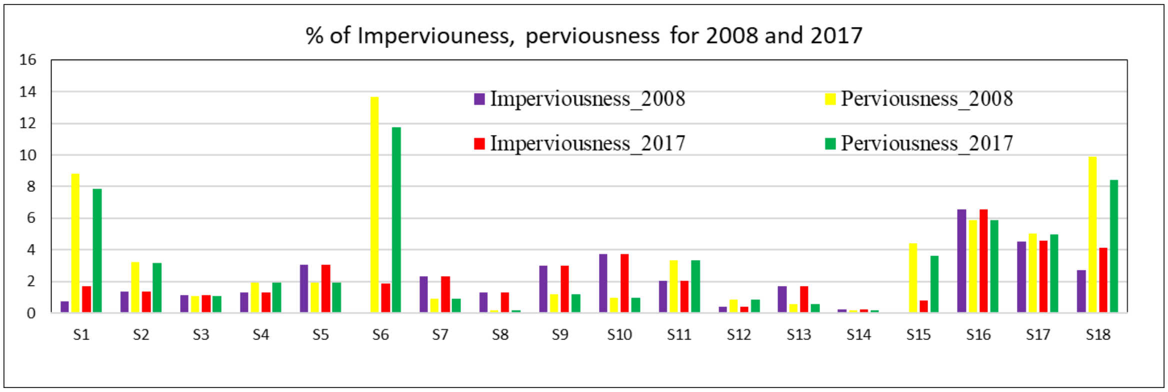


Figure 10. Sub-watershed-wise percentage of imperviousness and perviousness for the years 2008 and 2017.

Table 4. LULC changes for the zone-12 watershed between 2008 and 2017.

S. No.	Land use	Area in Sq.km		Percenatge (%) Change in LULC	Rate of change in LULC (%/year)
		2008	2017	2008 and 2017	2008 and 2017
1.	Barren rocky	0.34	0.34	0.00	0.00
2.	Builtup_compact	61.01	69.84	+5.08	+0.56
3.	Builtup_mixed	6.10	5.37	-0.42	-0.05
4.	Builtup_sparse	9.65	4.85	-2.76	-0.31
5.	Cropland	29.92	26.78	-1.81	-0.20
6.	Forest	16.75	16.75	0.00	0.00
7.	Industry	7.67	7.67	0.00	0.00
8.	Shrubland_dense	12.43	12.43	0.00	0.00
9.	Shrubland_open	22.26	22.10	-0.09	-0.01
10.	Transportation	1.35	1.35	0.00	0.00
11.	Waterbodies	6.23	6.23	0.00	0.00

4.2 HEC-HMS Model Analysis

In this study, the hourly rainfall and observed flow data for the period of September to October 2020 were selected to simulate the model. Sensitivity analysis was an important step in the model, which helps to identify the most sensitive parameter. This can be performed with the NSE index with a change in parameter values for different parameters of the model. In this study, a set of four parameters were selected to identify the most sensitive parameter. The Muskingum constant such as *K* includes travel time of flow in reach was mainly depends on the amount of flow and human activities. The Curve number values assigned to each sub-basin were calculated from land use and soil type. The parameters such as time of concentration, storage coefficient, and lag time involved in different methods mainly depend on curve number. The comparison of the simulated hydrograph with the observed hydrograph was generated by various sensitive scenarios for a range of parameter values increased or decreased by +/- 10%, +/-20%, +/-30%, and +/-40% (Figure 11).

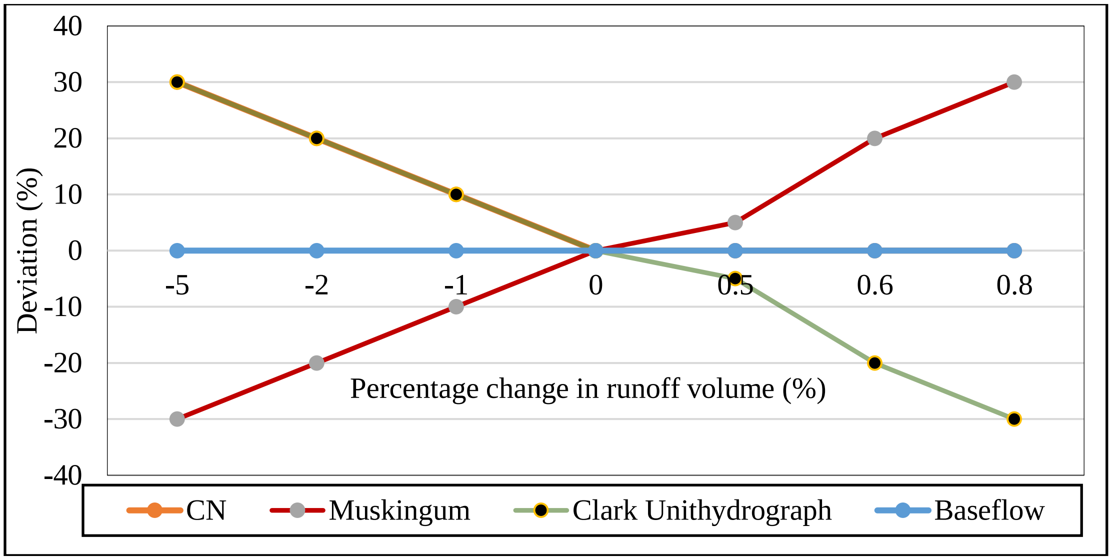


Figure 11. Model sensitivity analysis of parameters.

Based on the sensitivity analysis for the zone-12 watershed four parameters such as Muskingum, CN, and Clark Unit hydrograph are the more sensitive. Therefore, numerous types of scenarios with different combinations of modifying two parameters were performed. Later automatic calibration, a best-performing model with an NSE index value higher was selected. The best performance of the model was obtained by increasing the Muskingum value to 30% and decreasing the Clark Unit hydrograph, CN by 30% with NS equal to 0.744. A comparison of the flow hydrograph between the simulated and sensor gauge measured continuously at an hourly time scale (Figure 13) and the final model after calibration with observed flow had a good fit (Figure 12). The NSE value of 0.74 in HEC-HMS is comparatively less compared with the training phase value of 0.81 in ANN (Table 5). Moreover, the NSE values of 0.53, 0.66 in testing, and validation, respectively comparatively less with HEC-HMS. Overall, the average NSE value for the ANN is 0.66 which is less than the 0.74 value obtained in HEC-HMS. This indicates HEC-HMS entails good results for the zone-12 watershed with the complex input data for the September to October 2020 period. The remaining effect of efficiency in this urban watershed may cause due to drainage congestion problems, anthropogenic activities, and industrial release. The MAE (3.85) for the HEC-HMS is not too high compared with the ANN resulting (i.e., training, testing, and validation) average MAE (3.11), in this case, it indicates that ANN performed better. Similarly, the RMSE value of 0.5 for the HEC-HMS model is very low compared with ANN training (3.69), testing(18.91), and validation (20.71) values, which means HEC-HMS performed well. Therefore, these error values should be less for better model presentation. Overall, the error coefficient values presented above did not have much variation and but the RMSE value for HEC-HMS is too low, which indicates HEC-HMS even with complex input data performed well compared to ANN.

Table 5. Evaluation criteria for September and October 2020.

HEC-HMS		ANN		
		Training	Testing	Validation
NSE	0.74	0.81	0.53	0.66
MAE	3.85	1.96	4.0	3.39
RMSE	0.50	3.69	18.91	20.71
R^2	0.76	0.81	0.64	0.79

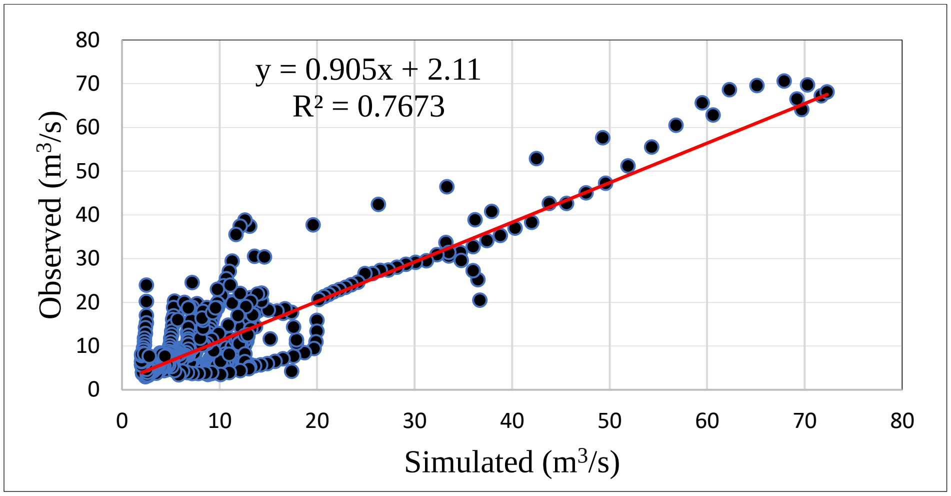


Figure 12. Comparison of discharge at outlet between simulated vs observed.

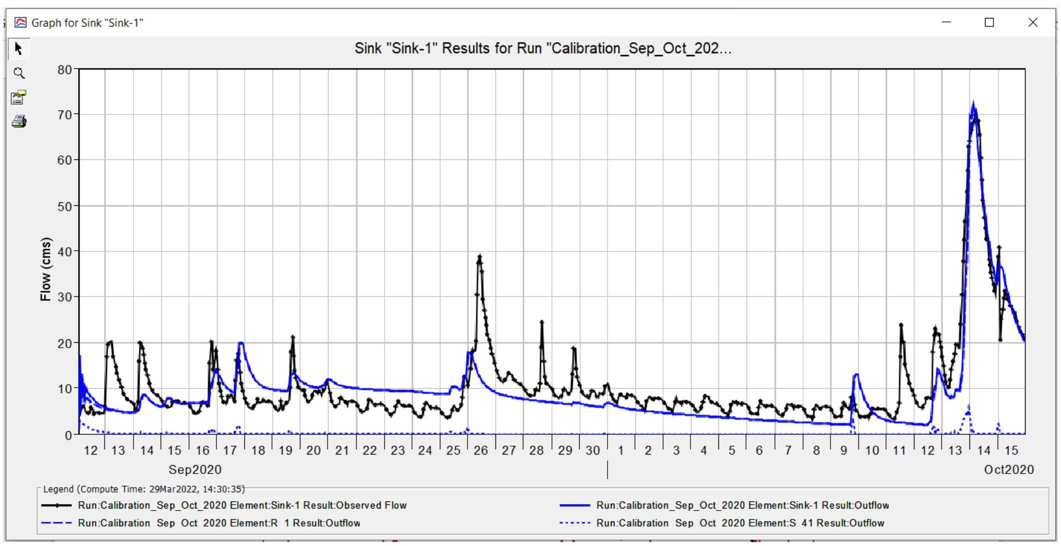


Figure 13. Model result between simulated and observed flow at sensor gauge for September-October 2020.

4.3 Optimization of Model Parameters

Optimization of parameters for the identified sensitive parameters was carried out using auto-calibration. Firstly, the random values for the parameters were used available from the literature (Rangari et al., 2020) but these values are not validated with observed flow data. Therefore, in this study, an attempt is made to study rainfall-runoff modeling and perform the optimization of watershed parameters for observed flow gauge data by two tools (HEC-HMS and ANN). Based on available datasets, the five methods were chosen for this study area namely: Surface, Loss, Transform method (i.e., Kirpich equation), Baseflow, and Routing. In the first phase, all the methods opted and input data collected from various sources were used for the model simulation. In the second phase, a calibration was carried out. Finally, the model is validated with these optimized parameters (Table 6).

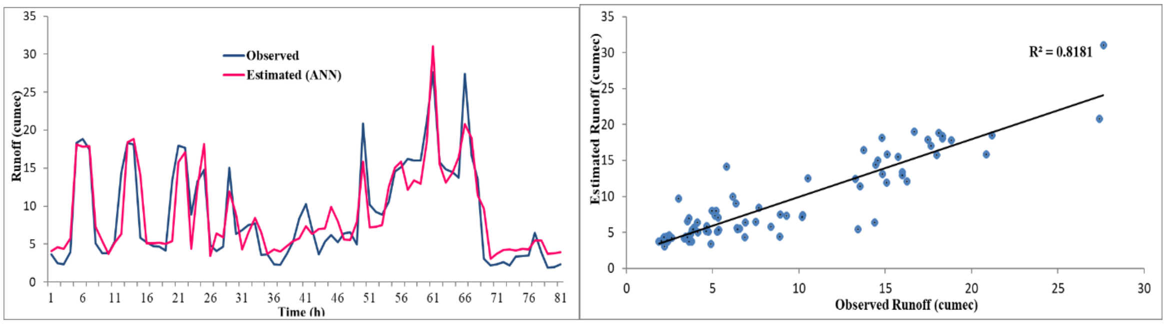
Table 6. Optimized parameter values for zone-12 watershed.

S. No.	Sub-basin	Curve Number		Time of concentration (hr)
		Initial	Optimized	
1.	S_1	83	35.5	4.75
2.	S_2	86	42.25	4.58
3.	S_3	85	98.25	4.5
4.	S_4	81	38.9	1.1
5.	S_5	86	98.25	1.25
6.	S_6	85	55.5	1.01
7.	S_7	90	97.25	0.23
8.	S_8	85	65.5	2.5
9.	S_9	85	65.25	1.25
10.	S_10	91	36.75	1.25
11.	S_11	86	75.75	2.5
12.	S_12	83	37.25	1.25
13.	S_13	89	94.82	0.5
14.	S_14	88	39.25	0.5
15.	S_15	83	39.25	3.25
16.	S_16	91	48.25	4.25
17.	S_17	94	38.25	3.25
18.	S_18	80	38.25	5.5

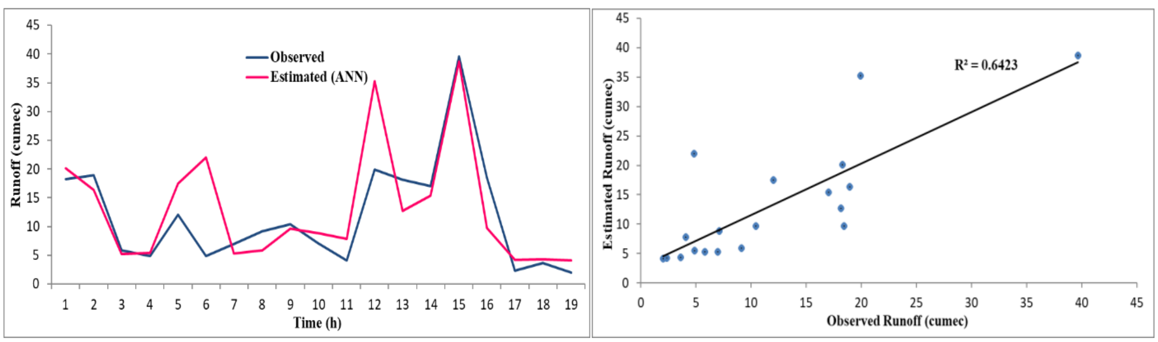
4.4 Artificial Neural Network (ANN) based Simulation and Modeling

ANN methodology is applied for the current time series hourly data; observed at the Urban Watershed under study to present the system simulation and modeling. The methodology involves the development of the model, validating the formulated model, and subsequently proceeding to the performance evaluation of the developed model. The collected real-time time series data is divided into three subsets in which, 70 percent of the data was used to train the network, 15 percent of the data to test the network, and the rest of the 15 percent of data was utilized for validating the model. A batch backpropagation algorithm was applied among the network layers with a constant learning rate (η) of 0.15 and momentum rate (α) of 0.8 and a sigmoid transfer function employed as an activation function between the layers (Govindaraju, 2000a & 2000b). During the development of the model study, one hidden layer and two hidden layer architectures were tried to establish better performance indices like correlation coefficient (R), coefficient of determination (DC), absolute error (AE), and absolute relative error (ARE), however, while selecting the representative model for the study R and DC were considered to be specific selection criterion characteristics. The reader is herewith suggested to have more information on ANN literature on its application, particularly in hydrologic engineering such as (Govindaraju 2000a; 2000b)etc.

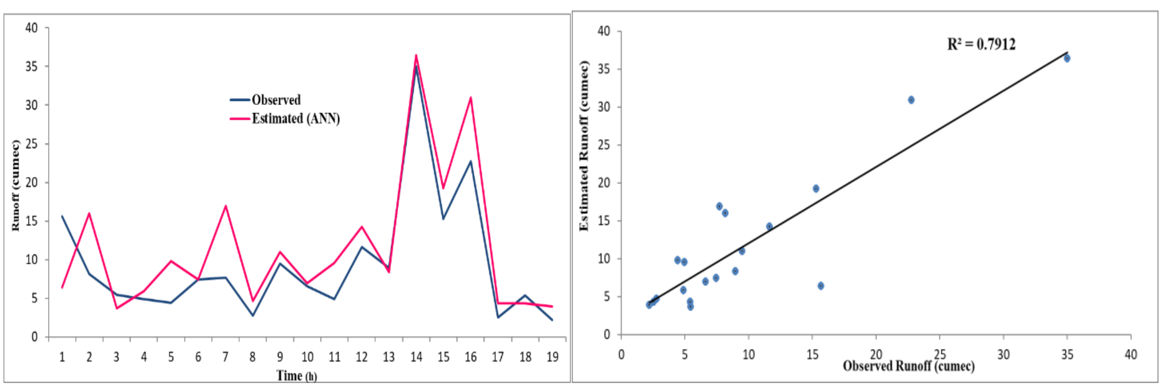
Rainfall (R) at time step 't' i.e R_t is mapped as an input parameter for runoff as an output parameter at time step 't' as Q_t. Since the runoff is a function of the independent hydrological event rainfall and rainfall affects the runoff based on the time of concentration with time lags, the present runoff at time step't' i.e Q_t. is mapped with R_t along with previous steps rainfall such R_{t-1}, R_{t-2}, R_{t-3}, etc., and also Q_{t-1}, Q_{t-2}, etc., as previous runoff is also a function rainfall of its proceeding time intervals. Many models were developed and evaluated based on the said conceptual understanding and applied to see the effect of rainfalls of the previous one hour to twelve hours and runoff up to the previous six-hour time steps. ANN architecture [19-48-1] with twelve previous time steps of rainfall and six previous steps of runoff were mapped with current runoff along with current rainfall at time step 't', which yielded significantly optimized performance indices values out of all the trials made in the study. Hence, [19-48-1] architecture was presented as the representative model for the area under study as it performed precisely to yield significant R and DC values of 0.910 and 0.77 during training, 0.810 and 0.630 during testing, and 0.890 and 0.740 during validation phase respectively. A very less and minimum mismatch may be observed in the graphical representation of the representative model during the training, testing, and validation phases and optimized scattered plots show the good generalization capability of the model performance in all the phases (Figure 14).



(a) Training



(b) Testing



(c) Validation

Figure 14. Comparative plots of observed and estimated runoff and their corresponding scatter plots for Begumpet gauge station of zone-12 watershed.

5. Conclusion and Future Work

This study reveals the rainfall-runoff modeling for the zone-12 watershed of the *GHMC* area based on the latest heavily recorded monsoon 2020 rainfall. The gauge Ultrasonic Level Transmitter installed in September 2020 was used for calibrating the model. This study introduces a novel approach that utilizes high-resolution images to extract land use and land cover (LULC) data for the year 2017, as well as two months of continuously recorded hourly rainfall data, and observed gauge flow data at the outlet of the watershed to evaluate the reliability of the model. The rainfall-runoff model for the zone-12 watershed was simulated using two established models, HEC-HMS and ANN. The models were calibrated and validated with the observed flow data. The validation results of both the HEC-HMS and ANN models showed good performance in simulating flows. The evaluation of model performance was conducted using statistical parameters such as NSE, and Coefficient of determination, and the following results are herewith presented.

- The sensitivity analysis for this study indicated that the input parameters such as CN, time of concentration, and "*K*" parameter values are more sensitive to less sensitive in the same order of sequence.
- The HEC-HMS model used for rainfall-runoff modeling in the zone-12 watershed reveals NSE as 0.744, R^2 as 0.767, and PBIAS as -11.52. Hence, this study indicates that the HEC-HMS can model hourly flows in the zone-12 watershed of *GHMC.*
- Among many trials performed, the ANN [19-48-1] architecture will be the representative model for this study area as it achieved precisely significant *R* and DC values of 0.910 and 0.77 during training, 0.810 and 0.630 during testing and 0.890 and 0.740 during validation phase respectively.
- Finally, HEC-HMS is suitably applied to evaluate the runoff process where diversified inputs are playing complex phenomenon and the ANN study supported the HEC-HMS for a fine-tuning application as a cross-comparison.

The current study suggests that in the future, we plan to extend this study to evaluate the model's performance with the highest length of rainfall-runoff records (i.e., at least 5 years of continuous southwest monsoon flow data) for this frequent flood-prone zone. Reliable sensitivity parameters have been used to test the performance evaluation of the model. It is also to state that the current study attracts detailed research in the urban context and the same study may be spread over the entire city location very shortly.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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