Evaluation of Hydrological models for Gandak River Basin

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Preface

The concept of hydrological modelling is widely accepted among different river basins in India and the world for getting the answers of complex questions related to basin hydrology. Gandak River is one of the major tributaries of Ganga basin and runs through international borders and different climatic regions as well. Major floods have been recorded for the basin in the past and with changing climate patterns it will continue to be challenging for hydrologists and policy makers to find solutions for the basin. Hydrological modelling can be a useful tool to provide suitable quantification of flows related to extreme weather events.

Today, an ample amount of satellite based remote sensing datasets are available which are able to capture the magnitude and spatio-temporal variation of hydro-meteorological components. It becomes more useful as in case of transboundary river basins such as Gandak River Basin, which majorly lies in Nepal and only a part of which comes under Indian territory. However, the use of remote sensing products only does not have assurance to be accurate predictions of runoff components as different hydrologic models are having variety of method and approaches to incorporate backhand. Therefore, it becomes necessary to evaluate the model performances with the available observed dataset. Gandak River Basin is very complex in nature due to its size and topographical features. Recently, machine learning approaches are also found effective in data-scarce regions. In mountainous regions, where rapid changes in meteorological conditions, soil moisture, snowmelt processes, and spatial variability of precipitation complicate hydrological response, Machine learning and Deep Learning algorithms offer flexibility by bypassing the need for detailed physical parameterizations. In order to modify the outputs from physically based models, transfer learning, hybrid models with combining physical and ML-based components, and data augmentation techniques are increasingly being used to further improve performance in such challenging environments.

This report focuses on comparative analysis of the performance of three widely used hydrological models. It also focuses on improvement of performance of rainfall-runoff modelling through advanced machine learning algorithms for Gandak River Basin. The study has been carried out by Er. Suryansh Mandloi, Scientist-B & PI, Dr. Pankaj Mani, Scientist-G & Head CFMS Patna, Er. Shubham Saurabh, Scientist-C, Er. Minotshing Maza, Scientist-C, Dr. Pravin Patil, Scientist-C, Dr. Vishal Singh, Scientist-D and Executive Engineer, Lower Ganga Divison-1, CWC Patna under an able guidance of centres' former coordinator Dr. A.K Lohani, Scientist-G & Dr. Senthil Kumar, Scientist-G & Coordinator, CFMS Patna.

(M. K. Goel)
Director

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Chapter 1: Introduction

Hydrologists and environmental scientists employ the advanced technique of hydrological modelling to analyze and comprehend the intricate processes of water flow within a watershed. The hydrological modelling technique in its simplest form predicts the behaviour of water in different scenarios by accounting for a number of inputs like precipitation, evaporation, infiltration and terrain, and predicts outputs as surface runoff and groundwater flows. Considering these hydrological modelling is essential for the implementation of sustainable water management techniques, since it offers detailed information on the flow of water throughout the basin. Today, hydrologists are able to develop precise models that helps in efficient management of water resources, assessment of flood risks, design of water infrastructure projects, and prediction of the effects of land use changes or climate variability on hydrological cycle by using computer software available in the water domain.

Today, with the advancements of computing facilities there are many hydrologic models are present for decision makers. With the availability of multiple hydrologic models, the comparison these models become a necessity for better planning of the water resource and for providing efficient flood forecast. Hydrologic models are used to simulate the behaviour of water systems, including river flow, groundwater recharge, and evapotranspiration. These models utilize various parameters and algorithms to predict the movement of water through watershed under different scenarios. During the comparison of hydrologic models it is important to consider the factors such as complexity of model, accuracy of model in predicting streamflow, sensitivity of model to input data, computational efficiency, and agility in handling extreme events. Also, the selection of an appropriate model majorly depends on the specific objectives of the study and the available dataset for model calibration as well as validation. For decision-making processes in sectors like agriculture, urban planning, and disaster management, model comparison will help in getting more accurate and reliable outputs. Ultimately, a thorough comparison of hydrologic models can help identify strengths and weaknesses of each model and better decisions in water resources planning and management. As described by many researchers (Moges et al 2020, Lohani A K) hydrological models are prone to uncertainties which further leads to disagreement between the observed values and model simulated outcomes. The random or systematic errors in the input and output dataset, errors due to non-optional parameter values and errors due to incomplete or biased model structure required to be address properly for model accuracy. A systematic analysis of dataset will help in capturing the information of biases present in the data itself.

For the present study, three of the most commonly used hydrological models are being considered viz HEC-HMS, SWAT+ and MIKE 11 NAM. The models are considered for the simulation of rainfall runoff processes. For this purpose, a model must incorporate the changes in rainfall patterns and should be able to represent the extreme events with high accuracy and low uncertainty. Northen Bihar faces a repeating problem of heavy floods and Gandak River Basin in no exception. Therefore, the study primarily focuses on heavy rainfall-runoff events for model calibration rather than focusing on low flow events. As the hydrologic models having stationary parameters and mathematical equations uses these fixed parameters over the period of simulation, it is therefore becomes necessary to analyse first the input data itself. The report shows the comparison of models mentioned above with detailed review of literature. The report also discusses the methodology adopted for hydrological modelling. Under this study, physically based semi-distributed modelling approach, Hydrologic Response Unit (HRU) based approach and lumped modelling approach is being considered in order to capture the details of the subcatchments. The semi-distributed approach helps in utilising the benefits of distributed modelling and the lumping of parameters, together at the same time. HRU bases approach is also kind of semi-distributed method on large scale but the key difference is HRUs can capture spatial heterogeneity based upon unique combinations of landuse, soil type and slope class.

The latest advancements in earth observation datasets have enabled researchers to utilise more than one source of input. With the emergence of high-resolution satellite imagery, machine learning algorithms, and advanced data analysis techniques, researchers and policymakers now have access to more precise and detailed information. These datasets allow to track changes in land use, monitor environmental indicators such as deforestation and urbanization, and study the impacts of hydrological extreme events on basin scale. With the availability of dataset of different spatio-temporal resolutions, it is interesting to see whether or not a particular dataset is able to capture the hydrological events with precision. Therefore, the present study deals with the analysis of CHIPRS, IMERG and APHRODITE precipitation dataset for Gandak River Basin and utilises these for modelling purpose.

The objectives of the study are as follows:

1. To develop multiple hydrologic models using HEC-HMS, SWAT and MIKE 11 NAM for inter-comparison of flows for Gandak river basin.
2. Evaluation of model performance with respect to observed discharge data for Gandak river at their respective CWC GD sites.

Chapter 2: Study Area

3.1 Description of Study area

Gandak River Basin has total catchment area of 40,553 sq km. One-seventh part of the basin lies in India and major six-seventh part lies outside India. The river starts its journey at an altitude of 7620 meters in Tibet having latitude 29º18'N and longitude 83º58'E near Nepal border. Considerable spatial variation in average annual rainfall is observed in the basin. The values are found to be as high as 2030 mm in northern Himalayan region and reduces upto 1100 mm in the southern plains.

The study area is selected in two ways, one for analysis of precipitation and other hydrological factors, contains complete Gandak basin. Second, for the analysis of floods and waterlogging conditions we are focusing on the lower Gandak basin, which lies in India. The length of main river in India is 260 km. The Lower Gandak basin has flat topography impending the natural flow of surface runoff. The unfavourable outfall conditions due to inadequate drainage caused by accumulation of heavy sediments near outfall. Additionally, stagnant water can build up between the commands, causing drainage issues behind the embankments of the Gandak and Burhi Gandak rivers when water levels rise too high for the countryside to flow through the sluice gates.

The Gandak river combines seven major streams in Nepal region which are termed as 'Sapt-Gandaki' means seven rivers which form one Gandaki/Gandak/Narayani are as Kaligandaki, Budhigandaki, Setigandaki, Madi, Marsyangdi, Daraudi and Trishuli. The river has major left bank tributaries named as Bhabsa, Harha and major right bank tributaries as Mahi, Kakra, Gandaki, Dhamati and Ghogri in the lower plains. Saran embankment, Champaran embankment and Tirhut embankments are the major embankments protecting the countryside from riverine flooding. The low-lying lands of lower Gandak basin are known as *'Chaurs'* which remains submerged for long periods due to drainage congestion. The upper part of the basin lies in the central Himalayan range which is home of multiple glaciers and glacial lakes. Around 127 total glacial lakes (size>0.01 sqkm) are present in the basin (Mohanty et al, 2021). Three of those are categorized under high GLOF prone lakes.

The Indian part of the basin is termed as Lower Gandak Basin and it covers parts of six districts in Bihar namely (i) Pashchim Champaran, (ii) Purba Champaran, (iii) Muzaffarpur, (iv) Vaishali (v) Saran, (vi) Gopalganj and two districts in Uttarpradesh namely (i) Kushinagar and (ii) Maharajganj.

Prepare the following maps:

1. Index Map showing basins and states
2. Sub-basin wise map
3. LULC map
4. DEM map
5. Geological map of the study area
6. Soil map for the study area
7. District map in Indian part

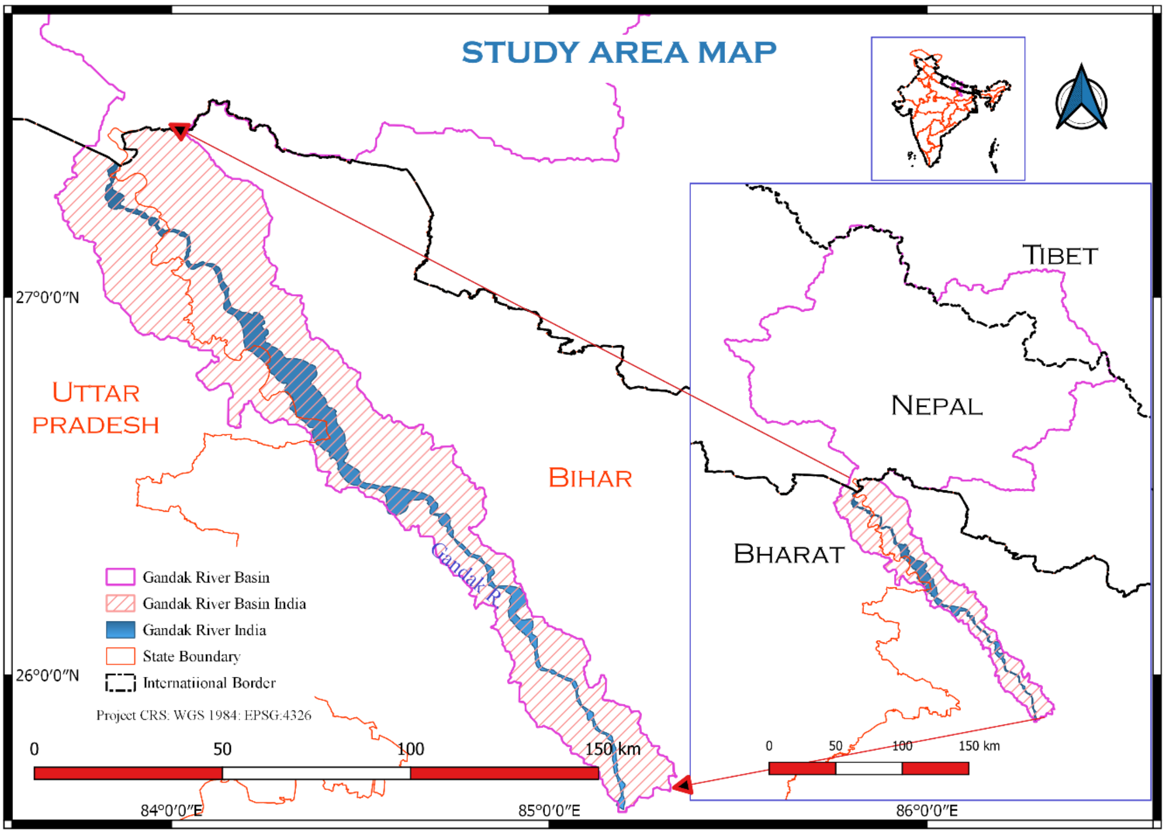


Figure 1: Study area map Gandak Basin and Indian part

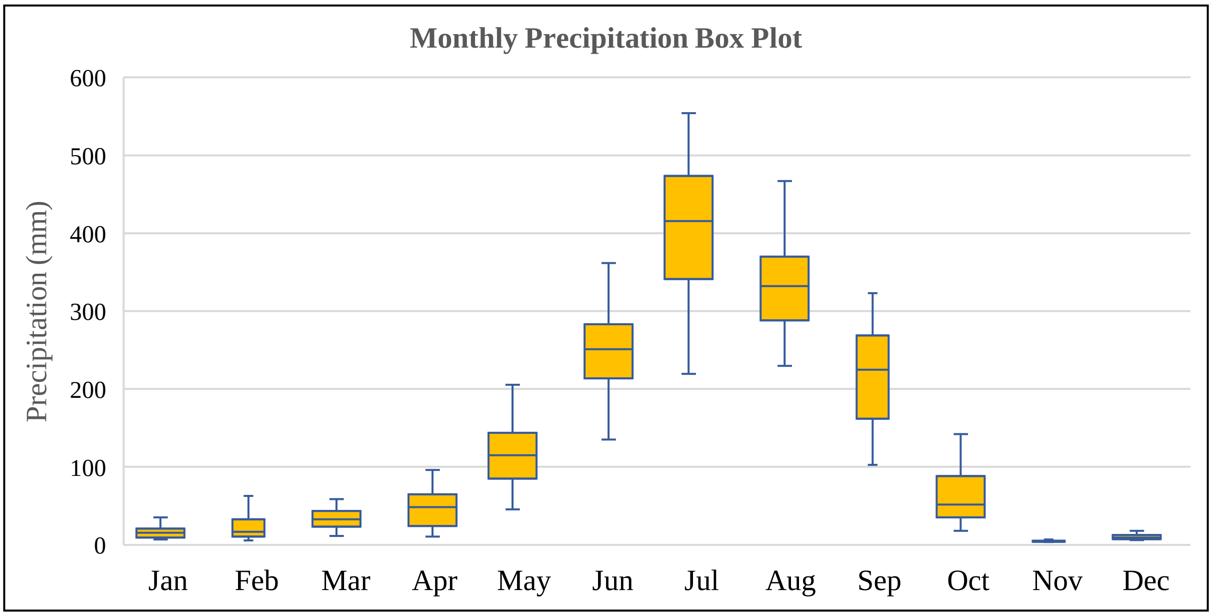


Figure 2: Monthly Precipitation Box plot

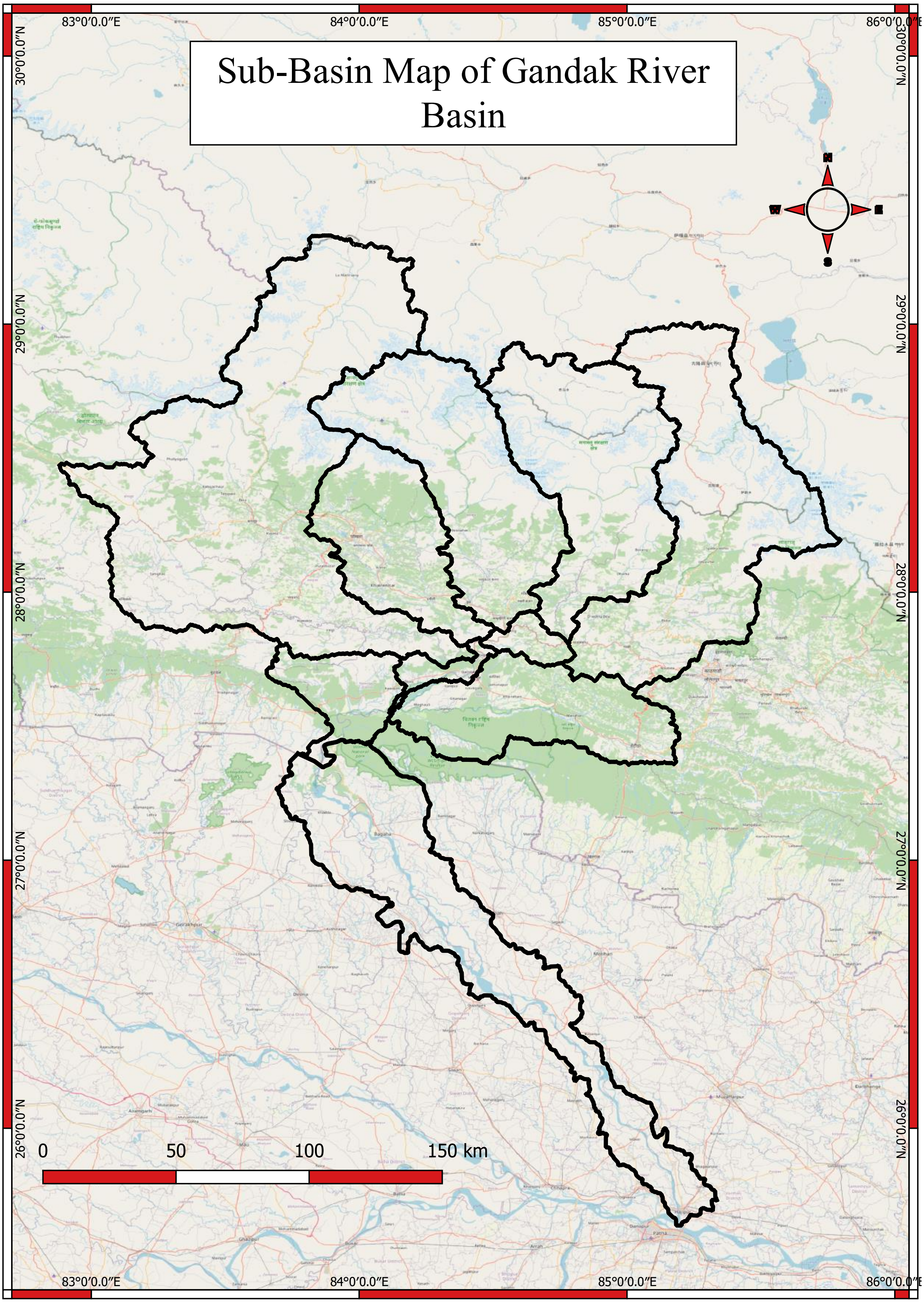


Figure 3: Subbasins map of Gandak River Basin

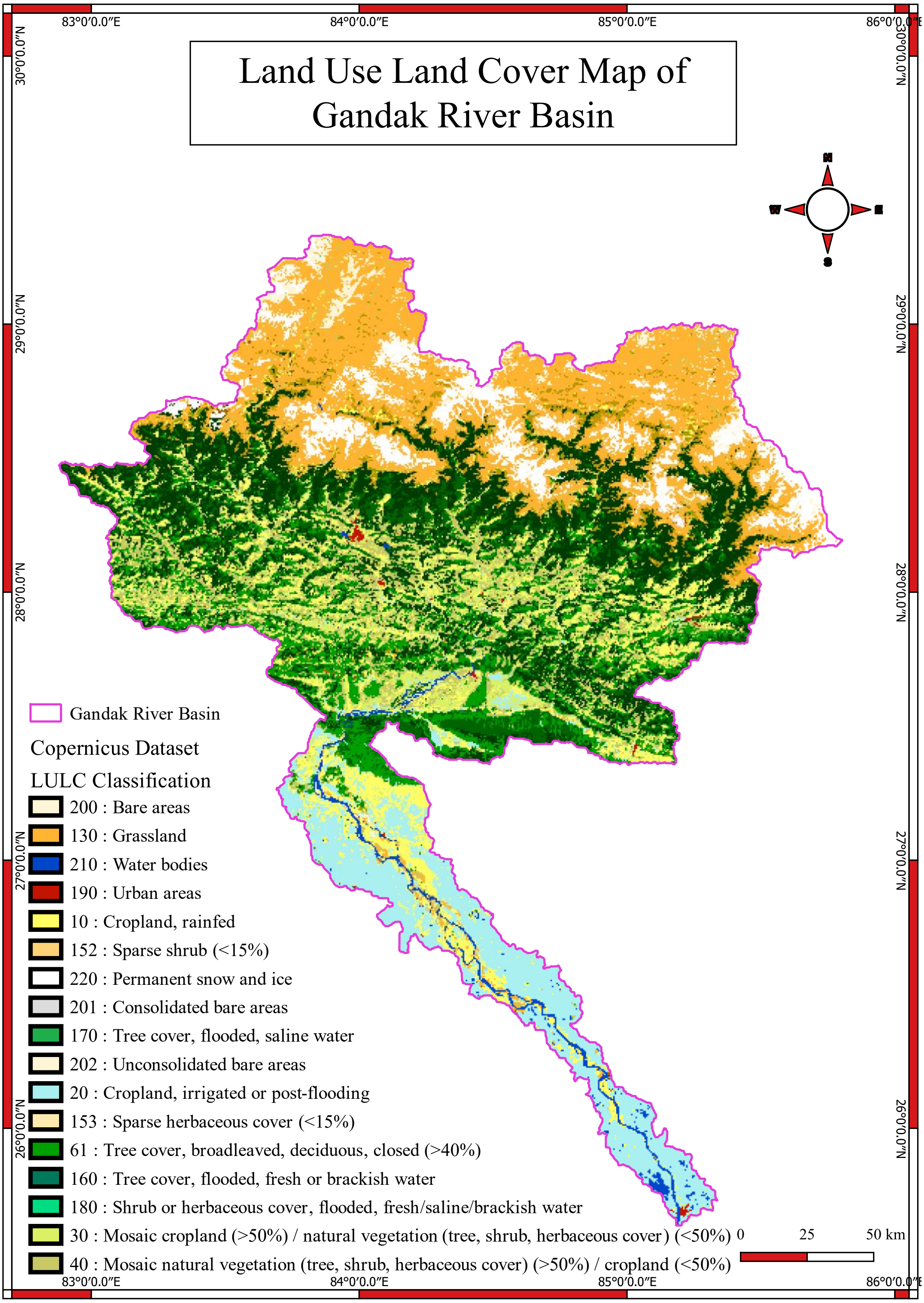


Figure 4: LULC map of Gandak River Basin

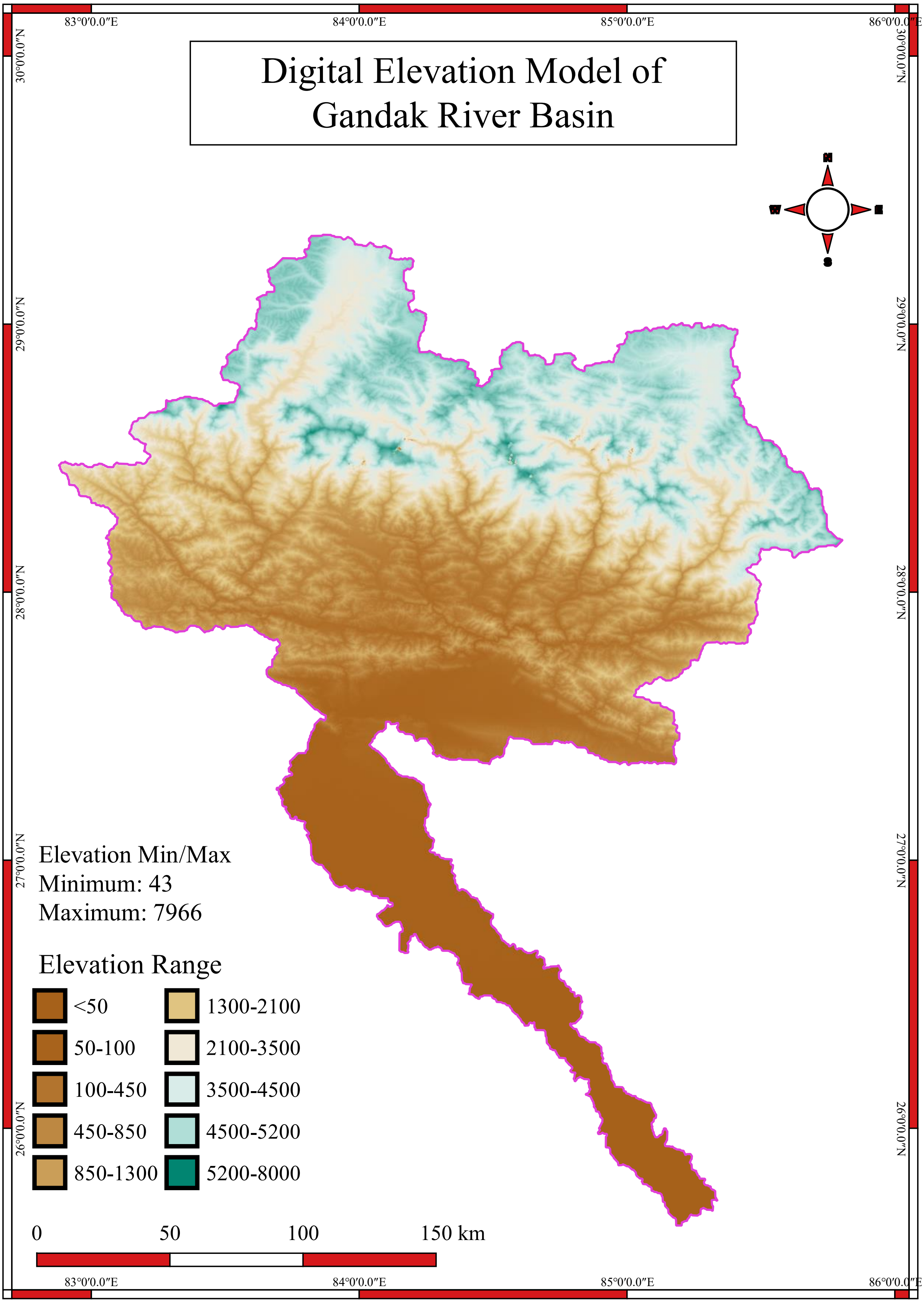


Figure 5: Digital Elevation Model of Gandak River Basin

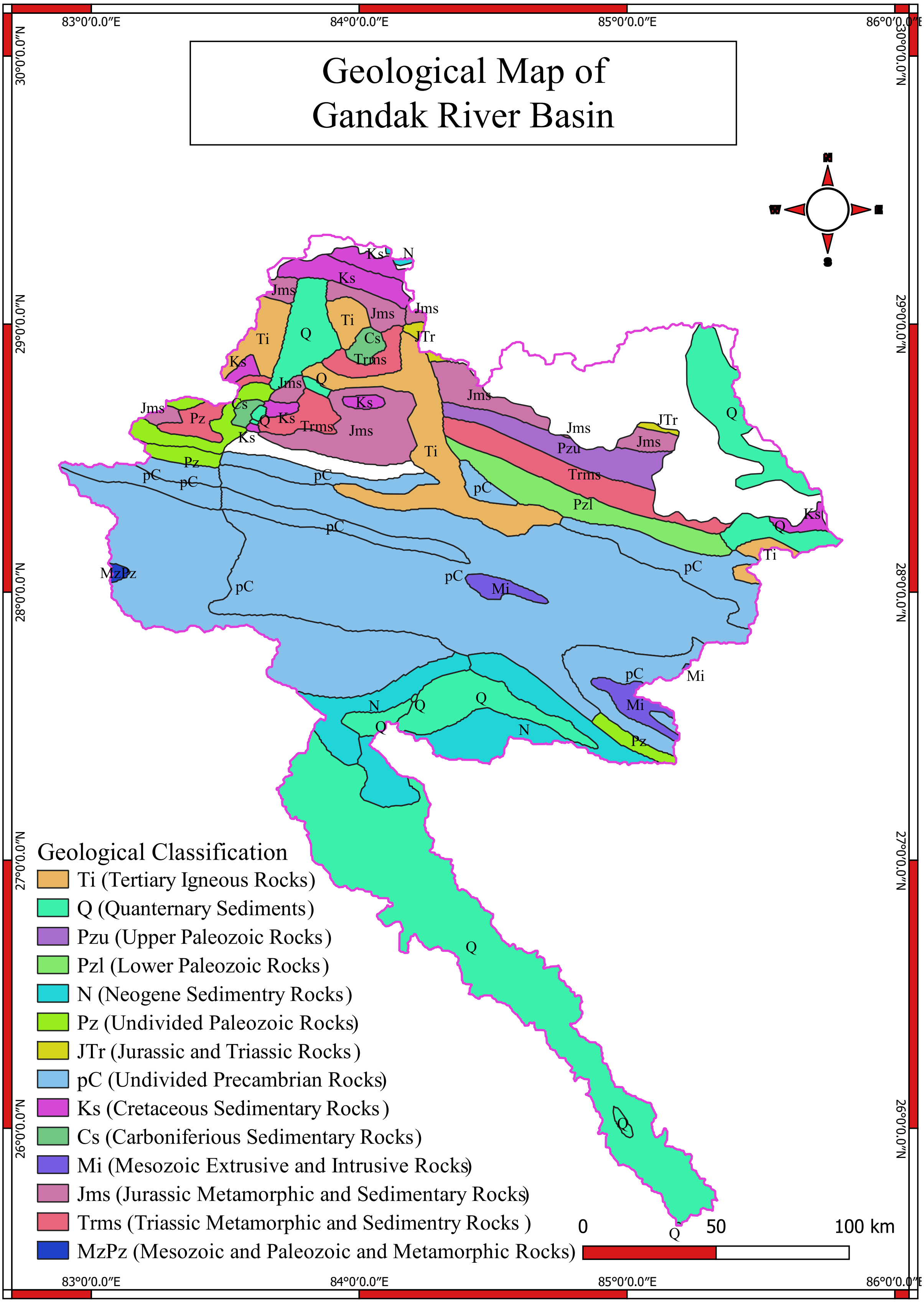


Figure 6: Geological map of Gandak River Basin

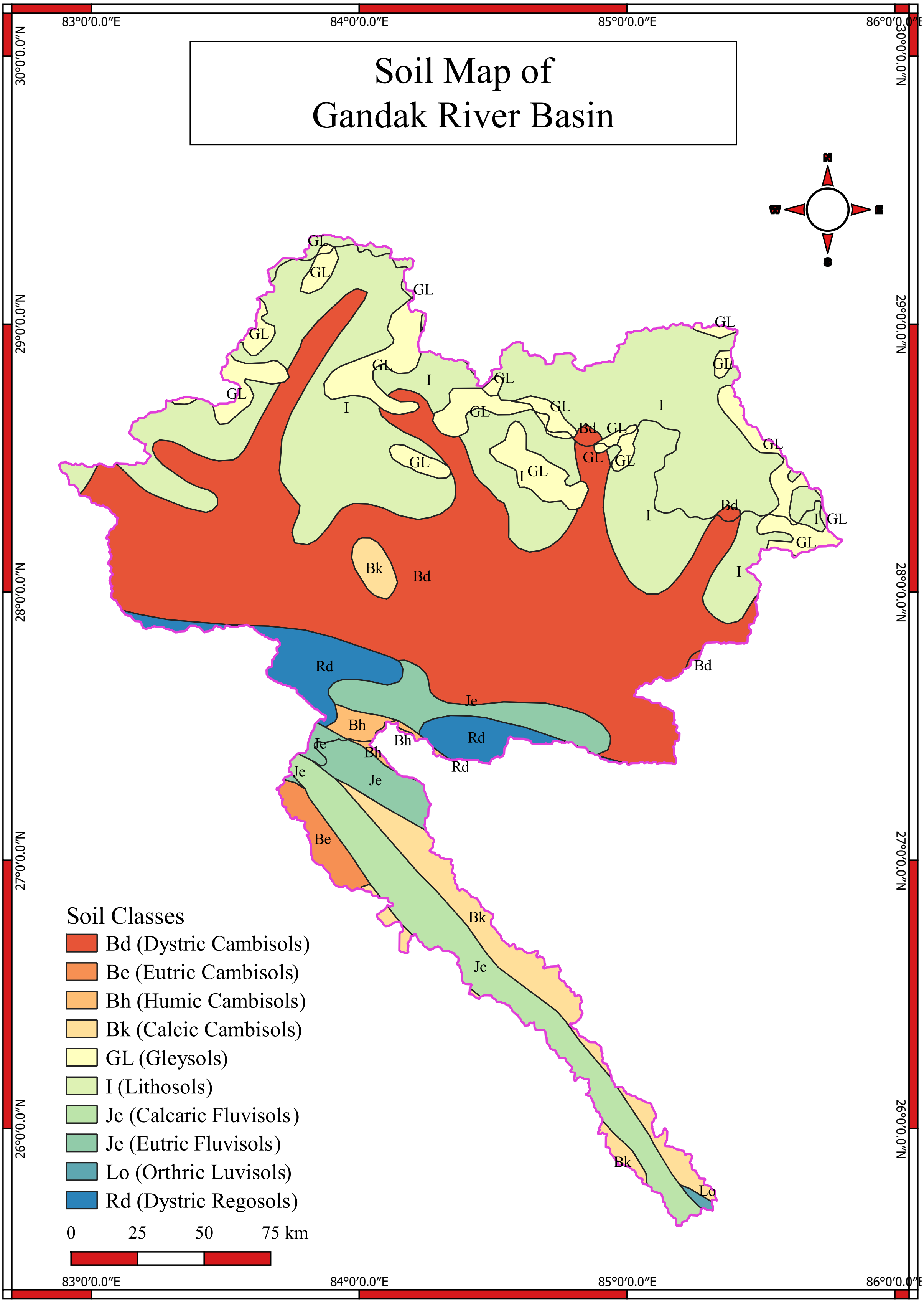


Figure 7: Soil map of Gandak River Basin

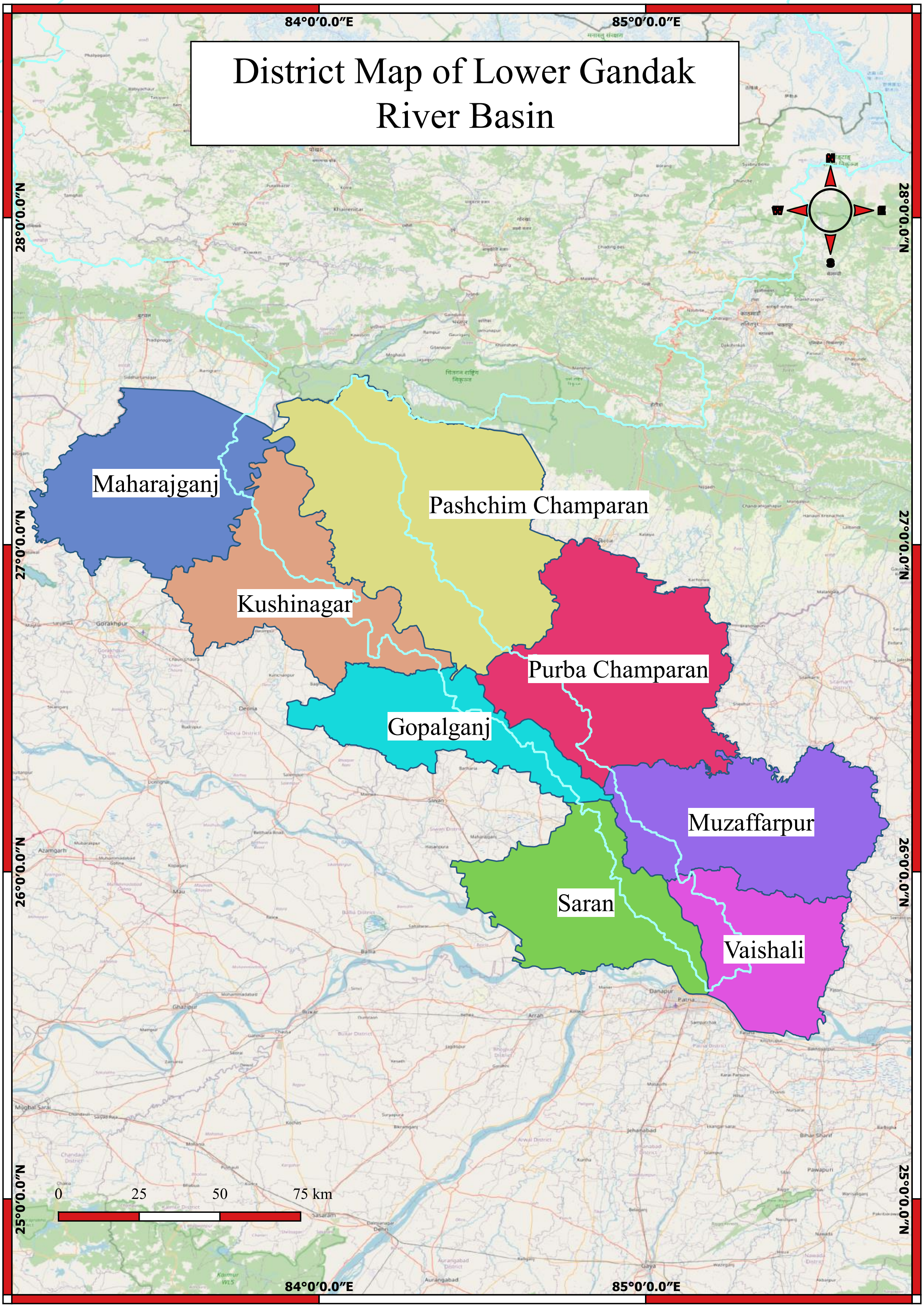


Figure 8: District map of Gandak River Basin

Chapter 3: Review of Literature

2.1 Hydrological Modelling

Hydrological modelling is the representation of real-world hydrologic problems into the system. In the initial stage of the development, the models used the mathematical equations to represent the hydrologic processes and today these models are known as process-based or physically-based model. In these models, plenty of diverse datasets is required to solve the equations and require extensive computations to reach to the outputs. Therefore, complete understanding about the river basin and the knowledge of the physical processes involved is a must for the modeller when using these models. These models are best for small-scale applications where data is available in abundance but nevertheless these are applied to large-scale basins as well and proven worthy. However, these models need extensive calibration even after collection of different required dataset and also, sometimes these models are difficult to use when a modeller is unaware of the real hydrology of the basin. In such cases, the gap is filled by the models which are data-driven or completely depends on creating the relationship between available inputs such as temperature, precipitation and evapotranspiration and observed outputs such as water level and discharge. These models are considered as black box or data-driven models and there is no physical significance of how the outcome is processed in these models. Today wide range of dataset is available in terms of remote sensing derived products which can be utilised for physically based modelling. Also, a wide range of hydrologic models are also available which requires extensive calibration and validation The calibration/validation exercise should be covering as diverse conditions as possible.

Some sort of essential characteristics needs to be considered for the selection appropriate hydrologic modelling tools. These could be based upon modelling purpose and objective, data requirements and availability, flexibility and customization of the model, model structure and complexity, model's performance and reliability, user community and developer's support, and finally whether its available in open-source domain or required licensing. Different studied categorised models as per their modelling objectives e.g. Brannstorm et al. (2019) categorized essential characteristics for the selection of modelling tools based upon whether the model is open-source, availability of useful tutorials and graphical user interphase and applicability to nexus. El-Nasr et al. (2005) conducted a comparative study to assess the performance of the fully distributed MIKE SHE model and the semi-distributed SWAT model in describing the different phases of the hydrologic cycle in a catchment. The study aimed to determine if both models are equally capable of capturing the hydrological processes given the availability of data in the catchment. Plesca et al. (2012) also emphasized the importance of using a variety of hydrological models to infer water flux understanding and explore catchment functioning. The study conducted in a tropical montane rainforest catchment in Southern Ecuador highlighted the need to extend models developed to capture specific hydrological processes. Khaniya et al. (2017) discussed the significance of hydrological simulation in assessing the effectiveness of Low-Impact Development (LID) tools before implementation. Various models, including HEC-HMS and SWAT, have been applied to evaluate the hydrological effects of urbanization. Additionally, Chathuranika et al. (2022) compared the streamflow simulation capacities of SWAT and HEC-HMS in the Huai Bang Sai watershed in Thailand. The results of their study aimed to provide recommendations for stakeholders to improve water usage policies in the watershed. Furthermore, Ackerman et al. (2008) highlighted the importance of using consistent methodologies in dam break studies to understand the potential consequences of dam failure. Ngangbam et al. (2019) emphasized the integration of hydrologic and hydraulic models with ground survey inputs for urban flood scaling and early warning systems. The study conducted in Guwahati city, India, aimed to establish flood runoff thresholds and scale flood events in flood-prone urban regions. In conclusion, the literature review of hydrologic models such as HEC-HMS, SWAT, and MIKE Hydro demonstrates the importance of model comparison, performance evaluation, and application in various hydrological studies and assessments. The studies reviewed emphasize the need for selecting appropriate models based on specific objectives and available data to improve water resource management and flood forecasting capabilities.

The comparison of hydrologic models is a crucial aspect of hydrological studies to determine the most suitable model for a specific watershed. Borah et al. (2003) provided a comprehensive review of eleven watershed-scale hydrologic and nonpoint-source pollution models, including MIKE SHE and SWAT. Borah et al. (2004) further discussed the applications of three selected models, which included MIKE SHE and SWAT, highlighting their components and functionalities. El-Nasr et al. (2005) conducted a comparative study between the fully distributed MIKE SHE model and the semi-distributed SWAT model to assess their performance in describing the hydrologic cycle of a catchment. Devia et al. (2015) briefly discussed the MIKE SHE and SWAT models among others, emphasizing ongoing research on the compatibility of model results with observed discharges. Chathuranika et al. (2022) specifically compared the streamflow simulation capacities of SWAT and HEC-HMS in the Huai Bang Sai watershed, providing valuable recommendations for water usage policies. Additionally, Aqnouy et al. (2023) evaluated various hydrological models, including MIKE SHE and SWAT, to simulate discharge behavior scenarios in the Oued Laou watershed. Overall, the literature highlights the importance of comparing hydrologic models such as MIKE SHE, SWAT, and HEC-HMS to determine their suitability for specific watershed characteristics and objectives. Further research is needed to critically evaluate and select the most appropriate model for accurate hydrological assessments. Integration of different models can be done in order to improve the accuracy of modelling system as compared to one single model. This can provide valuable insights about the modelled domain which might not be captured by one single model.

Hydrological models play a crucial role in understanding and predicting the behaviour of water systems in various watersheds. Different models have been developed and utilized for this purpose, each with its own strengths and weaknesses. In a review conducted by Borah et al. (2003), eleven watershed-scale hydrologic and nonpoint-source pollution models were compared, including MIKE SHE and SWAT. Devia et al. (2015) also discussed the SWAT model along with other models like VIC and HBV, highlighting the ongoing research on which model provides the most compatible results with observed discharges. El-Nasr et al. (2005) conducted a comparative study between the fully distributed MIKE SHE model and the semi-distributed SWAT model to assess their performance in describing different phases of the hydrologic cycle in a catchment. Similarly, Chathuranika et al. (2022) compared the streamflow simulation capacities of SWAT and HEC-HMS in the Huai Bang Sai watershed, providing valuable recommendations for stakeholders to improve water usage policies. In a study by Filianoti et al. (2020), a performance matrix was introduced to compare computer hydrological models for flood predictions, where HEC-HMS and MIKE 11 NAM were identified as the best models based on various evaluation parameters. Abdulkareem et al. (2018) reviewed hydrological models used in Malaysia, showing that physical-based models were the most commonly used. Furthermore, Keller et al. (2022) emphasized the need to critically evaluate and select appropriate hydrological models for specific objectives, considering the wide range of models available. Aryal et al. (2018) quantified sources of uncertainty in climate change impact assessments on hydrology, while Kumar et al. (2020) evaluated GIS-based semi-distributed hydrological models in the Bhagirathi-Alaknanda River catchment in India. Overall, the comparison of hydrological models such as HEC-HMS, SWAT, and MIKE NAM in various studies highlights the importance of selecting the most suitable model for specific watershed characteristics and research objectives. Further research and evaluation are necessary to improve the accuracy and reliability of hydrological modelling for effective water resource management and flood forecasting.

Another problem for modelling arises when the region is data scarce. The upper part of Gandak River Basin lies in data scares Himalayan region. Detailed literature review has also been done in this direction. Multiple studies have been conducted in the past addressing the problems and solutions of hydrological modelling in data scarce regions. Pandey et al. (2012), proposed a parsimonious hydrological modelling approach which can be used for data scarce dryland regions. This approach directly models the dominant hydrological processes as constraints making the model more reliable to work with limited available information. The dominant processes which are considered here are evaporation, overland flow, transmission losses and subsurface flow. Dile et al. (2014), evaluated suitability of CFSR climate data for hydrological modelling in Upper Blue Nile River Basin. The study suggests although CFSR data not perform as good as observed weather dataset, it can provide significant information about the weather in data scarce regions. Darbandsari et al. (2020), compared seven lumped conceptual hydrological models, which were calibrated using five different optimization functions and the effects of using Degree-Day or SNOW17 snowmelt estimations were compared. It is important to notice form the results of this study that the more complex snowmelt estimation method in the model didn’t improve the model performance.

A detailed review of available literature for water management models has been carried out in order to get an understanding about modelling capabilities and applicability of these model for the basin scale. The hydrologic models which are considered for review under the present study are:

1. Hydrologic Engineering Center Hydrologic Engineering Model (HEC-HMS)
2. Soil and Water Analysis Tool+ (SWAT+)
3. MIKE 11 NAM

2.1.1 Hydrologic Engineering Center Hydrologic Engineering Model (HEC-HMS)

The Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS) is a powerful software package for precipitation-runoff simulation, designed to be applicable in a wide range of geographic areas and to solve a variety of problems (Charley, 1995; Scharffenberg, 2008). It is a new-generation software that supersedes the HEC-1 program, with enhanced technical capabilities and operational features (Peters, 1996). HEC-HMS is particularly useful for flood modelling, with the ability to simulate reservoirs, lateral weirs, pump stations, and channel loss methods (Scharffenberg, 2008). It also supports deterministic hydrologic simulation for engineering studies, with the capability to address a wide range of studies and the flexibility to perform tasks in any order (Scharffenberg, 2003).

Yusop et al. (2007) utilized HEC-HMS to model stormflow hydrograph in an oil palm catchment. Oleyiblo et al. (2010) applied HEC-HMS for flood forecasting in Misai and Wan'an catchments in China, using HEC-GeoHMS for processing digital elevation models. Halwatura et al. (2013) calibrated and validated the HEC-HMS model for runoff simulation in a tropical catchment, emphasizing its reliability for hydrological simulations. Asadi et al. (2013) used HEC-HMS for flood forecasting in Iran, dividing basins into sub-basins and employing the Geospatial Hydrologic Modeling Extension, HEC-GeoHMS. Gebre (2015) calibrated and validated the HEC-HMS model for runoff simulation in the upper Blue Nile River Basin, demonstrating its effectiveness in assessing hydrological responses. Bhuiyan et al. (2017) assessed the applicability of using RADARSAT-2-derived soil moisture data in HEC-HMS for flood forecasting in a cold region watershed. Gumindoga et al. (2017) simulated ungauged runoff in the Upper Manyame Catchment in Zimbabwe using HEC-HMS, highlighting its contribution to water resources programs. Tassew et al. (2019) conducted rainfall-runoff simulation in the Lake Tana Basin using HEC-HMS, delineating the catchment and extracting properties from a Digital Elevation Model. The characteristics of watershed and its parameters are related by regression-based methods. With the advancements of satellite derived products more and more watershed characteristics are becoming available for analysis. Cheng et al. (2021) explored the applicability of HEC-HMS and its parameter regionalization in small ungauged watersheds in hilly areas, applying the model to three typical small watersheds in Henan Province. Aryal et al. (2017) considered Linear Scaling and Quantile Mapping regionalization methods to correct the bias in climate dataset. Overall, these studies demonstrate the versatility and effectiveness of HEC-HMS in various hydrological applications.

Study by Halwatura et al. (2013) suggest under transform methods, Snyder Unit Hydrograph method is better as compared to Clark Unit Hydrograph method in case of an ungauged tropical catchment, whereas under loss methods deficit constant loss method performed better as compare to SCS CN method. In the same study, the critical parameters are found to be initial deficit, maximum storage, constant rate and imperviousness. The model efficiency reported in terms of coefficient of performance (Cp) during validation period as 0.98 and relative error as 0.12% which indicates a reliable simulation of flows.

Bhuiyan et al. (2017) showcased the HEC-HMS model’s very good performance on daily continuous simulations as NSE value of 0.87 and deviation of runoff volume as -17.9%. The model incorporated Soil Moisture Accounting (SMA) loss method, SCS Unit hydrograph as transform method, recession baseflow method and Muskingum routing method. Monthly average evapotranspiration, Inverse Distance precipitation method along with Temperature Index snowmelt method is utilised for meteorological model setup. Parameters sensitivity analysis reveals soil storage, tension storage, maximum infiltration and maximum canopy storage are the crucial parameters affecting the performance of model. Soil storage is ranked as first, and maximum infiltration and soil percolation termed as second and third in the parameter’s sensitivity ranking. However, in the event mode the model NSE is found to be 0.74 with -4.83% deviation from runoff volume, which indicates model performed better on continuous timescale as compared to event-based simulations. Fleming et al. (2004) showcased the calibration of annual simulation should be based on semi-annual mode with parameters taken under wet conditions in order to predict the wet conditions flows accurately. This however leads to over-predict the flows during the dry season.

Another study on Application of HEC-HMS Model for Flow Simulation in the Lake Tana Basin by Tassew et al. (2019) shows efficiency of HEC-HMS model during validation period for four different events as a mean value of NSE as 0.884 and mean R^2 as 0.925. In this study SCS Unit Hydrograph method used for transform and SCS Curve Number method used as loss method based upon applicability, limitations and availability of dataset. Univariate gradient optimization package used with peak-weighted root mean square error (PWRMS) objection function in the study which reveals curve Number scale factor, initial abstraction scale factor and impervious area percent identified as crucial parameter in loss method.

The snow model which is a component of the HEC-HMS, has been used in various studies to simulate snowmelt and rainfall runoff. It has been found to be reliable in simulating snowmelt and runoff in the Himalayas (Verdhen, 2013), and has been enhanced over time to include features such as reservoir simulation, lateral weirs, and snowmelt (Scharffenberg, 2008). However, it has also been noted that the model may have difficulty reproducing peaks in late winter and early spring runoff (Gyawali, 2013). The HEC-HMS as a whole has been improved to address these issues, with the addition of a reservoir element and the capability to simulate transient events (Scharffenberg, 2003). Furthermore, the latest developments in HEC-HMS are enhancing its performance by introducing Energy Balance methods along with Rain-on-snow event simulations capabilities. In order to improve the accuracy of Snow Water Equivalent simulations both the point calibration schemes and distributed calibration schemes are included in the model.

It is important to consider the best modelling approaches after the selection of particular model. The combination of different methods should be such that it maximizes the overall model performance for that detailed review of available literature becomes necessary as it is not practically possible to simulate the model with all the available methods and compare the results. Previous studies showcased a number of comparisons between different methods available in the HEC-HMS model and some of the studies are discussed here. James et al. (1992) suggested that Green Ampt method performed better in case of six storms in which precipitation excess was more than 1 inch. Fleming et al. (2004) developed a GIS based methodology for estimation of parameters for SMA method. The paper also discussed about the selection of calibration period based upon representative average ratio of rainfall-runoff among the available dataset. Also, the parameter variations with seasons are discussed and emphasise on seasonal parameters sets is made rather than assigning a single parameter value for the annual simulations.

Sahu et al. (2023) in the review article elaborated about the utilization of multiple methodologies using HEC-HMS model in order to simulate streamflow with precision. The article also described SCS-CN loss method most suitable for event based hydrologic modelling and SMA for long term continuous hydrological modelling. The Deficit and Constant method also showcased as one of the effective and accurate methods but least utilized by the modelling community.

Mishra Shrikant (2009) provided a systematic overview of uncertainty and sensitivity analysi techniques in hydrological modelling. The systematic framework showcased multiple methods viz Monte Carlo simulation, First order and Second order analysis, Point estimate method, First order reliability method, Logic tree analysis, Stepwise regression, Mutual information analysis and Classification tree analysis. Among these methods the study suggests to use Monte Carlo

Simulation for hydrological modelling applications due to its general applicability and lesser assumptions. Aryal et al. (2020) reported the main sources of uncertainty in HEC-HMS model as initial deficit, maximum storage, constant rate and imperviousness parameters for the loss method.

2.1.2 Soil & Water Assessment Tool (SWAT)

The Soil and Water Assessment Tool commonly known as SWAT is one of the most commonly used hydrologic modelling software which is applicable to wide range of problems related to basin hydrology and yield estimations, sediment and solute transport etc. The amount of available literature on SWAT showcased its successful applications in different conditions. Romanowicz et al. (2005) found that the SWAT model's sensitivity to soil and land use data pre-processing procedures significantly impacts the modelling of rainfall-runoff processes. Wagener et al. (2004) focused on rainfall-runoff model identification in both gauged and ungauged catchments, emphasizing the importance of conceptual lumped models. Jayakrishnan et al. (2005) discussed recent advances in applying SWAT and the SWAT-GIS interface for water resources management, highlighting the role of computer technology in revolutionizing hydrologic studies. Kannan et al. (2007) conducted sensitivity analysis and identified the best evapotranspiration and runoff options for hydrological modelling using the SWAT-2000 model. Adjei et al. (2015) evaluated the application of satellite-derived rainfall data for hydrological modelling in the Black Volta basin, showing a strong correlation with rain gauge measurements. Alemayehu et al. (2018) compared Climate Forecast System Reanalysis (CFSR) and Water and Global Change (WATCH) rainfall data with gauge observations for hydrologic applications in the Mara Basin. Fuchs et al. (2021) explored the impact of pesticide application timing on pesticide concentrations using the SWAT+ model, emphasizing the importance of considering application timing for accurate predictions. Mirzaei et al. (2021) proposed a Stacked Long Short-Term Memory (SLSTM) model for daily rainfall-runoff simulation, highlighting the use of machine learning technology in hydrological modelling. Koshuma et al. (2021) compared in situ-based simulations with satellite products like CMORPH and TRMM for rainfall-runoff modelling in the Upper Omo-Gibe Basin. Salele et al. (2023) utilized SWAT to simulate runoff in pervious and impervious urban areas, mapping cover changes over time to estimate runoff from different land types. Overall, these studies demonstrates the diverse applications of SWAT for rainfall-runoff modelling, highlighting the importance of data quality, model sensitivity, and technological advancements in improving hydrological studies.

The Soil and Water Assessment Tool (SWAT) has also been widely used in various studies to model rainfall runoff and its impacts on the environment. Guo et al. (2019) highlighted the importance of SWAT in modelling soil water erosion, especially in regions affected by climate and land use changes. Yonaba et al. (2020) utilized the SWAT model to simulate surface runoff in a Sahelian watershed, showcasing the significance of incorporating dynamic land use/land cover changes for accurate modelling. Additionally, Fuchs et al. (2021) explored the impact of pesticide application timing on surface water exposure patterns using SWAT+, a revised version of the SWAT model. Furthermore, Martins et al. (2021) investigated the potential impacts of land use changes on water resources using SWAT in a tropical headwater catchment, emphasizing the model's ability to accurately reproduce rainfall distribution. Worku et al. (2021) studied the response of hydrological processes to climate change scenarios in the Jemma sub-basin, recommending water management structures based on SWAT modelling results. Overall, the diverse applications of SWAT for rainfall runoff modelling in various environmental contexts, emphasizing the model's strengths and limitations in capturing the complex interactions between climate, land use, and hydrological processes.

SWAT requires careful parameterization for accurate predictions. Different parameterization approaches are used by researchers in order to improve the efficiency of the SWAT model in their respective basins of interest. Spatial variability, watershed decomposition, adjustments to curve number and return flows are some of the strategies adopted by the modellers. Manguerra et al. (1998) used this approach for the evaluations of SWAT model's potential to predict the streamflow runoff in the basin with substantial subsurface drainage. Romanowicz et al. (2005), suggested soil properties calculations are crucial before averaging profile data in order to get significant hydrologic response in SWAT. The study also emphasised on catchment size threshold values which considerably affects the model performance. In other studies, regression based regionalized model parameter are considered which are based on watershed characteristics. Gitau et al. (2010) used regression-based parameters, improving the model performance as compared to model calibrated parameters. Based on such approaches parameters sensitivity analysis also reported in the literature. Spruill et al. (2000) reported hydraulic conductivity, alpha baseflow factor, drainage area, channel length and channel width as most sensitive parameters. This study also highlights SWAT performance on daily and monthly time scales. The model performed better in case of monthly total flows but could not picked the timings of peak flows and recession rates in the daily simulations. Veith et al. (2010) evaluated parameters sensitivity for SWAT model and concluded the sensitivity of surface runoff parameters as highest and groundwater parameters as least sensitive. Also, the surface runoff parameters sensitivity increases in areas with high evaporation and localized thunderstorms. However, in case of subwatersheds where snowfall and rainfall both occurs, parameters of all categories are sensitive. Kumar et al. (2009) used SWAT autocalibration tool to calibrate fourteen parameters for daily streamflow records spanning over a period of seven years. The study emphasises on the need of manual calibration of the model for underestimated low flows corrections. However, the different parameter sets on different watersheds did not affect the calibrated model much. Authors also discussed about the non-uniqueness of calibration parameters which means different parameter sets can produce similar outputs and therefore the key challenge is of the identification of the most optimal parameter values during the calibration process. Baseflow recession constant, Curve number, Surface runoff lag, Channel Manning's n, and Soil and water capacity are mentioned as significant parameters in the study.

As discussed earlier, initially Manguerra et al. (1998) emphasized the importance of improving model performance without tedious calibration by addressing issues such as spatial variability and curve number adjustments. Over the period of time detailed analysis has been done by different authors and results were not just limited to adjustments of Curve number only but including multiple parameters. Arnold et al. (2012) discussed various calibration techniques for SWAT, including manual and automated methods, to simplify the parameterization process. Selection of calibration process not only depends upon the model complexities and modelling objectives but it's also depends on experience and expertise of the modeller. The parameterization methods are not limited to the streamflow simulations but used in the studies related to sediment transport and pollution management as well. Bekele et al. (2007) focused on multi-objective automatic calibration of SWAT for streamflow and sediment concentration predictions, highlighting the need for efficient parameterization methods. Panagopoulos et al. (2011) implemented SWAT to identify critical diffuse pollution source areas, emphasizing the importance of appropriate parameterization for effective pollution management. Similarly, Winchell et al. (2018) evaluated the uncalibrated SWAT model's ability to predict pesticide concentrations in vulnerable watersheds, demonstrating the importance of parameterization in accurate predictions. Zhao et al. (2018), investigated CN2 (SCS CN for soil condition II), ALPHA_BF (Baseflow alpha factor in day) and SOL_K (Saturated hydraulic conductivity in mm/hr) as most sensitive parameters for simulating peak flows, average flows and low flows respectively.

The impact of urbanization on the hydrological processes in small watersheds is also the concern in present world. Land use change impacts on hydrology of watershed and hydrological processes in urbanization regions using SWAT was studied by Du et al. (2013), with fixed and varied parameterization approaches. Authors also conducted sensitivity analysis of the SWAT model in the Yarra River catchment, showcasing the model's utility in simulating catchment-scale hydrologic processes. Akoko et al. (2021) recommended increased efforts in local data availability and multidimensional approaches for future SWAT simulations, including improved model parameterization. Haas et al. (2021) addressed the unrealistic forest growth predictions of SWAT's default parameterization by re-parameterizing forest dynamics for species-specific representation. Yuan et al. (2021) highlighted the wide variation in calibrated parameter values for phosphorous loss reduction in the Western Lake Erie Basin, emphasizing the need for realistic parameterization in SWAT applications.

SWAT model parameterization is a crucial aspect of watershed modeling for accurate predictions of hydrological processes. Moriasi et al. (2019) introduced the SWAT-LUT, a user-friendly tool for updating land use in the SWAT model, allowing for the processing of multi-year land use data. Hashem et al. (2020) evaluated SWAT soil water estimation accuracy in different locations, highlighting the challenges of soil water content measurements and the variability in soil water estimates across different scenarios. Jakada et al. (2020) proposed a methodology for runoff modelling in small karst watersheds using the SWAT model, emphasizing the importance of field investigations and tracer tests for improving hydrological process understanding. Furthermore, Akoko et al. (2021) recommended increased efforts in local data availability and a multidimensional approach for future SWAT model simulations, particularly in the context of model parameterization and dataset inputs. Haas et al. (2021) and Haas et al. (2022) addressed the representation of forests in hydrological models, emphasizing the need for improved forest dynamics parameterization for better hydrological predictions at the watershed scale. Yuan et al. (2021) highlighted the wide variation in calibrated phosphorous-related parameter values in different studies using the SWAT model, suggesting the need for more consistent parameterization practices. Verma et al. (2022) discussed ongoing developments in water resources management incorporating the SWAT model, emphasizing the model's capabilities in simulating agricultural watersheds and predicting runoff, sediment transport, and erosion under various management scenarios. In conclusion, SWAT model parameterization plays a critical role in accurately simulating hydrological processes in watersheds, and ongoing research focuses on improving parameterization practices to enhance model performance and prediction accuracy. Also, among different methods for finding suitable parameter sets Parameter Solution (ParaSol) was most efficient.

In order to test the model's reliability, it is important to have a check on model's uncertainties. Uncertainty analysis involves identification and quantification of sources of uncertainties. Past studies showcased different methods and enhance the knowledge about SWAT model's behaviour under different modelling conditions. White et al. (2005) performed multi-sites and multi-variable analysis using multi-objective function for SWAT Model, in order to identify sensitive parameters and reduce the uncertainty. Veith et al. (2010) reported SWAT model's performance for prediction of streamflows showing less uncertainty under humid climatic conditions but the uncertainty is more in case of arid or semi-arid climates. Kumar et al. (2009) addressed significant parameters of SWAT shows a restricted range of uncertainty as compared to non-significant once. Also, during the recalibration process considering only the significant parameters can reduce the uncertainty to great extent. Zhao et al. (2018), applied Parameter Solution (ParaSol), Sequential Uncertainty Fitting (SUFI2) and Generalized Likelihood Uncertainty Estimation (GLUE) methods for quantification of parameters sensitivity and uncertainty in the SWAT model. The results of this study showcased SUFI2 performance was slightly better as compared than GLUE for the prediction of uncertainty of the model.

2.1.3 MIKE by DHI

The use of MIKE for hydrological modelling in rainfall-runoff studies has been a prevalent topic in recent literature. Different packages of MIKE are being used for different applications. Al-Khudhairy et al. (1999) demonstrated the potential of the MIKE SHE system in simulating the hydrological regime of a drained grazing marsh under agricultural land use. The model was able to predict the influence of various water management strategies on pumped discharge and soil moisture storage in the catchment. Bao et al. (2011) focused on the effect of estimating areal rainfall on the simulation accuracy of runoff prediction using the MIKE 11/NAM rainfall-runoff model. Vansteenkiste et al. (2014) investigated the effects of hydrological model structure and calibration on climate change impact results in hydrology, utilizing five different hydrological models with varying spatial resolutions and process descriptions. Furthermore, Karim et al. (2015) integrated conceptual rainfall-runoff modelling, river system modelling, and hydrodynamic modelling (MIKE 21) to estimate hydrological connectivity in floodplain inundation in northern Australia. Kumar et al. (2018) used MIKE 11NAM rainfall-runoff and MIKE BASIN models to analyze water availability in the Shipra River basin under changing hydrological conditions. Broekhuizen et al. (2019) compared the differences between SWMM, MOUSE, and MIKE SHE models in simulating rainfall runoff from green areas in urban drainage systems. Altaf et al. (2019) focused on modelling snowmelt runoff in the Lidder River basin using a coupled model to estimate the contribution of snowmelt to total streamflow. Finally, Ma et al. (2020) presented an optimized modelling strategy for setting up deterministic distributed hydrological simulations (MIKE SHE) in the Var catchment, emphasizing the importance of spatial discretization in understanding catchment hydrological phenomena. Overall, the use of MIKE in hydrological modelling for rainfall-runoff studies has proven to be effective in simulating various scenarios and understanding the impacts of different water management strategies on catchment hydrology.

MIKE 11 NAM model is extensively being used for rainfall runoff processes in several studies. Andersen et al. (2006) utilized the NAM rainfall-runoff model to assess the impacts of climate change on hydrology and nutrients in a Danish lowland river basin. The study incorporated predictions from the HIRHAM regional climate model as external forcings for the NAM model, providing insights into future scenarios for the Gjern river basin. Odiyo et al. (2012)

also employed the MIKE 11 NAM model to estimate Latonyanda River flow contributions to the Luvuvhu River downstream of Albasini Dam. Furthermore, Craciun et al. (2014) investigated the impact of overland flow and topography on groundwater in the Ciurea-Tinoasa hydrographical basin using the MIKE 11 software and the NAM module. Kumar et al. (2018), developed a runoff simulation model for the Arpasub-basin of the Seonath river basin in India using the MIKE 11 NAM approach. Wickramaarachchi et al. (2021) evaluated the performance of the MIKE 11 NAM rainfall-runoff model using different calibration objectives in the upper Gin catchment, Sri Lanka. Pareta (2023) conducted hydrological modelling of the largest braided river in India using the MIKE Hydro River NAM software package, incorporating TRMM/GFS rainfall, PET, and snowmelt data. These studies collectively demonstrate the widespread use of the MIKE NAM model in rainfall-runoff modelling for various hydrological assessments and predictions.

The calibration process of MIKE NAM model can be broadly divided in two categories as (i) Manual calibration in which trial and error based calibration is done and (ii) Computer based automatic calibration. As per DHI documentation (DHI, 2009) of the NAM model, the model consists of nine main parameters for mimicking the surface root zone storage and groundwater storage. The groundwater storage includes upper and lower groundwater storage layers. Upper GW storage layer has fast response time to generate the baseflow component whereas the lower storage layer has relatively slow response to generate the same. Based upon the degree day factor the calculations for snowmelt runoff is being done in the model. U_{max} and are the primary parameters to be changed in order to adjust the water balance in the simulations (DHI, 2009).

Doulgeris et al. (2011) applied the NAM model in the Strymonas River catchment to simulate daily discharge into Lake Kerkini, representing the catchment with four reservoirs. The calibration method used in the paper is based upon overall volume error and overall root mean square error. The method includes multi-objective optimization problem solved by the shuffeled complex evolution algorithm. Combined approach of using autocalibration and manual calibration has been used in the study and results showcased the use of GW extended parameters and snowmelt parameters significantly improve the model performance. procedure used in the study Odiyo et al. (2012) computed Latonyanda River flow contributions to Luvuvhu River using the MIKE 11 NAM model and showcased underestimation of relatively high peak flows. The study also stated that the L_{max} is crucial for seasonal water balance and Umax primarily affects peak flows and accumulated water volume. Singh et al. (2014) calibrated the model for Vinayakpur intercepted catchment in Chhattisgarh state. Hafezparast et al. (2013) used an auto-calibrated NAM model to investigate peak and monthly flows in the Sarisoo River Basin, achieving an R2 value of 0.74. Craciun et al. (2014) focused on the impact of overland flow and topography on groundwater in the Ciurea-Tinoasa hydrographical basin using the MIKE 11 software, connecting the watershed to the HD network. Teshome et al. (2020) verified the MIKE 11-NAM model for simulating streamflow in the Bina basin and showcased that overland flow runoff coefficient is a crucial parameter for calibration process. Also, the time constant for routing overland flow (CK1,2) is among one of the important parameters affecting calibration process. Discussing about the sensitivity of parameters, Teshome et al. (2020) also pointed Lmax as one of the most sensitive parameters. While, Aredo et al. (2021) optimized nine model parameters for the Shaya catchment in Ethiopia during calibration. Lmax and Umax were identified as most sensitive parameters by the researchers. Furthermore, Mureithi et al. (2022) explored the use of satellite data, specifically NASA's

GEOS-5, for estimating run-off time series in sparsely gauged basins. The paper concluded GOES-5 satellite derived dataset produces satisfactory runoff estimates after adequate calibration of the model. The sensitivity analyses done by the authors showed that CQOF and CK 1,2 affects the streamflow most and CIF and TIF affects least. Pareta (2023) utilized TRMM/GFS rainfall, PET, and snowmelt data as inputs to a rainfall-runoff model based on the MIKE Hydro River NAM software package. The most significant parameters from this study were found to be CQOF, CK 1,2 and Lmax. The major limitation in this study was the availability of local rainfall data and accuracy of rating curves at the gauging stations. The paper suggested use of MIKE 11 NAM model for flood forecasting and early warning system design.

Madsen et al (2000), emphasised on MIKE 11 NAM model's calibration algorithms and found that these algorithms can consider model errors by defining appropriate weights that can indicate importance to be given to particular portions of the hydrograph while calibrating the model. A set of Pareto optimal solutions has been used in the study and based upon the priorities of specific model applications authors suggested that a single solution could be chosen accordingly. The methodology used the Monte Carlo sampling algorithm by comparing the distributions of parameters corresponding to best and worst model simulations. Two sample Kolomogorov-Smirnov test was used in order to assess degree of parameter sensitivity.

2.2 Long Short-Term Memory (LSTM) Model applications in hydrological modelling

Long Short-Term Memory (LSTM) networks have emerged as powerful tools for hydrological modeling and streamflow forecasting. It can effectively capture and reproduce known hydrological processes, such as soil moisture and snow cover, by learning from input data rather than relying on pre-defined theoretical assumptions (Lees et al., 2021). Recently, LSTM model is also being utilised for improving the physical based model performance. Many researchers used this model as independent model for rainfall-runoff modelling and many other used the LSTM model in association with physical based models for incorporating the complex processes which are repetitive in difficult to incorporate by other means. The LSTM model in such situations, provides valuable addition to the overall model performance. These models have demonstrated superior performance compared to traditional physically-based hydrological models, particularly for short-term streamflow predictions (Sabzipour et al.,2023). Training of LSTM model is one of the important keys. As it is data driven model it is important to capture long term records. Researcher also explore about the applicability of LSTM models on multiple basins e.g. Kratzert et al., developed a catchment aware rainfall-runoff model for large-scale hydrological applications and demonstrate the suitability of LSTM model for rainfall-runoff forecasting in case of dynamic reservoirs and storage operations. LSTM models can be trained on multiple basins simultaneously, outperforming regionally and individually calibrated hydrological models. One step further the authors showcased that Entity-Aware-LSTM architecture further enhances performance by learning catchment similarities (Kratzert et al., 2019). The comparison of LSTM models with traditional hydrological models also drawn interest of researchers in recent past. Arsenault et al., used LSTM models for generating streamflows at 148 ungauged catchments of north-eastern part of North America. The model outperformed physical based model for majority of the pseudo-ungauged catchments (Arsenault et al., 2023). Not limited to this Hashemi et al., explored the effective ways to robust the performance of LSTM model in terms of training approach and look-back hidden unit size (Hashemi et al., 2022). Gauch et al. (2021) focused on prediction of extreme flood peaks and proposed two LSTM-based architectures that can jointly predict discharge at multiple timescales within a single model, which is more computationally efficient than training separate models for each timescale. Attempt has also been made by Hunt et al. (2022) for comparison of LSTM model with Global Flood Awareness System (GloFAS), depicting outperformance of LSTM model as compared to both raw and bias-corrected version of the physical based GloFAS models.

In order to capture the complex hydrological processes advancements have seen seen in terms of integration of LSTM with HEC-HMS. This concept exploits the strengths of both physical and data-driven modelling approaches. Wang et. al., (2023) introduced a hybrid model, Ia-LSTM, which aims to improve runoff predictions by combining the structured framework of HEC-HMS with the adaptive learning capabilities of LSTM. This integration is particularly beneficial in scenarios where data availability is limited, as highlighted by Zarei et. al., (2024), who compared hybrid-lumped-LSTM models with semi-distributed models like HEC-HMS in data scarce regions. The application of LSTM in hydrological modelling has also been explored in the context of flood monitoring and forecasting. The underestimation of peak flows in HEC-HMS simulations and improvement with hybrid HEC-HMS-LSTM approach is also highlighted by the author. Koutsovili et. al. (2023) developed an early flood monitoring system that combines LSTM predictions with HEC-HMS outputs, demonstrating the potential for enhanced accuracy in short-term flood forecasting. Yeditha et al. (2023) showcased the use of satellite precipitation products with LSTM and Extreme Learning Machines (ELM) for generation of rainfall-runoff models. In another study, Lastly, Deulkar et. al., (2025) provided a comparative assessment of LSTM, artificial neural networks (ANNs), and HEC-HMS for runoff modelling, emphasizing the evolving landscape of hydrological modelling techniques and the increasing role of machine learning in this field. Overall, the integration of LSTM with HEC-HMS represents a promising direction for enhancing hydrological modelling and flood forecasting. The studies reviewed indicate that while HEC-HMS remains a robust tool for hydrological simulations, the incorporation of LSTM can significantly improve predictive accuracy, particularly in data-limited environments. Future research should continue to explore these hybrid approaches to further refine and validate their applications in diverse hydrological contexts. Overall, LSTMs offer a data-driven approach that advances both scientific understanding and predictive capabilities in hydrology.

Chapter 4: Methodology & Data used

2.1 Modelling philosophy

Hydrological events are dependent on various factors and climatic conditions. The recorded dataset can provide some valuable information about the development of such conditions. The purpose of modelling is being able to capture such events using sophisticated computational techniques. The ability of model to mimic the past and predict the future events highly depends upon the generalisation of model parameters which is further dependent on the dataset itself. It is therefore necessary to have a systematic analysis of the available dataset in order to check the current trends and inferences about the parameter's range. For this purpose, hydrometeorological series needs to be identified first for any possible monotonic trend components. Non parametric Mann-Kendall's test is one of the widely used trend analysis approach (Hirsch and Slack 1984; Helsel and Hirsch 1992). The test itself does not require any normality assumption but it is accepted that the series should be independent and it should not have any serial correlations as well. Innovative trend analysis approach is used for the analysis of hydrometeorological dataset of Ganda River Basin. Innovative trend analysis offers a modern, simple, and effective procedure for trend analysis, allowing for the identification of trend variations within the record itself and helping to identify surplus and deficit parts of a time series. The innovative-Şen trend method provides possible trend components within significance limits and offers categorically significant trends with detailed quantitative information. However, only Mann-Kendall's test is performed for different time-series analysis in the study.

The methodology would therefore involve:

1. Hydrometeorological (APHRODITE, CHIRP, and IMERGE Gridded dataset) and DEM (SRTM 30m) data download
2. Data collection for streamflow/ gauge data (CWC/ WRD Bihar)
3. Data preprocessing and catchment delineation
4. Model parameters assessment and optimization
5. Model simulation with selection of different methods
6. Model calibration and validation
7. Model uncertainty analysis
8. Evaluation of model performance indicators
9. Output comparison for selecting best hydrologic performance
10. Identification of systematic errors in modeled output
11. Development of hybrid physical based & data-driven model
12. Performance evaluation of LSTM corrected model

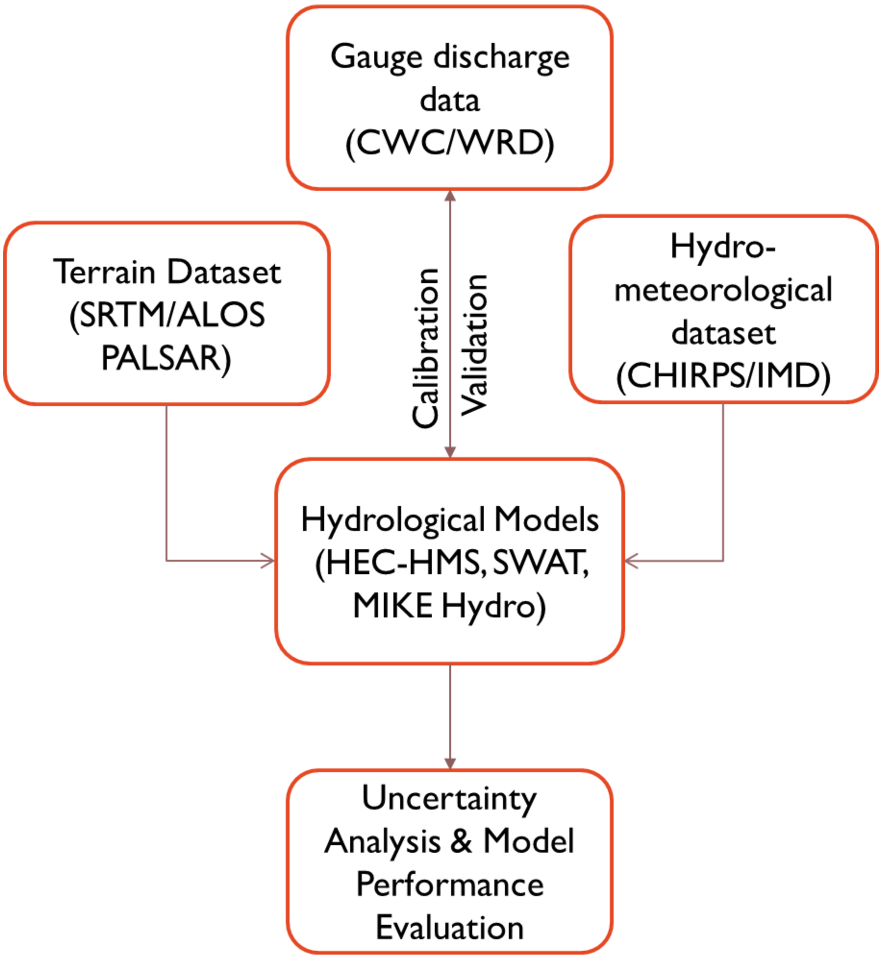


Figure 9: General philosophy of Hydrologic Modelling

2.2 Dataset inventory

2.2.1 Precipitation dataset

(a) Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)

CHIRPS is a 35+ year quasi-global rainfall data set. Spanning 50°S-50°N (and all longitudes) and ranging from 1981 to near-present, CHIRPS incorporates our in-house climatology, CHPclim, 0.05° resolution satellite imagery, and in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring. (https://www.chc.ucsb.edu/data/chirps)

(b) Integrated Multi-satellitE Retrievals for GPM (IMERG)

IMERGE is NASA's algorithm which combines information from the GPM satellite constellation to estimate precipitation over the majority of the Earth's surface. IMERG is particularly valuable over areas of Earth's surface that lack ground-based precipitation-measuring instruments, including oceans and remote areas. IMERG fuses precipitation estimates collected during the TRMM satellite's operation (2000-2015) with recent precipitation estimates collected by the GPM mission (2014-present) creating a continuous precipitation dataset spanning over two decades. (https://gpm.nasa.gov/data/imerg)

The beauty of IMERGE data is that it provides 30-minute precipitation products along with monthly and daily products at a spatial resolution of 0.1°x0.1°. The limitation with this half hourly data is the temporal range is starting from year 2000 and the final run for v06 data production halted in September 2021. The dataset is used for visualisation of extreme rainfall conditions in the basin.

(c) Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation (APHRODITE)

AOHRODITE gridded precipitation is a set of long-term (1951 onward) continental-scale daily products that is based on a dense network of rain-gauge data for Asia including the Himalayas, South and Southeast Asia and mountainous areas in the Middle East. The gridded products are available for four sub-domains--Monsoon Asia, Middle East, Russia, and Japan--as well as a combined domain. The time-varying data have a 0.25°x0.25° or 0.5°x0.5° degree horizontal resolution in each domain, except for Japan, which has a 0.05°x0.05° degree horizontal resolution. Climatological daily mean precipitation and temperature data are available for Monsoon Asia at 0.05°x0.05° resolution. (https://climatedataguide.ucar.edu/climate-data/aphrodite-asian-precipitation-highly-resolved-observational-data-integration-towards)

Table 1: Precipitation dataset sources

Sl. No.	*Data type*	*Availability*	*Spatial Resolution*	*Source*
1.	CHIRPS	1981-Present	0.05°x0.05°	UCSB http://chg.geog.ucsb.edu/data/chirps/
2.	GPM IMERGE TRMM 3B43V7	1998-2019	0.1°x0.1°	NASA Global Precipitation Measurement Mission https://pmm.nasa.gov/GPM http://trmm.gsfc.nasa.gov/ https://gpm.nasa.gov/data/imerg
3.	APHRODITE	1951-Present	0.05°x0.05°	NCAR Climate Data Guide https://climatedataguide.ucar.edu/climate-data/aphrodite-asian-precipitation-highly-resolved-observational-data-integration-towards

2.2.2. Elevation dataset

SRTM 30m dataset is used for model development. The data is pre-processed using HEC-HMS. After fill sinks, flow direction, flow accumulation, streams are delineated by assigning appropriate threshold value. The model created multiple subbasins of varying area and very small subbasins are merged with neighbouring large subbasins in order to avoid excessive calculations during simulations.

2.2.3 Temperature dataset

Multiple datasets are available for global temperature with different spatial and temporal resolutions. The list of the dataset along with source and resolution are showcased here:

Table 2: Temperature dataset sources

Sl. No.	***Dataset Source***	***Dataset Name***	***Spatial Resolution***	***Temporal Resolution***

1.	NASA GISS	GISTEMP	2° x 2°	Monthly, Annual
2.	NOAA	GHCN, Climate at a Glance	Station-based, 5° x 5°	Daily, Monthly, Annual
3.	ECMWF/ Copernicus Climate Change Service (C3S)	ERA5/ ERA5, ERA-Interim	31 km (~0.25°)	Hourly, Monthly
4.	Berkeley Earth	BEST	1° x 1°	Monthly, Annual
5.	WorldClim	WorldClim	1 km, 5 km (~30 arc-seconds, 2.5 arc-minutes)	Monthly, Annual
6.	University of East Anglia CRU	CRU TS	0.5° x 0.5°	Monthly, Annual
7.	Cowtan and Way	Cowtan and Way	1° x 1°	Monthly, Annual

Copernicus Climate Change Service ERA5 dataset is selected for the modelling application as it is available at finer spatio-temporal resolution as compare to other datasets.

2.2.4 Evapotranspiration dataset

The Penman-Monteith-Leuning Evapotranspiration V2 (PML_V2) products which are the advanced version of MODIS dataset, are utilised for getting evaporation and evapotranspiration dataset. The dataset is available at 500m spatial resolution and has temporal resolution of 8-days. It has a temporal coverage from 2000-2023. Four bands viz. ET_water, Es, Ec and Ei were used. ET_water represents evaporation from the waterbodies. Ec represents vegetation transpiration, Es represents soil evaporation, Ei shows interception from vegetation canopy.

Table 3: Evapotranspiration dataset sources

Sl. No.	***Dataset Source***	***Dataset Name***	***Spatial Resolution***	***Temporal Resolution***
1.	NASA MODIS	MOD16A2	500 m	8-day, Monthly, Annual
2.	FLUXNET	FLUXNET2015	Site-specific	Sub-daily to monthly
3.	NASA GLDAS	GLDAS-2.1	0.25° x 0.25°	3-hourly, Daily, Monthly
4.	Global Land Evaporation Amsterdam Model (GLEAM)	GLEAM	0.25° x 0.25°	Daily, Monthly
5.	Copernicus Global Land Service	Global Land Evapotranspiration	1 km	10-day, Monthly
6.	FAO	WaPOR	250 m, 100 m	Daily, Monthly, Seasonal

7.	European Space Agency (ESA)	ETMonitor	5 km	Monthly

Global Land Evaporation Amsterdam Model (GLEAM) data is also considered for hydrological modelling of Gandak River Basin as it contains daily ET dataset.

2.2.5 Solar radiation dataset

Solar radiation dataset is important for calculations of component of runoff generated from snow cover. Multiple datasets are compared for assimilation of the same into the hydrological model setup. The list is as follows:

Table 4: Solar radiation dataset sources

Sl. No.	***Dataset Source***	***Dataset Name***	***Spatial Resolution***	***Temporal Resolution***
1.	NASA Surface Meteorology and Solar Energy (SSE)	Surface meteorology and Solar Energy (SSE)	Varies (typically 1°)	Hourly, Daily, Monthly
2.	National Renewable Energy Laboratory (NREL)	National Solar Radiation Database (NSRDB)	4 km (global data)	Hourly, Daily, Monthly
3.	European Space Agency (ESA)	Climate Change Initiative - Solar Surface Radiation	0.05° x 0.05° (~5 km)	Monthly
4.	World Bank	Global Solar Atlas	Varies (typically 1 km or higher)	Monthly averages
5.	Climate Data Store (CDS) - Copernicus	ERA5-Land	9 km	Hourly, Daily, Monthly

Copernicus CDS data is being utilised for hydrological model setup.

2.2.6 Snow related dataset

Table 5: Snow-related dataset

Sl. No.	***Dataset Source***	***Dataset Name***	***Spatial Resolution***	***Temporal Resolution***
1.	National Snow and Ice Data Center (NSIDC)	Global SnowPack	Varies (typically 25 km)	Daily, Weekly, Monthly
2.	ESA Climate Change Initiative (CCI)	Snow	Varies (typically 0.25° x 0.25°)	Monthly
3.	Copernicus Climate Change Service (C3S)	ERA5-Land	9 km	Hourly, Daily, Monthly
4.	Indian Space Research Organisation (ISRO)	Snow and Glacier Studies	Varies	Seasonal to annual
5.	Himalayan Cryosphere Project	Glacier and Snow Data	Varies	Seasonal to annual

2.2.7 Groundwater dataset

Table 6: Groundwater dataset sources

S.No	**Source**	**Spatial Resolution**	**Temporal Resolution**	**Data Availability**
1	GRACE (Gravity Recovery and Climate Experiment)	Approximately 300 km	Monthly	April 2002 – June 2017
2	GRACE-FO (GRACE Follow-On)	Approximately 300 km	Monthly	May 2018 – Present
3	Global Groundwater Monitoring Network (GGMN)	Global, station-based	Varies by country	Varies by country
4	FAO AQUASTAT	Global	Annual	Varies, updated periodically
5	US Geological Survey (USGS)	National (USA)	Varies by project/study	Varies, historical to present
6	Global Land Data Assimilation System (GLDAS)	0.25° x 0.25° to 1° x 1°	3-hourly, daily, monthly	2000 – Present

GRACE dataset is considered for analysis of groundwater fluctuations in the basin. Dataset from Central Groundwater Board is also requested for validation of GRACE dataset.

As mentioned above wide range of dataset is available at present moment and it is not practical to incorporate each one of these in to the models. However, the dataset is selected based upon the criteria of temporal and spatial resolution, relevance to study area, data availability and quality. Briefly, the data should give accurate representation of study area and consistency for modelling purpose.

2.3 Trend analysis of hydrometeorological dataset

The Mann-Kendall (MK) test is a widely used non-parametric test for detecting trends in time series data. In the MK test, several parameters and statistics are calculated to assess the presence and significance of trends. Here's an overview of the significance of various parameters and statistics in the Mann-Kendall test:

Table 7: Parameters of MK test

Parameter	***Result Interpretation***	***Significance***	***Description***
S (Test Statistic)	Positive: Upward trend, Negative: Downward trend	Measures direction of trend	Sum of the signs of all pairwise comparisons between data points.
Var(S) (Variance of S)	Higher value: more spread in S	Needed to calculate Z	Variance of S, adjusted for tied observations if present.

Z (Standardized Test Statistic)	$Z > 0$: Increasing trend $Z < 0$: Decreasing trend	Used to test trend significance	Normalized value of S under normal distribution assumptions.
p-value	$p < 0.05$: Significant trend $p \geq 0.05$: No significant trend	Tests Null Hypothesis (H_0)	Probability that the observed trend occurred by chance.
Kendall's Tau (τ)	$\tau \approx +1$: Strong upward trend $\tau \approx -1$: Strong downward trend $\tau \approx 0$: No trend	Measures strength and direction of trend	Non-parametric rank correlation coefficient between time and observed values.
Sen's Slope (Optional)	Positive: Increasing rate Negative: Decreasing rate	Quantifies the trend	Median of all slopes between pairwise data points, giving trend magnitude per time unit.

2.1 HEC-HMS Model

Hydrologic Modeling System (HMS) is developed by U.S. Army Corps of Engineers, Hydrologic Engineer Centre for simulation of rainfall-runoff processes of dendritic watershed systems. It is widely applicable in both the large river basins and small urban areas as well. The main components of HMS are Basin Model Manager, Time-series Manager, Meteorological Model Manager and Control Specifications Manager. The basin model manager incorporates information of reaches, subbasins, junctions and outlet points. Terrain Data Manager hold the terrain files which further used in Basin Model Manager once the terrain is created. Time series data manager has precipitation, evapotranspiration, stage, snow water equivalent, crop coefficient, sediment load, sunshine gauge and observed discharged time-series dataset etc. Paired Data Manager is another component which deals with handling of hydrometric data, e.g. data related to stage-discharge, area-elevation-capacity curves of reservoirs etc. Model also has optional Grid Data Manager which can handle basin related information in the gridded form. Under Meteorological Model Manger precipitation, temperature, windspeed, pressure, dewpoint and ET related information can be assigned to different subbasins or grids. Control Specification Manger is used for setting up different simulation periods e.g. calibration period and validation period. It requires information of simulation start date and time, simulation end date and time with time interval on which model has to perform the calculations.

HEC-HMS model parameters are set to subbasins and reaches. Each subbasin has canopy, snow, surface, loss, transform and baseflow methods. Similarly, for reaches routing method and loss/gain method needs to be defined. Kinematic wave, Lag, Lag and K, Modified Puls, Muskingum, Muskingum-Cunge, Normal depth, Straddle Stagger are the reach routing options available in HMS. Once all the parameters are set, simulation run is created in order to perform model simulations. Multiple simulation runs can be created in the same model which are associated with basin model, met model and control specification, in order to analyse different scenarios. The simulated results are compared with the observed discharge at gauging locations and model performance analysis is being performed. The calibration process required if the model performance is not good enough. Optimization trial manger is used for the optimizing model parameters for calibration period. After calibration HMS model run performed for validation period and results are analysed. Uncertainty analysis is being performed for calculating the uncertainty associated with model results using Uncertainty Analysis Manager.

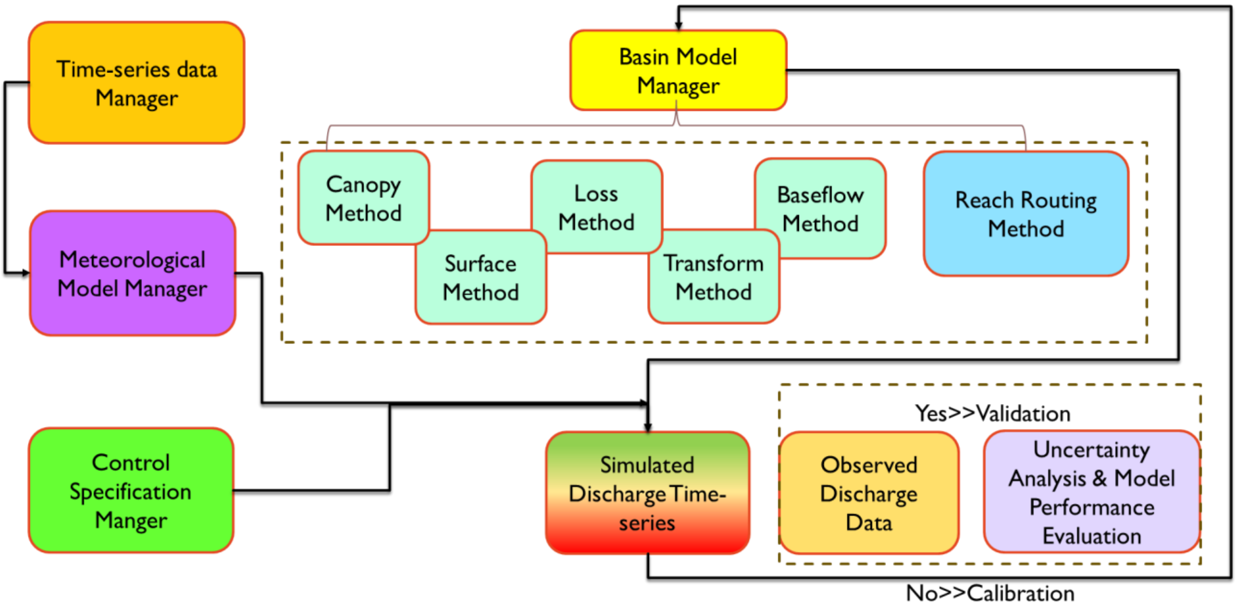


Figure 10: Flow chart of HEC-HMS setup

2.3 SWAT Model

Soil and Water Assessment Tool (SWAT) is a continuous, physically based and semi-distributed model. SWAT was developed by United States Department of Agriculture (USDA) Agricultural Research Service (ARS). The model was initially developed for agricultural basins but today it is extensively used in different watersheds for climate change impact assessment, pollution control, watershed management and sustainable agriculture practices. It simulates the water balance components of hydrological cycle, estimates soil erosion and sediment yield, models nutrient cycling and transport and other water quality parameters as well. It also assesses the impact of change in land use patterns and management practices on the water resources of the basin. SWAT setup is prepared using LULC map, slope map and soil data for Hydrological Soil Group (HSG) maps. Model inputs require data of precipitation, temperature, wind speed, solar radiation and relative humidity. Hydrologic Response Units (HRUs) are generated based on the given inputs. It is an 8-digit hydrologic unit which accounts for complexities of basin. Runoff from each HRUs is calculated separately and added together to get total response odf the basin. Reach or main channels and tributary channels are incorporated in the basin. Daily precipitation input is required in SWAT model, if the daily precipitations is not provided to the model, average monthly precipitation values can be given. The SWAT weather generator model developed by Nicks (1974), generates daily precipitation time series for model. Similarly for sub-daily precipitation values a double exponential function is used. The model uses normal distribution in order to generate maximum and minimum temperatures and solar radiation. Also, for generating the daily wind speed from mean monthly wind speed, a modified exponential equation is used. SWAT also incorporates snow module which requires of snow cover, snow melt and elevation band information. For snow cover a user defined threshold value is considered in the model, below which snow cover depletes non-linearly. The areal depletion curve is set for such depleting snow cover in the model. However, the snow melt rate is affected by air temperature as well as the snow pack temperature. SWAT also considers different elevation bands in order to consider the orographic effects of the model. The soil temperature also taken into account by the model based upon snow cover, plant and residue cover. For simulation of rainfall-runoff process model considers different processes such as canopy storage, infiltration, redistribution, evapotranspiration, lateral subsurface flows, storage, surface runoff and return flows. User defined maximum canopy water storage based upon maximum leaf area cover index can be used in the model. However, different methods like Green-Ampt are also available in the model for separate calculations of canopy storage. If precipitation data is available at smaller time-steps Green-Ampt infiltration model can be used in SWAT. The movement of water through the soil profile is also considered in the SWAT model and termed as redistribution component which uses a storage routing technique. With the storage routing SWAT predicts flow through each soil layer in the root zone. However, if the temperature of the soil layer falls below 0°C, redistribution ceased in that particular layer. Calculation of interflow is done along with redistribution and the zone of soil is considered between zero-to-two-meter depth. The interflow calculations are based upon kinematic storage model. SWAT computes potential soil and water evaporation as function of potential evapotranspiration (PET) and it has three modules for calculation of PET as Hargreaves, Priestley-Taylor and Penman-Monteith. Finally, the surface runoff is calculated in the form of runoff volume and peak runoff rates for each HRU. The surface runoff is computed using Modified SCS Curve Number (CN) method in which there exists a non-linear relationship between soil moisture and CN. The CN is inversely proportional to the soil moisture deficit and towards wilting point the CN tends to become lower. Similarly, the peak runoff rates are also calculated using modified rational method.

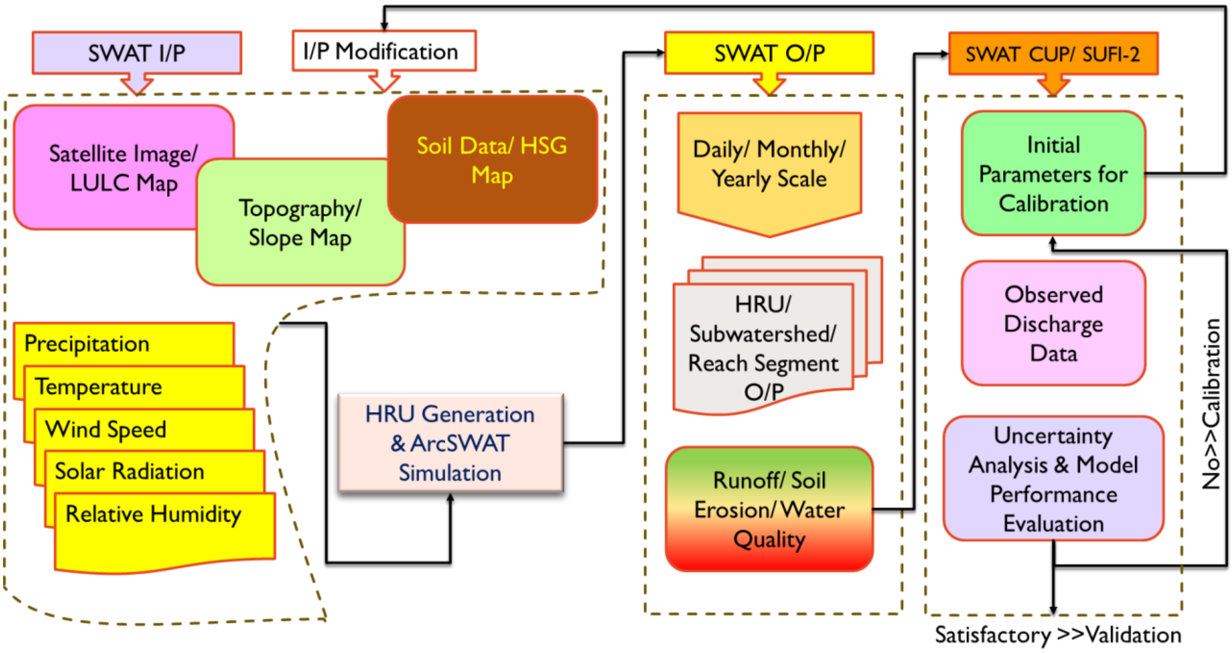


Figure 11: Flow chart of SWAT model preparation

2.4 DHI MIKE Model

DHI MIKE model is used for simple rainfall-runoff processes on a watershed scale. It is extensively used for water resources planning and management. The other areas of applications are river routing, hydropower and reservoir applications, groundwater recharge applications and reservoir sedimentation etc. The model setup is created using MIKE Zero, under which MIKE 11 NAM module is present. The inputs required are topographical data in terms of Digital Elevation Model (DEM), Land use information, soil data and the hydrological data in terms of precipitation and snow, evaporation etc. In DHI MIKE rainfall-runoff modelling can be done using two available models (1) Nedbør-Afstrømings-Model (NAM) and (2) Unit Hydrograph model (UHM). The NAM model is one of the most commonly used models and it was developed by Danish Hydraulic Institute (DHI). The NAM model is lumped in nature and consists of three main zones and one optional zone as (i) Surface zone, (ii) Root zone, (iii) Groundwater zone and (iv) Snow storage which is optional. Parameters required to be set for these zones. Under surface storage zone, maximum water content in surface storage (U_{max}) in mm and maximum water content in root zone storage (L_{max}) in mm has to be defined. The parameters for root zone include, (a) Root depth in mm, (b) Root zone capacity in mm, (c) Soil moisture content at field capacity in mm and (d) Soil moisture content at wilting point in mm. The groundwater zone parameters are (a) Maximum upper and lower groundwater storage capacities, (b) Groundwater recharge rates and (c) Baseflow recession constant. In case of snow cover is present in the watershed, maximum snow storage (C_{max}) and Degree-day coefficient for snowmelt in (mm/°C/day) needs to be defined. Other than these evapotranspiration parameters need to be set for the model which are Maximum evaporation rates (E_{max}) in mm/day and Minimum soil moisture content for evapotranspiration (L_{min}) in mm. Under Unit Hydrograph Method (UHM), Rainfall Runoff Transformation parameters, Loss model parameters and Hydrograph shape parameters are required. Transformation parameters include (a) Time to peak in hours, (b) Peak discharge in cumecs and (c) Base time in hours. Similarly for Loss model (a) Initial loss in mm and (b) Continuing loss in mm/hour needs to be defined. Finally, under hydrograph shape parameter unit hydrograph ordinates are set for the model.

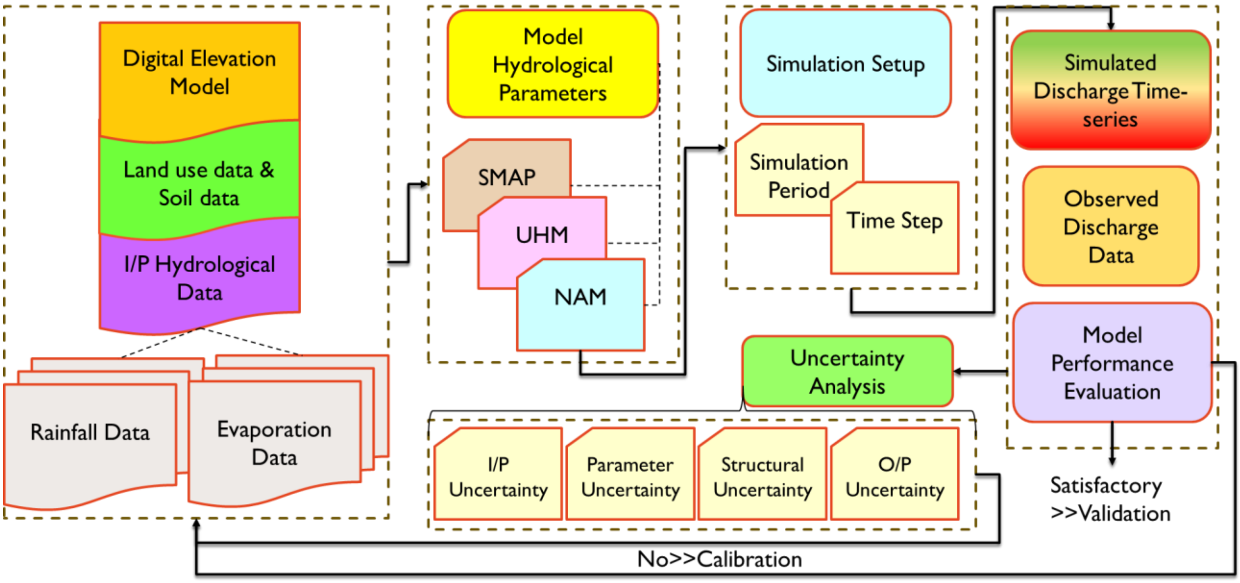


Figure 12: Flow chart of MIKE 11 NAM model setup

2.5 Model Performance Evaluation

Assessment of accuracy of model performance based upon the observed dataset is crucial aspect of hydrologic modelling. From visual comparison of hydrographs to statistical performance matrix, residual analysis and multi-criteria assessment, hydrograph separation and component analysis there exists a wide range of analysis to evaluate model performance. The simplest and most commonly used objective functions (criteria) in hydrologic models' evaluation and calibration are selected here. Nash-Sutcliff Efficiency (NSE) developed in 1970, defines how accurately the model simulation predict the values as compared to the real observed values. The range of NSE is from $-\infty$ to 1. NSE > 0.75 indicates very good model performance. Range between $0.65 < \text{NSE} \leq 0.75$ shows good model performance. Similarly, $0.50 < \text{NSE} \leq 0.65$ represents satisfactory model performance whereas, $0.00 < \text{NSE} \leq 0.50$ poor model performance, but with significant room for improvement. However, $\text{NSE} \leq 0.00$ means model is unable to capture the real-world problems and it shows unacceptable model performance. There are multiple factors affecting the NSE of model which are quality of dataset, temporal and spatial scale of model setup, calibration and validation process and complexity of the model. Percent Bias commonly known as PBias measures the average tendency of the simulated values to be larger or smaller than the observed respective values in a model. It quantifies the bias in model prediction. The ideal value of PBias should be zero, with the low values indicates accurate model simulation. Positive values show overestimation whereas negative values show underestimation. In the hydrological applications commonly interpretation of the PBias is as, PBIAS < ±10% means very good model performance, ±10% < PBIAS < ±15% indicates good model performance, and ±15% < PBIAS < ±25% represents satisfactory model performance. However, PBIAS > ±25%: Indicates unsatisfactory model performance. Root mean square error RMSE is another widely used statistical matric, which provides mean magnitude of predictive errors. It primarily focuses on large errors as it is based on quadratic nature of weights. Therefore, it is suitable for analysing the model performance for extreme values (both highs and lows). Lower RMSE indicates better model performance and higher RMSE indicates large discrepancies between model output and observed dataset.

- Nash-Sutcliffe efficiency $\text{NSE} = 1 - \frac{(Qobs - Qs_{im})^2}{(Qobs - Q'_{obs})^2}$
- Percent Bias $\text{PBIAS} = [(Q_{obs} - Q_{sim})/Q_{obs}]*100$
- Root mean square error $\text{RMSE} = \frac{\Sigma[(Qobs - Q'_{obs})* [(Qsim - Q'_{sim})]}{\Sigma\,(Qobs - Q'_{obs})^2 * \Sigma(Qsim - Q'_{sim})^2}$

2.6 Model Calibration

Calibration of the model is one of the key steps in hydrological modelling. A well calibrated model should be accurate, consistent, stable, reproducible and physically plausible. Here accuracy represents the model performance based upon NSE and other criteria. Consistency is the ability of model to perform smoothly and appropriately under different time scales and conditions. The stability of model is checked against its outputs with small changes in input parameters. If drastic change in outputs is observed with minute change in the input the model is unstable and thus its reliability is under question. Similarly, a well calibrated model should be reproducible which means it should be recalibrated or validated by different users under different conditions with a well-documented procedure. Finally, the physical plausibility of the model is considered by analyzing the parameter range, which should be realistic and should lie within acceptable limits. There are many ways to calibrate a model some of those are (i) Manual calibration, (ii) Automatic calibration, (iii) Single objective calibration, (iv) Multi-objective calibration, (v) Sequential calibration, (vi) Joint calibration and (vii) Regional calibration. Selection of the particular method for calibration depends upon the modelling requirements computational intensity, time adequacy for the process, and also familiarity for the modeler. Manual calibration requires experienced modeler and its time-consuming process, whereas automatic calibration uses optimization algorithms e.g. Nelder-Mead simplex algorithm which comes under gradient based methods and Particle Swarm Optimization (PSO), genetic algorithms, Shuffled Complex Evolution (SCO) which falls under global optimization methods. Different models have pre-defined objective functions for calibration. For any model calibration, these objective functions need to be set up for variables (e.g., streamflow, groundwater level) that will be optimized during the calibration process. The least-squares method, a common method in the model calibration, is equivalent to the minimization of the sum of squares of the residuals (also called objective function or fitness measure). The general form for a steady state is given by,

$$\mathrm{Obj} = \sum_{i=1}^{n} W_i\,[S_i^0 - S_i^C]^2$$

where W_i is a weighted factor, S_i^0 is the observed data, S_i^C is a simulated result, i is the index for location points, and n is the number of location points. Automatic calibration requires computational resources and sometimes get trapped in local minima. A well calibrated model is the necessity of hydrological modelling process. However, the model should not be over calibrated in order to maximize the efficiency otherwise it might not work properly with different dataset.

Table 8: Automatic calibration & Uncertainty analysis tools

Feature	***DDS****	***DREAM****	***CALSI****
Type	Global Optimization	Bayesian Calibration	Hybrid Framework
Uncertainty Analysis	Limited	Extensive	Limited
Efficiency	High	Moderate to low	Moderate to low
Parameter sensitivity	Indirectly considered	Not Primary Focus	Directly Integrated
Computational Demand	Moderate	High	Moderate

DDS*: Dynamically Dimensioned Search
DREAM*: Differential Evolution Adaptive Metropolis
CALSI*: Calibration and Sensitivity Index

2.6.1 Parameter Sensitivity Analysis

In order to calibrate the model appropriately it is important to consider the model parameters sensitivity. Fine tuning of model parameters with in the parameter range improves model's overall efficiency. However, it is important to consider that too much fine tuning could result over-calibration of model for the calibration period. There are different methods to find parameters sensitivity in different models. SWAT+ gives varity of methods to perform sensitivity analysis as Latin Hypercube Sensitivity (LHS), Sobol, Fourier Amplitude Sensitivity Analysis (FAST), Random Balance Design Fourier Amplitude (RBD-FAST) and Delta-Moment. Latin Hypercube Sampling (LHS) is a statistical method used for efficiently exploring parameter spaces in sensitivity analysis by ensuring a stratified and representative sampling across all input variables. Unlike random sampling, LHS divides the range of each parameter into equally probable intervals and samples systematically, reducing variance and improving computational efficiency. LHS ensures that each parameter's range is evenly covered without clustering, leading to more reliable sensitivity analysis compared to purely random sampling techniques. It is particularly useful in complex environmental and hydrological models where multiple parameters interact, enabling a more comprehensive understanding of model behavior and uncertainty propagation.

The Sobol method is used to assess the influence of model parameters on output variability. The Sobol method in SWAT+ evaluates both first-order and total-order sensitivity indices, providing insights into how individual parameters and their interactions affect hydrological outputs. It uses Monte Carlo-based variance decomposition, ensuring a comprehensive exploration of parameter space to quantify their contributions to model output variance. Due to the need for a large number of simulations, Sobol analysis in SWAT+ is computationally intensive, requiring high-performance computing for efficient execution.

2.7 Model Validation

Model validation is another important step in modelling process. This showcases validity of the model with the dataset which was not used during the calibration process. It ensures that the model is not just set correct for the specific conditions and it has adaptability for working under different environments without degrading the output quality. It is performed in order to check model's robustness and predictive ability. The performance of the model is evaluated against the validation dataset and standards are set as same as during calibration period. However, a slight loss in performance is acceptable as the data is different. Qualitative assessment of the output has also been made which involves visual inspection of hydrographs in order to check any major discrepancies in the modelled output, scatter plots to identify the systematic bias in the model, flow duration curves for accurate representation of high flows, low flows and variability of flows in the flow regime. Once the model is validated it can be served in wide range of applications e.g prediction and forecasting, Decision support, Risk assessment, scenario analysis and environmental impact assessment etc.

2.8 Uncertainty Analysis

Uncertainty analysis of hydrologic model gives the insights about limitations and potential errors associated with it. Multiple statistical techniques are available for the characterisation of uncertainties in the model. Preliminary uncertainty analysis is performed in order to understand the potential range of model outputs, in cases where uncertainty involved in input data and parameters. This mainly incorporates sensitivity analysis of model parameters. The parameter values in this case are based upon literature review. Diverse sets of parameters are selected based upon similar conditions using Monte Carlo simulations. The model is further simulated and output variability analysed in order to identify the most sensitive parameters. The main outcome of preliminary uncertainty analysis is getting insights of critical model parameters which further can be utilised at the time of model calibration. With preliminary uncertainty analysis parameter range as well as the model behaviour can be understood in a systematic manner. However, the results of preliminary uncertainty analysis may not be much reliable as the model is yet to be validated and therefore some parameters might have underemphasised or overemphasised. In order to get accuracy, it is therefore becoming necessary to perform uncertainty analysis once the model is validated. Comprehensive uncertainty analysis is being performed to quantify the uncertainty in model outputs after model validation. This gives more reliable assessment as compared to the previous analysis. The process remains similar as preliminary uncertainty analysis and the results are analysed for any changes in parameters sensitivity ranking based on model output behaviour. The results are more representative as compared to previous results as it incorporated ground truth observed dataset during the validation process.

Table 9: Uncertainty types in Hydrological Modelling

Type	***Description***	***Example***
Input Uncertainty	Errors in input data like rainfall, discharge, DEM	Rain gauge errors, satellite precipitation bias etc.
Parameter Uncertainty	Sensitivity due to uncertain model parameters	Runoff curve number, soil infiltration rate etc.
Structural Uncertainty	Limitations in model equations or assumptions	Using Muskingum routing instead of a full 2D hydraulic model
Calibration & Validation Uncertainty	Errors in observed data used for calibration	Streamflow measurement errors at gauging stations
Forcing Data Uncertainty	Errors in future projections like climate models	GCM rainfall uncertainty in climate impact studies

There are multiple methods available for performing uncertainty analysis. Monte Carlo Simulation is a statistical technique that uses random sampling and probability distributions to model uncertainty and predict outcomes in complex systems. The method involves running thousands or millions of simulations to generate a probability distribution of possible results, helping in better uncertainty quantification. Generalized Likelihood Uncertainty Estimation (GLUE) is another probabilistic approach used to quantify uncertainty in hydrological and environmental models by evaluating multiple parameter sets. It relies on the concept of equifinality, where different parameter combinations can produce equally acceptable model outputs, assigning likelihood weights based on performance criteria. Bayesian Uncertainty Analysis is also a probabilistic approach but it incorporates prior knowledge and observed data to estimate uncertainties in model parameters and predictions. It uses Bayes' theorem to update parameter distributions, providing a posterior probability distribution that reflects both prior beliefs and new evidence. Ensemble Modeling combines multiple models to improve predictive accuracy and reduce uncertainty in simulations. By aggregating outputs from different models, it captures a range of possible outcomes, enhancing robustness and reliability. First-Order Second Moment (FOSM) is a probabilistic method used to estimate uncertainty by approximating the mean and variance of a function based on first-order Taylor series expansion. It assumes that input uncertainties are small and normally distributed, making it computationally efficient for engineering and environmental modelling. Bootstrap Resampling is a statistical technique that generates multiple samples from an original dataset by randomly sampling with replacement. It helps estimate confidence intervals, assess model stability, and improve uncertainty quantification, especially when data is limited. All of the above-mentioned methods are widely used in hydrology, climate modelling, and environmental sciences for robust uncertainty quantification and decision-making under uncertainty.

A short summary of working of these methods are as follows:

Table 10: Methods for performing uncertainty analysis

Method	***Working***
Monte Carlo Simulation	Runs the model multiple times with random parameter variations
GLUE (Generalized Likelihood Uncertainty Estimation)	Assigns likelihood to different parameter sets based on performance
Sensitivity Analysis	Identifies parameters that most influence output
Bayesian Uncertainty Analysis	Uses probability distributions instead of single values
Ensemble Modeling	Runs multiple models or scenarios to get a range of predictions
First-Order Second-Moment (FOSM)	Uses statistical moments (mean, variance) to estimate uncertainty
Bootstrap Resampling	Resamples historical data to generate uncertainty estimates

2.9 Hybrid HEC-HMS-LSTM model for correction of peak flow underestimation

The physically-based rainfall-runoff models such as HEC-HMS are commonly used to simulate river discharge using meteorological inputs, basin characteristics, and calibrated parameters. However, model often exhibit limitations when region is data scarce and basin is large and complex in nature. Recently, hybrid modelling approach with the fusion of physical based rainfall-runoff models with machine learning/ deep learning algorithms like Long Short-Term Memory (LSTM) are being incorporated in such cases. Systematic underestimation of peaks is observed in GRB without any exceptional rainfall or temperature anomalies. The HEC-HMS model was already calibrated using available data and Q_sim captured seasonal flow patterns reasonably well, the systematic underestimation pointed towards hidden processes or data non-stationarity not captured by the physical model. Data-driven correction model using Long Short-Term Memory (LSTM) are capable of learning temporal dependencies and correcting systematic simulation errors. The LSTM model was trained to learn the mapping between past sequences of simulated flows from HEC-HMS output and the actual observed discharges. The LSTM model effectively acting as a post-processor to the HEC-HMS model. The aim was to use this neural network to generate corrected discharge values that are closer to the observed values while leveraging the existing HEC-HMS outputs as the base. LSTM is a robust deep learning architecture specifically designed to learn temporal and sequential relationships within time-series data. It is a variant of RNN that was created to solve the limitations of conventional RNNs, particularly the exploding and vanishing gradients problem that blocks long-range learning. LSTM achieves this by possessing a memory cell and three gate mechanisms that allow it to selectively recall or vanish the information over time. This makes it well-suited for hydrological time series data modelling, where past behavior of flows, seasonality, and temporal trends can play a large influence on future discharge values. At a broad level, an LSTM model starts with an input layer, which accepts the time-series data as sequences. These sequences are created through a look-back/lag window, which defines the number of past time steps to be utilized in forecasting the present output.

The data were normalized with a MinMaxScaler to transform the values between 0 and 1, the standard procedure applied in neural networks to enhance efficiency in learning. During training, the predictions were inverse-transformed to get true discharge values so that performance may be compared through standard hydrologic metrics. Sliding window approach is adopted by LSTM architecture. Model performance was measured by splitting data into 70% for calibration (training) and 30% for validation (testing) as per typical hydrological model practices. In the next step performance is evaluated in terms of Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Percent Bias (PBIAS). Results indicated that the LSTM-corrected discharge exhibited considerably better performance than raw HEC-HMS outputs, especially in peak flow areas. The sliding window method in LSTM modelling is a technique used to transform a time series into a supervised learning task by creating sequences of input-output pairs. Here, a window of fixed size moves over the time series data, capturing a sequence of past observations (inputs) to predict a future value (output). For example, if the window length is 'n', the model uses 'n' consecutive time steps as input to forecast the (n+1)th value. This method enables the LSTM to capture temporal relationships and trends in the dataset. Due to which it is suitable for using in rainfall-runoff modelling, where historical hydrological conditions affect the future flow. The sliding window approach is essential in pre-processing the data for sequence learning tasks and assists the LSTM in generalizing well across different temporal structures.

In LSTM modelling under the sliding window approach transforms a univariate time series: $\{x_1, x_2, \dots, x_T\}$, into a supervised learning dataset by creating overlapping sequences of inputs and targets. For a given window size w, each input sequence is defined as:

$$X^{(i)} = [x_i, x_{i+1}, \dots, x_{i+w-1}]$$

and the corresponding target is:

$$y^{(i)} = x_{i+w}$$

This means that the model learns to map from a sequence of w, past time steps to the next time step. In general, for each time step i, the sliding window moves one step forward, generating the next training pair $(X^{(i+1)}, y^{(i+1)})$. The LSTM is then trained to learn the function:

$$f: [x_i, x_{i+1}, \dots, x_{i+w-1}] \rightarrow x_{i+w}$$

This approach effectively allows the LSTM to capture temporal dependencies and learn patterns in the time series data. It can also be extended for multi-step forecasting, where the target $y^{(i)}$ includes multiple future values: $y^{(i)} = [x_{i+w}, x_{i+w+1}, \dots, x_{i+w+h}]$, for horizon h.

In hydrological applications of LSTM model such as peak flow correction, the input of simulated discharge from a hydrological model like HEC-HMS can be incorporated. The second essential component is the LSTM layer, where the input sequences are processed. Within each LSTM cell, there are three gates viz. input, forget and output for the management of flow of the data. The input gate decides what new information should be added to the current cell state, and the output gate decides what information should be forwarded to the next cell and the output. Together these create and maintain a dynamic memory for the input sequence which allows the model to learn both long-term and short-term dependencies. The forget gate specifies which information in the previous cell state needs to be disposed in upcoming stages. After going through the LSTM layer, the output is sent to a dense (fully connected) layer, which downsizes the output to one prediction value, e.g. the corrected streamflow. Finally, the model uses a loss function, typically Mean Squared Error (MSE), to measure accuracy of prediction on training. The simplified representation of the compete process is represented in fig. 13.

In LSTM models, epochs and learning rate are important hyperparameters which have a significant impact on the training performance of the model. Epoch is one full pass through the entire training dataset. Generally, multiple epochs are employed to repeatedly update model weights and reduce the error. The learning rate governs the magnitude of the weight updates during training. It specifies how rapidly or slowly the model learns. Large learning rate can lead to fast convergence but will surpass the optimum solutions, while small learning rate assure very fine updating. This might produce slow training and being trapped at local minima. It's critical to achieve a good number of epochs as well as the learning rate in order to experience good generalization and robust training for LSTM-based time series prediction tasks.

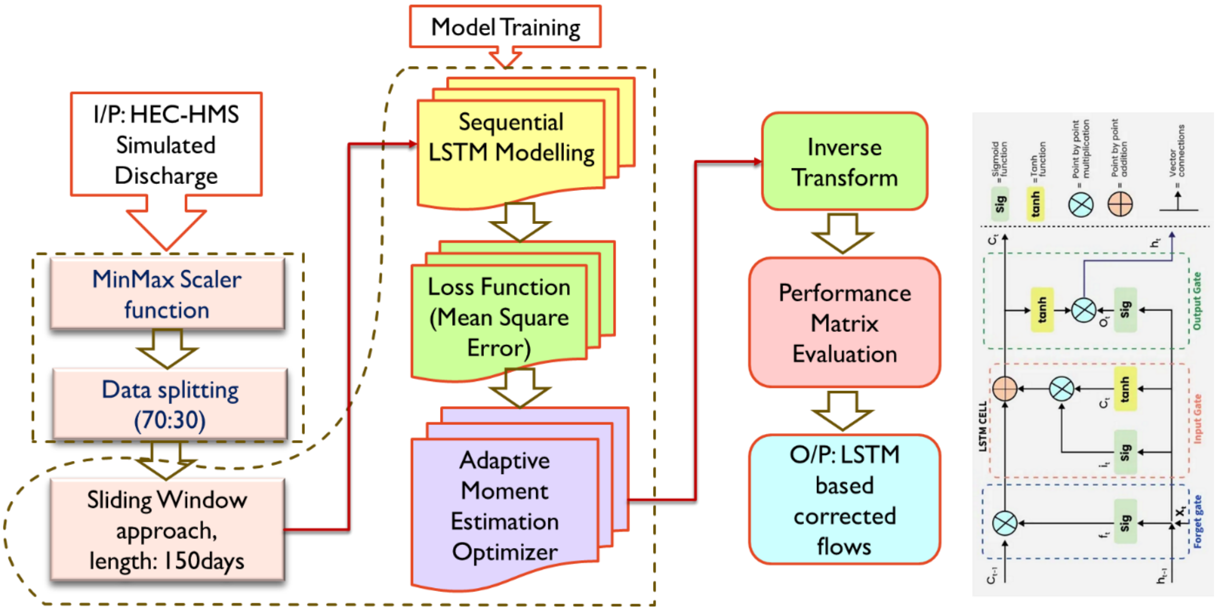
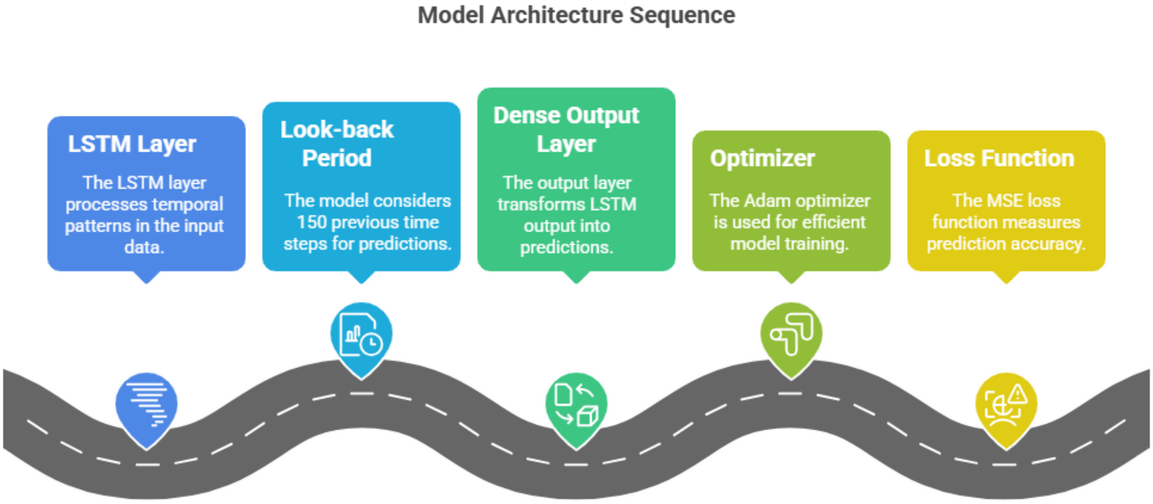


Figure 13: Flow chart for LSTM based post-processing for HEC-HMS simulations

To optimize the model, Adaptive Moment Estimation (Adam) optimizer is being utilized which is the state-of-the-art optimization algorithm that dynamically adjusts learning rates using first and second-order gradients. Adam is highly robust and converges quickly, which makes it suitable for deep learning models of complex time series. It is frequently used for training LSTM models because it is efficient and can deal with sparse gradients and noisy data. It has the benefits of two other extensions of stochastic gradient descent like AdaGrad and RMSProp which keeps adaptive learning rates for each parameter based on estimates of first (mean) and second (uncentered variance) moments of the gradients. In LSTM networks, Adam assists in speeding up convergence and enhancing the stability of training, particularly in handling complex nonlinear time series data. Its adaptability enables effective performance across a variety of problems without a need for exhaustive tuning of the learning rate, thus making it a suitable in deep learning processes.



LSTM Layer
The LSTM layer processes temporal patterns in the input data.

Look-back Period
The model considers 150 previous time steps for predictions.

Dense Output Layer
The output layer transforms LSTM output into predictions.

Optimizer
The Adam optimizer is used for efficient model training.

Loss Function
The MSE loss function measures prediction accuracy.

Figure 14: Simplified architecture of model training sequence

Chapter 5: Results & Discussion

5.1 Hydrometeorological analysis

The analysis of long-term climatological dataset carried for getting the complete understanding of changes in temperature and precipitation over the Gandak River Basin. Satellite based precipitation products like CHIRPS, IMERGE/TRMM and APHRODITE are used for precipitation dataset. The Mann-Kendall (MK) test is a widely used non-parametric test for detecting trends in time series data. In the MK test, several parameters and statistics are calculated to assess the presence and significance of trends. The parameters and statistics in the Mann-Kendall test provide information about the presence, strength, and significance of trends in time series data. They are used to assess whether observed trends are statistically significant and to quantify the magnitude and direction of the trends. The trends were observed using TRMM precipitation products ranging from 1998-2019 for the monthly precipitation values of June, July August and September months in which June, July and August are showing decreasing trends and there exists no trend for the month of September precipitations.

Table 11: Mankendall test results using TRMM precipitation products (1998-2019)

Parameter	***June***	***July***	***August***	***September***
Trend	Decreasing	Decreasing	Decreasing	No trend
H	True	True	True	False
P	0.027847	0.001924	0.004025	0.194595
Z	-2.199	-3.102	-2.876	-1.297
Tau	-0.342	-0.481	-0.446	-0.203
S	-79.000	-111.000	-103.000	-47.000
Varience of s	1257.667	1257.667	1257.667	1257.667
Slope	-0.200	-0.309	-0.291	-0.104
Intercept	10.212	16.067	14.651	8.745

5.1.1 Trend analysis for Global Precipitation Mission TRMM precipitation product (1998-2019)

TRMM 3B43V7 data product has been selected and analysed on cloud using Google Earth Engine. Monthly averaged TRMM precipitation products (mm/day) values have been analysed and the results for M-K test are showing decreasing trends for the months of June, July, and August with z-values of -2.199, -3.102 and -2.876 respectively. However, no significant trend has been analysed for the month of September. The slope values for June, July and August months are -0.2, -0.309 and -0.291 respectively.

5.1.2 Trend analysis for CHIRPS dataset (1981-2021)

CHIRPS dataset monthly mean precipitation values from 1981-2021 have been analysed. The M-K test for this dataset shows no significance trend and Sen's Slope Estimate has found to be -0.00066 and the Intercept: is 21.197. The maximum precipitation trend results for M-K test are showing decreasing trend (p = 0.0269, z = -2.2126, Tau = -0.241, s = -198.0, slope = -0.5138). However, the trend for number of rainy days is showing an increasing trend in the basin (p = 0.0103, z = 2.564, Tau = 0.279, s = 229, slope = 0.4).

5.1.3 Trend analysis for SMAP dataset (2016-2021)

The global soil moisture active passive dataset commonly known as SMAP has been analysed for GRB. The main constraint of this dataset is the temporal range availability which is only from March 2015 to present at 09 km spatial resolution. For the analysis the dataset is selected between 2016 to 2021. M-K test has been performed for this dataset, but no significant trend has been found. The test results are as, trend = no trend, h value = False, p value = 0.1434, z value = 1.4632, Tau value = 0.118, s value = 302.0, Variance of s value = 42316.0, Slope = 0.05729, Intercept = 13.087.

5.1.4 Trend analysis for GRACE dataset (2002-2016)

GRACE dataset has been analysed for GRB using all three products of Center for Space Research, University of Texas, GeoForshungs Zentrum (GFZ), Postdam and Jet Propulsion Laboratory, NASA. The M-K test results are showing decreasing trend in all three subdatasets. The z-value for these have found to be -7.699, -7.461 and -7.833 respectively whereas the slopes are -0.139, -0.134 and -0.143 respectively.

Table 12: Trend analysis for GRACE equivalent water thickness (mm) over GRB

Mann-Kendall test Parameters	***Center for Space Research, University of Texas***	***GeoForschungs Zentrum (GFZ), Potsdam***	***Jet Propulsion Laboratory, NASA***
Trend result	Decreasing	Decreasing	Decreasing
h value	True	True	True
p value	1.376e-14	8.526e-14	4.662e-15
z value	-7.699	-7.461	-7.833
Tau value	-0.412	-0.400	-0.420
s value	-5122.0	-4964.0	-5211.0
Variance of s value	442370.66	442372.66	442373.66
Slope	-0.139	-0.134	-0.143
Intercept	6.401	5.796	6.749

5.1.6 Other useful insights

Trend analysis for maximum precipitation and consecutive rainy days shows the increase maximum precipitation over the basin but an increase in number of consecutive rainy days. Trendline of maximum precipitation drops from 110 mm (1981) to below 80 mm (2020). The analysis of TRMM precipitation rates (mm/day) shows the monthly average precipitation rates (mm/day) trendline falls from 5 mm/day (1998) to slightly less than 4 mm/day (2019). Surface soil moisture data shows the monthly basin average soil moisture trendline tends to increase over a period of 2016 to 2021. The trends however are not so significant and therefore more detail about the pattern of rainfall over the basin are explored through spatial plots. Also, no significance trend found for total precipitation and mean monthly precipitation. However, GRACE dataset indicates a definite loss in terrestrial water storage in terms of equivalent water thickness over entire GRB. Data from CGWB is utilized for validation of insights derived with GRACE dataset.

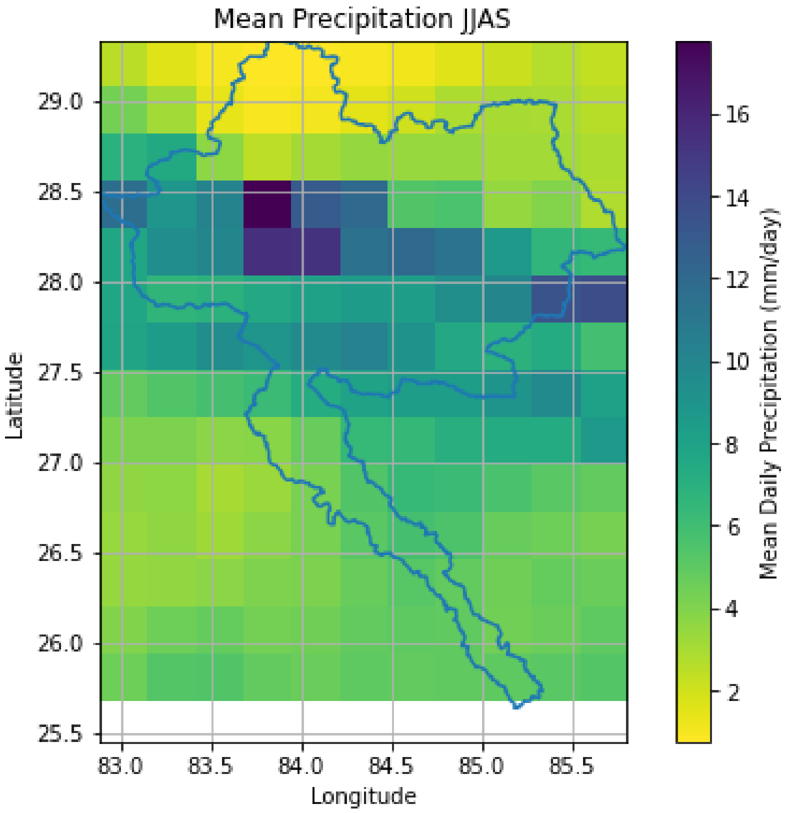


Figure 15: Spatial plot for Mean Precipitation (CHIRPS) during Monsoon (JJAS) over GRB

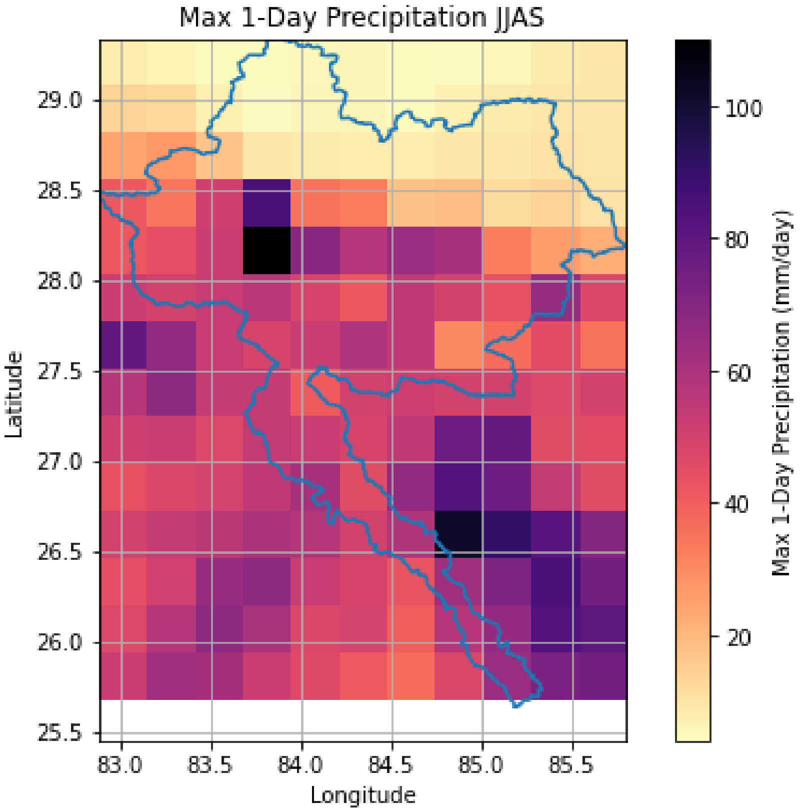


Figure 16: Spatial plot for Maximum 1-Day precipitation (CHIRPS) during monsoon (JJAS)

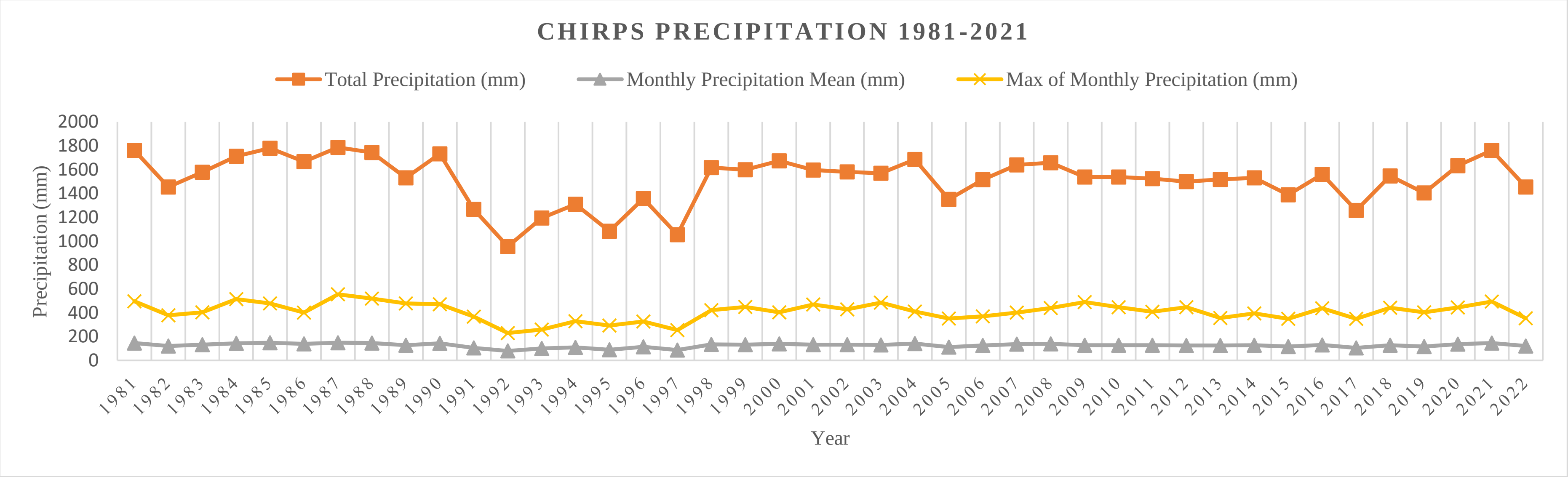


Figure 17: CHIRPS precipitation dataset for Gandak River Basin during 1981-2021

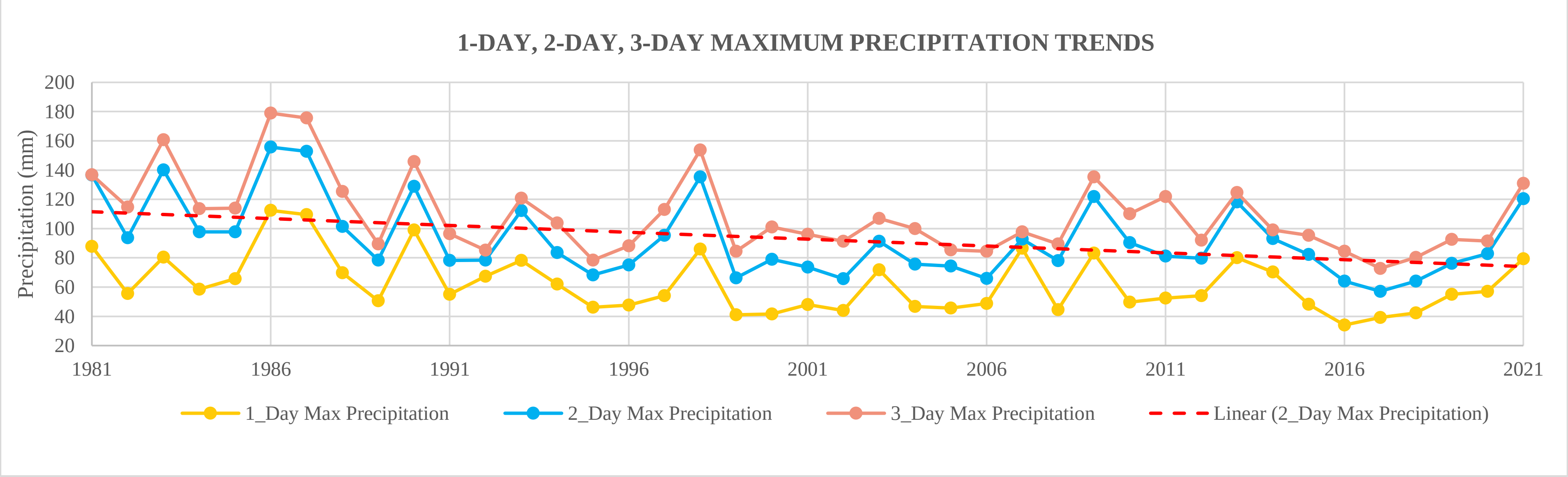


Figure 18: 1-Day, 2-Day, 3-Day Maximum Precipitation over Gandak River Basin during 1981-2021

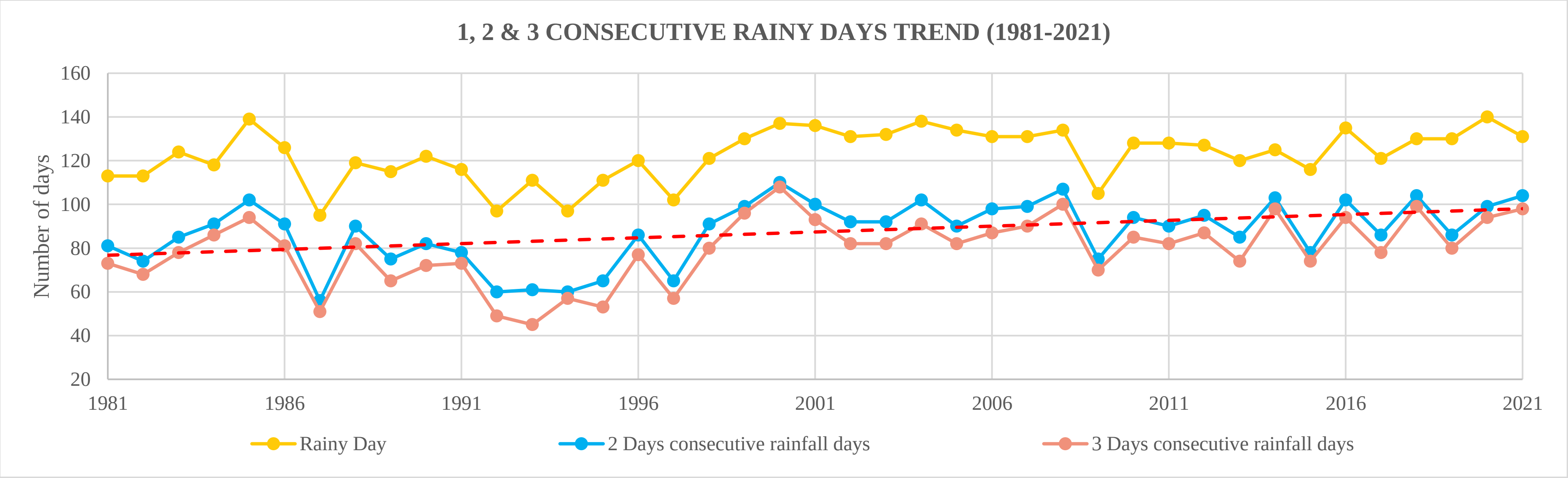


Figure 19: 1, 2 & 3 Consecutive rainy days trend for Gandak River Basin during 1981-2021

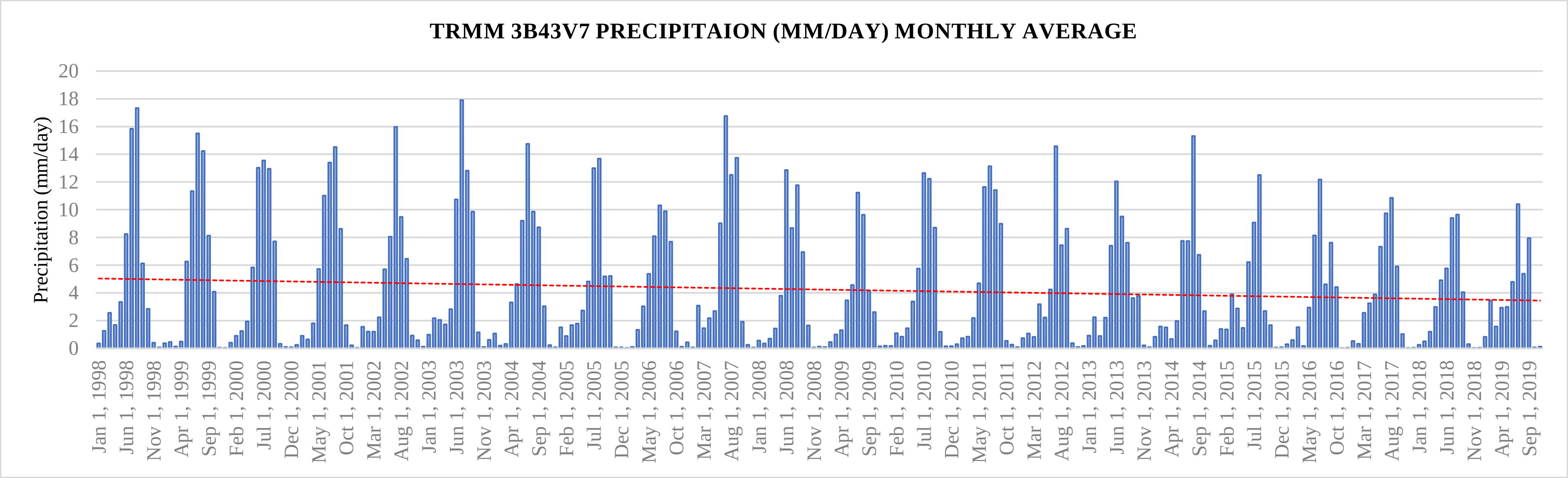


Figure 20: TRMM Precipitation (mm/day) monthly average for Gandak River Basin during 1998-2019

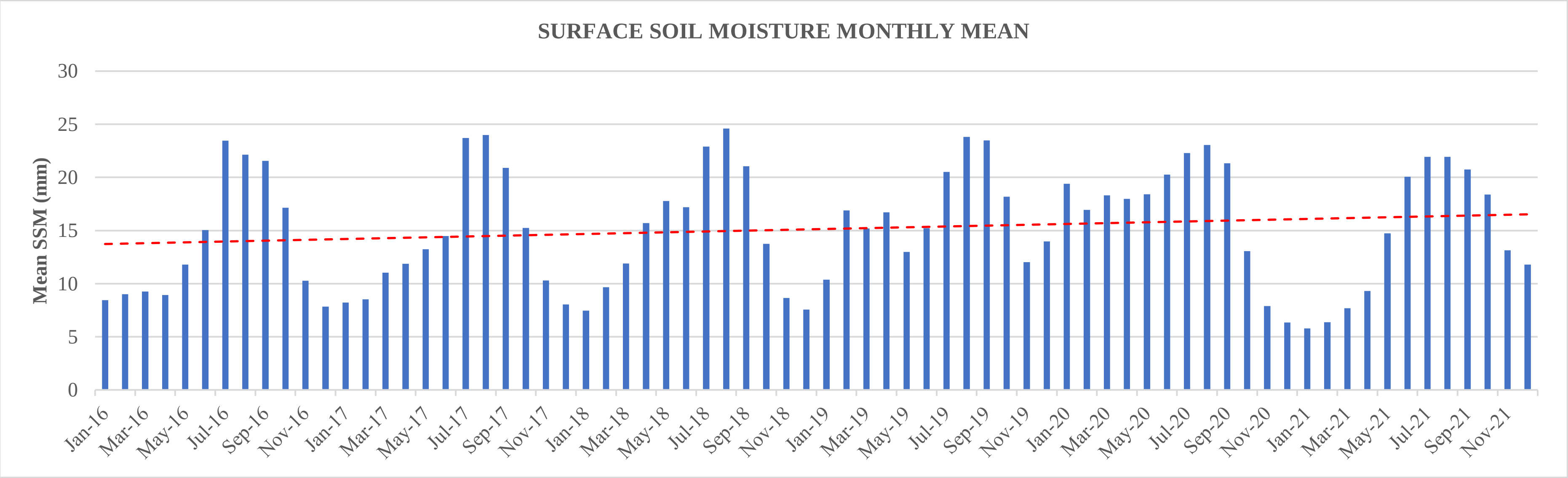


Figure 21: Surface soil moisture monthly mean for Gandak River Basin during 2016-2021

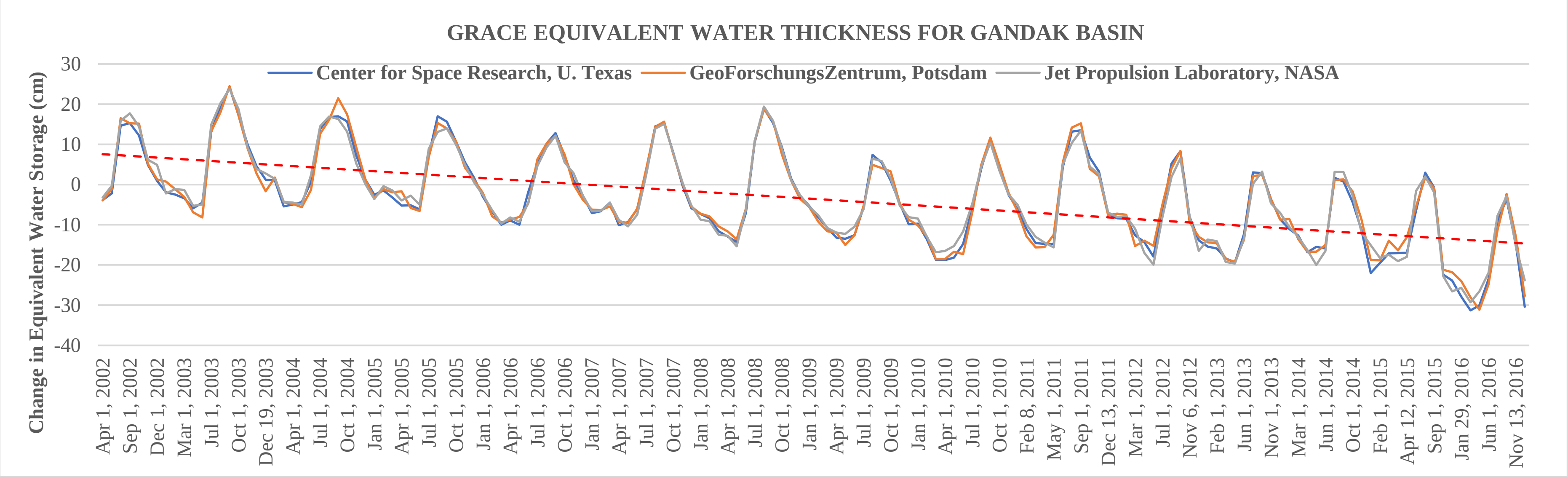


Figure 22: GRACE equivalent water thickness for Gandak River Basin during 2002-2016

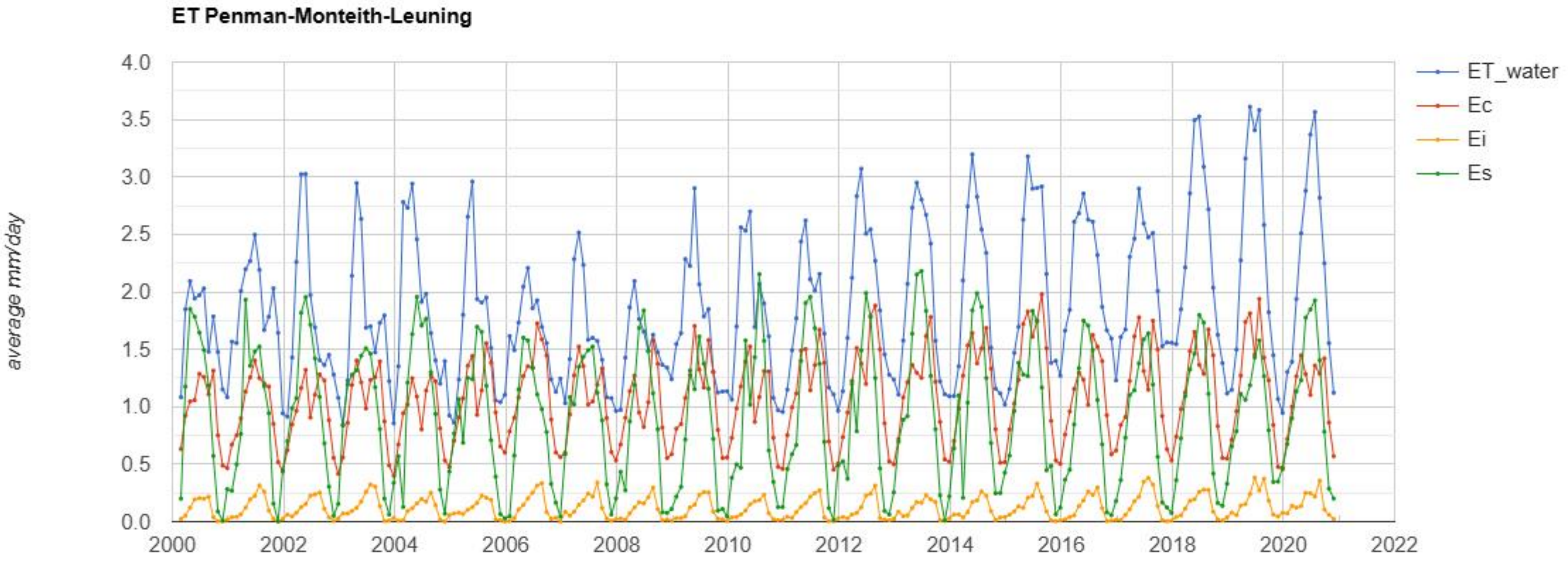
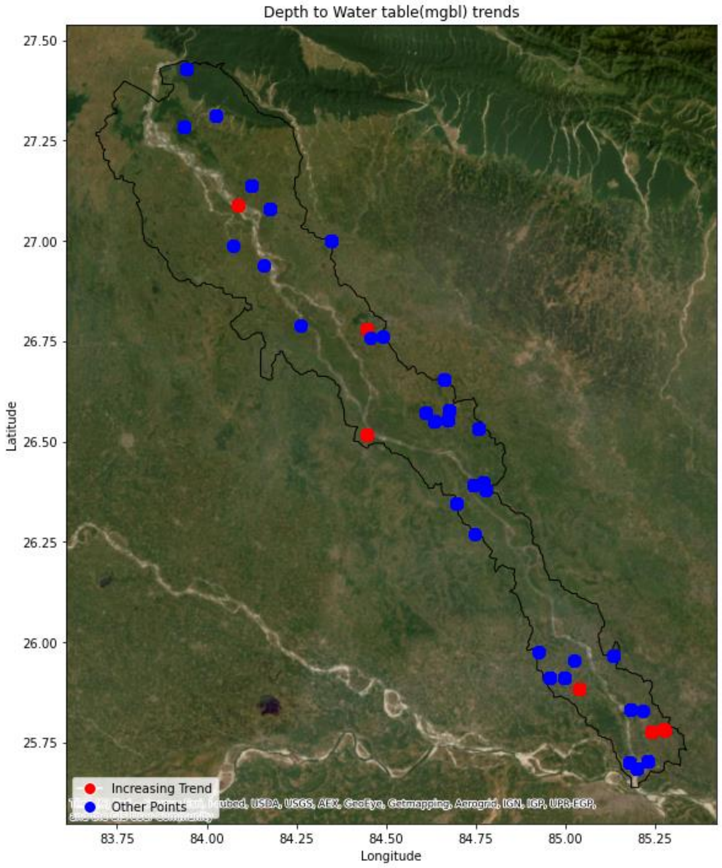
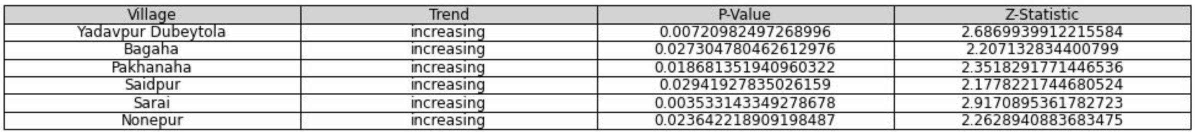


Figure 23: Evapotranspiration (ET) trends by Panman-Monteith-Leuning method

5.2 Validation of GRACE dataset with CGWB records of Depth to water table (mgbl)

An attempt to validate the GRACE dataset for the Indian part of the basin with the available depth to water table data from Central Groundwater Board has been made. For this purpose, the wells are identified in the Gandak Basin. Trend analysis for these wells over the period of available records has been made. The results shows an increasing trend in depth to water table across the wells (i.e. depleting groundwater in the region) from upstream to downstream part of Indian part of GRB. Although, not all the wells showing the increasing trend of depth to water table (mgbl) and the majority of wells showing no significant trend, the number may increase in future as per the insights of GRACE dataset.

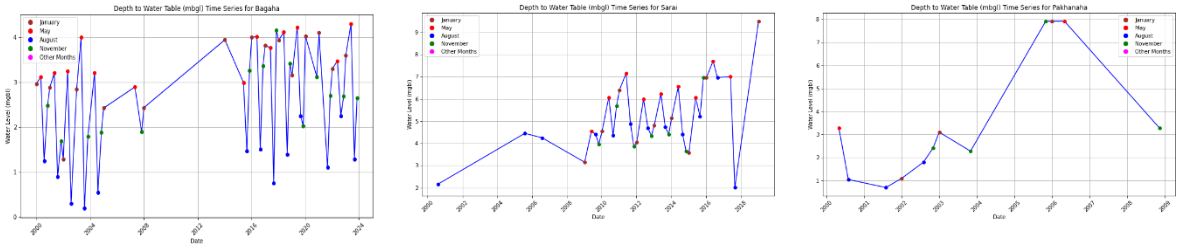




Village	Trend	P-Value	Z-Statistic
Yadavpur Dubeytola	increasing	0.00720982497268996	2.6869939912215584
Bagaha	increasing	0.027304780462612976	2.207132834400799
Pakhanaha	increasing	0.018681351940960322	2.3518291771446536
Saidpur	increasing	0.02941927835026159	2.1778221744680524
Sarai	increasing	0.003533143349278678	2.9170895361782723
Nonepur	increasing	0.023642218909198487	2.2628940883683475

Figure 24 Trends and locations of increasing depth to water table (mgbl) as per CGWB data

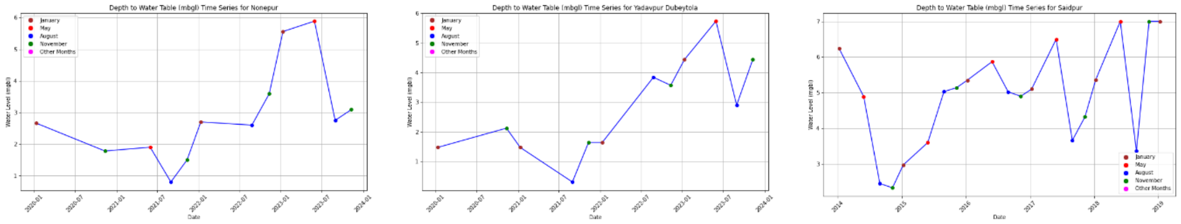
Data from Central Ground Water Board (CGWB) shows that most of the wells showing no significance decreasing trend in the basin. The data is not consistent and there are gaps in records, also at some places the length of record varies. However, six wells covering upstream to downstream are showing statically significant increasing trend for depth to water table (mgbl), which confirms that there is a decrease in groundwater over the period. The time series plots for Bagaha, Nonepur, Pakhanaha, Saidpur, Sarai, Yadavpur Dubeytola are as follows:



(a) Depth to water table (mbgl) time series plot for Bagaha

(b) Depth to water table (mbgl) time series plot for Sarai

(c) Depth to water table (mbgl) time series plot for Pakhanaha



(d) Depth to water table (mbgl) time series plot for Nonepur

(e) Depth to water table (mbgl) time series plot for Yadavpur Dubeytola

(f) Depth to water table (mbgl) time series plot for Saidpur

Figure 25: CGWB records of depth to watertable (mbgl) for the locations with increasing trend

5.2 Hydrologic Engineering Centre – Hydrologic Modeling System (HEC-HMS)

The HEC-HMS model setup is prepared for Gandak River Basin and the setup is considered from 2010-2012 for calibration period and 2013-2015 for validation period. The dataset collected from CWC consists discharge data for Dumariaghat and Lalganj sites and water level data for Hajipur location available only for Monsoon period (JJASO only). Multisite calibration and validation are showcased for Dumariaghat and Lalganj sites. The model performance criteria are based upon Nash-Sutcliffe Efficiency (NSE) which measures how well a model predicts the flow with reference to the observed flows, Root Mean Square Error Standard Deviation (RMSE Std Dev) which is the difference between observed and modelled values normalized to standard deviation, and Percent Bias (PBias) which gives insights about model's average tendency to overestimate or underestimate observed flows. NSE in general can be overemphasise for peak flows and not much sensitive for low flow errors. The limitation of NSE for such low flow conditions was emphasised by Pushaplatha et al. (2012). However, since our modelling domain is subjected to flood prone are other metrics like logarithmic Nash-Sutcliffe Efficiency (logNSE) or Kling-Gupta Efficiency (KGE), which are more suitable for low flow regimes are not considered here. Based upon the literature reviewed [43],[61],[74],[85] the following criteria is used for model's performance evaluation:

Table 13: Model performance evaluation matrix

Performance Rating	***NSE***	***Pbias (%)***	***RMSE Std Dev***
Very Good	NSE ≥ 0.70	Pbias ≤ ±5%	RMSE Std Dev ≤ 0.2
Good	0.65 ≤ NSE < 0.70	±5% < Pbias ≤ ±10%	0.2 < RMSE Std Dev ≤ 0.4
Satisfactory	0.50 ≤ NSE < 0.65	±10% < Pbias ≤ ±15%	0.4< RMSE Std Dev ≤ 0.6
Unsatisfactory	NSE < 0.50	Pbias > ±15%	RMSE Std Dev > 0.6

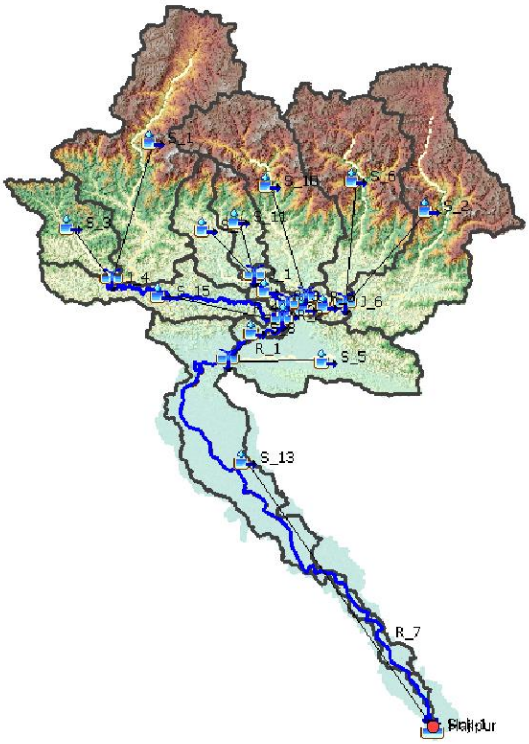


Figure 26: HEC-HMS model setup for Gandak River Basin (GRB)

5.2.1 Parameter Sensitivity Analysis

Parameter sensitivity analysis is performed for getting the sensitivity ranking of model parameters for the Soil Moisture Accounting (SMA) merhod. Tension storage and soil storage are found to be most sensitive parameters for the basin model followed by maximum percolation rate and groundwater storage coefficients.

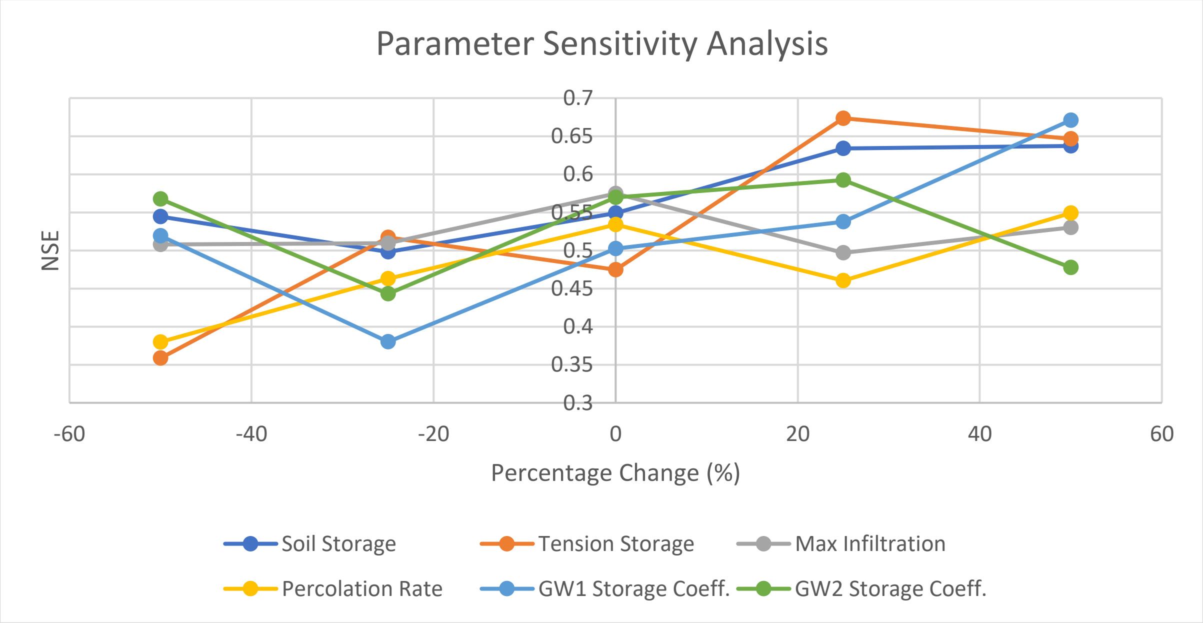


Figure 27: Uncertainty analysis for SMA method parameters in HEC-HMS model

Both manual and auto-calibration approaches are used in order to get the model performance to the desired accuracy. Summary of calibration after using model optimization tools are showcased here.

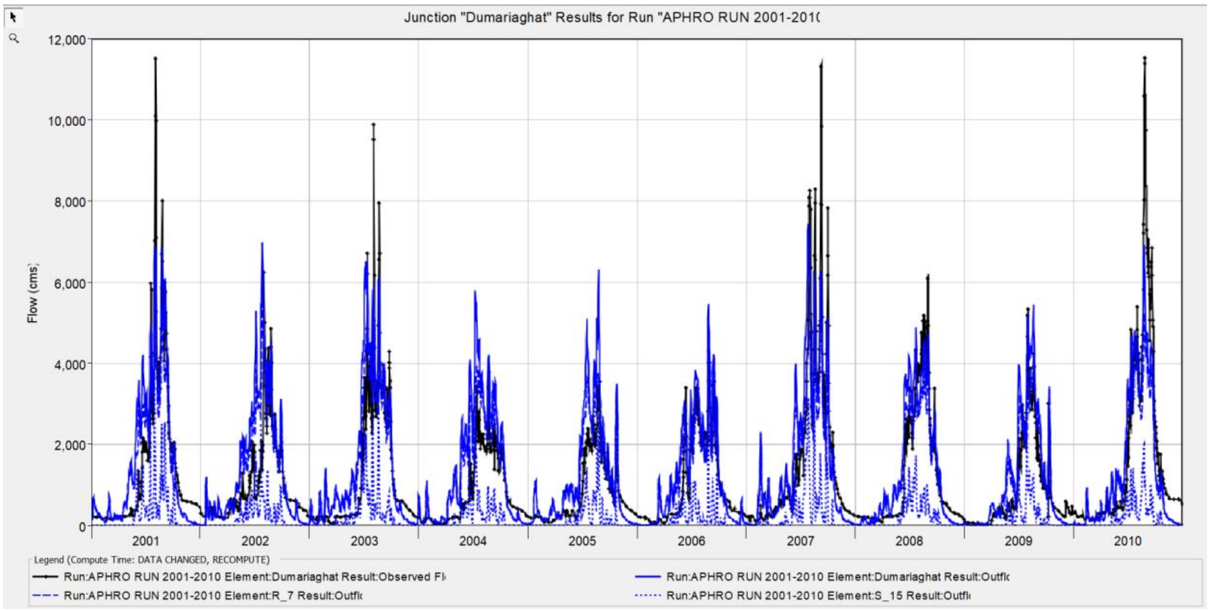
5.2.2 Long term simulations:

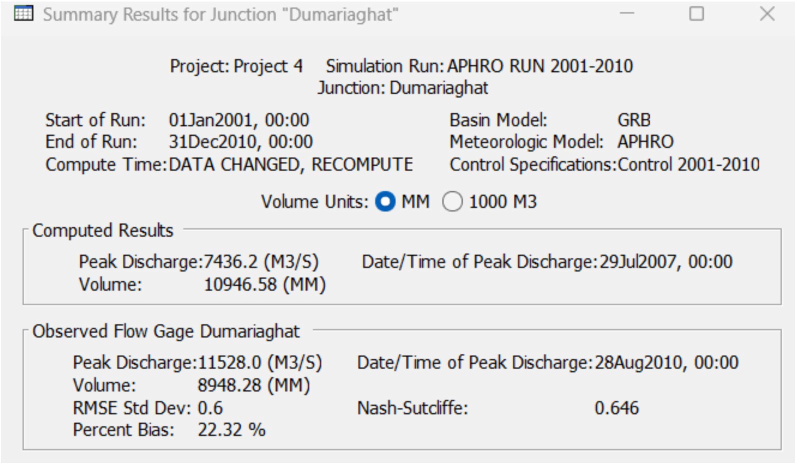
Multiple scenarios are developed for long-term simulations as well as short term simulations for the HEC-HMS model performance estimation. The details of these scenarios are mentioned in the table below:

Table 14: Scenario development for HEC-HMS simulations

Scenario	***Calibration NSE***	***Validation NSE***	***Graphical Interpretation***
APHRODITE, SMA, Lag & K with long term simulation (2000-2010 & 2011-2015)	Dumariaghat: 0.64 Lalganj: 0.65	Dumariaghat:0.65 Lalganj: 0.49	Peaks are underestimated, lags also inappropriate
APHRODITE, SMA, Muskingum with Short term simulation (2010-2012 & 2013-2015)	Dumariaghat: 0.81 Lalganj: 0.64	Dumariaghat: 0.70 Lalganj: 0.68	Peaks are underestimated but lags are corrected
APHRODITE, SCS CN, Muskingum with Short term simulation (2010-2012 & 2013-2015)	Dumariaghat: 0.85 Lalganj: 0.63	Dumariaghat: 0.56 Lalganj: 0.61	Peaks corrected but over-calibrated for Dumariaghat

The results for long-term simulations are mentioned in the figures below for Dumariaghat and Lalganj sites. Aphrodite dataset is being incorporated for simulations. However, on graphical inspection for comparison of precipitation dataset it is found that results are better with APHRODITE and IMERGE dataset as compared to CHIRPS dataset results. For the simulation period of 2001-2010 i.e. calibration period the model performance was found as NSE: 0.64, PBias: 22.32% and RMSE Std dev: 0.6.





Project: Project 4 Simulation Run: APHRO RUN 2001-2010
Junction: Dumariaghat

Start of Run: 01Jan2001, 00:00
End of Run: 31Dec2010, 00:00
Compute Time: DATA CHANGED, RECOMPUTE

Basin Model: GRB
Meteorologic Model: APHRO
Control Specifications: Control 2001-2010

Volume Units: ● MM ○ 1000 M3

Computed Results

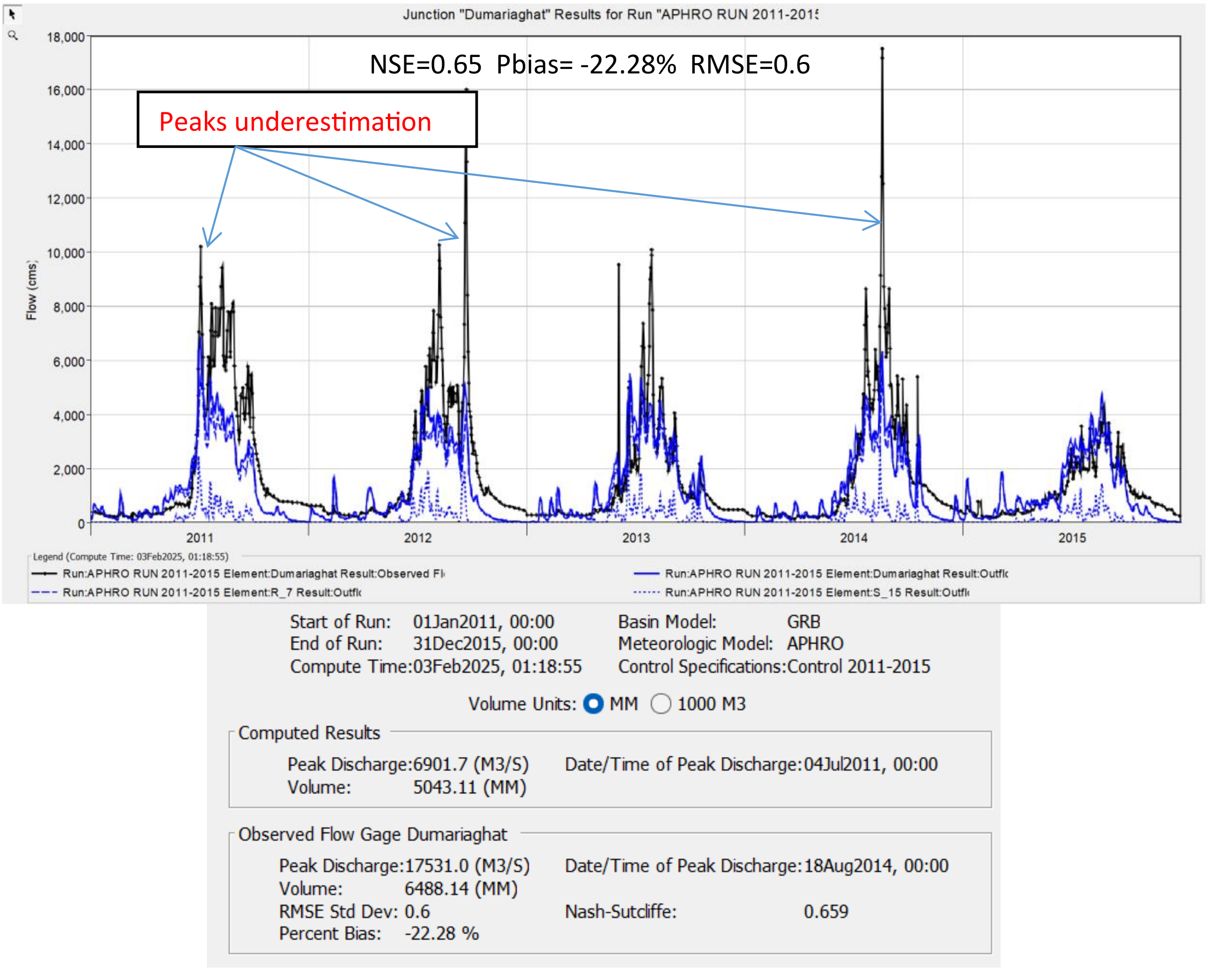
Peak Discharge: 7436.2 (M3/S)
Volume: 10946.58 (MM)
Date/Time of Peak Discharge: 29Jul2007, 00:00

Observed Flow Gage Dumariaghat

Peak Discharge: 11528.0 (M3/S)
Volume: 8948.28 (MM)
RMSE Std Dev: 0.6
Percent Bias: 22.32 %
Date/Time of Peak Discharge: 28Aug2010, 00:00
Nash-Sutcliffe: 0.646

Figure 28: HMS long term simulations performance matrix at Dumariaghat during calibration period (2001-2010) with APHRODITE precipitation. SMA loss method and Lag & K routing method

During the validation period of 2011-2015 for Dumariaghat the NSE is found to be 0.65 with RMSE Std dev as 0.6 and PBias value of -22.28%. The performance of HEC-HMS model under these scenarios can be considered as "good".



Start of Run: 01Jan2011, 00:00
End of Run: 31Dec2015, 00:00
Compute Time: 03Feb2025, 01:18:55

Basin Model: GRB
Meteorologic Model: APHRO
Control Specifications: Control 2011-2015

Volume Units: ● MM ○ 1000 M3

Computed Results

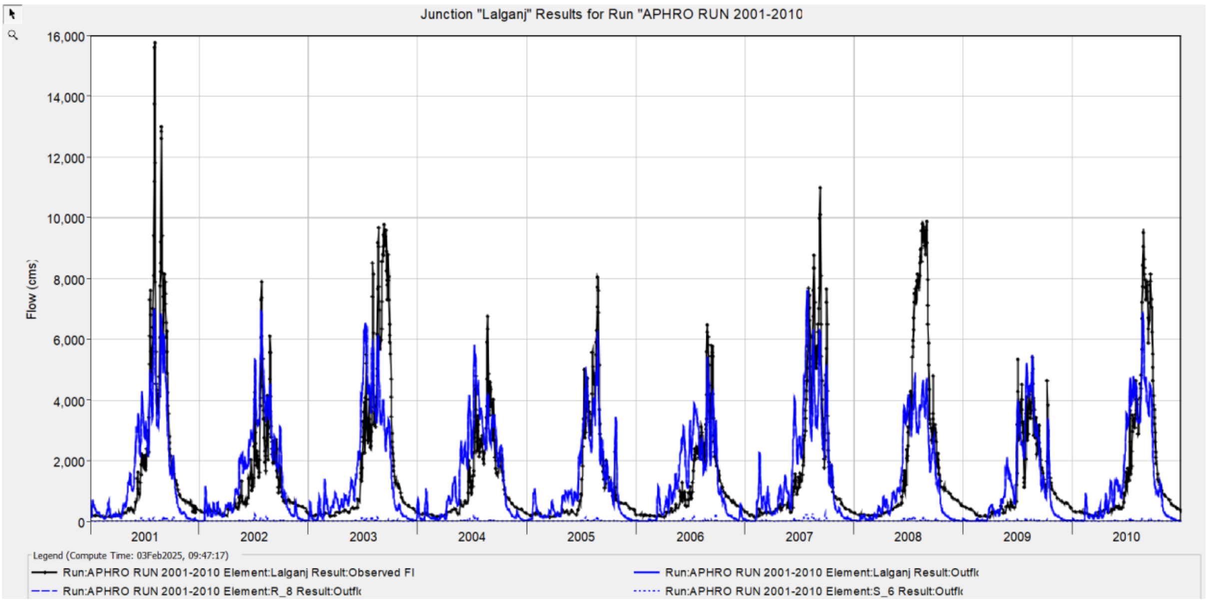
Peak Discharge: 6901.7 (M3/S)
Volume: 5043.11 (MM)
Date/Time of Peak Discharge: 04Jul2011, 00:00

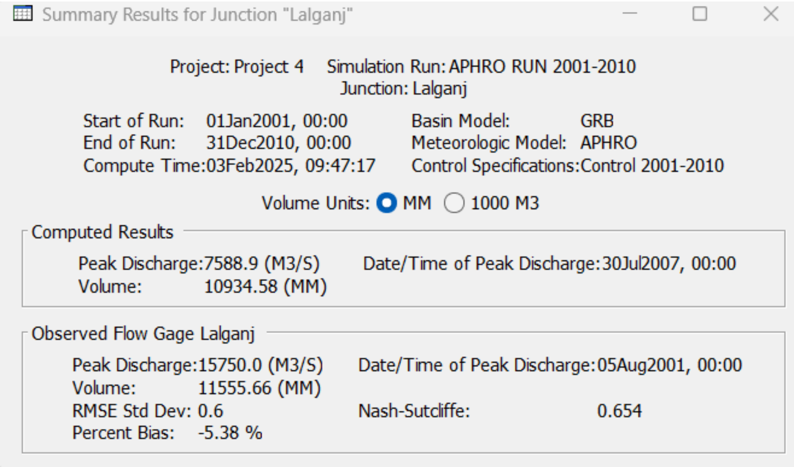
Observed Flow Gage Dumariaghat

Peak Discharge: 17531.0 (M3/S)
Volume: 6488.14 (MM)
RMSE Std Dev: 0.6
Percent Bias: -22.28 %
Date/Time of Peak Discharge: 18Aug2014, 00:00
Nash-Sutcliffe: 0.659

Figure 29: HMS long term simulations performance matrix at Dumariaghat during validation period (2011-2015) with APHRODITE precipitation. SMA loss method and Lag & K routing method

Models are also calibrated and validated for Lalganj site. During the calibration period of 2001-2010 the performance of HEC-HMS model can be summarized as “good” as NSE: 0.65, RMSE Std dev: 0.6 and PBias: -5.38%. However during the validation period, the model was not performing well and values are found to be as, NSE: 0.49, RMSE Std dev: 0.7 and PBias: -30.78%. Therefore, detailed investigation about such severe degradation has been made. It was found that the major diversions from Gandak barrage needs to be incorporated in order to get better performance during the calibration and validation.




Summary Results for Junction "Lalganj"

Project: Project 4 Simulation Run: APHRO RUN 2001-2010
Junction: Lalganj

Start of Run: 01Jan2001, 00:00
End of Run: 31Dec2010, 00:00
Compute Time: 03Feb2025, 09:47:17

Basin Model: GRB
Meteorologic Model: APHRO
Control Specifications: Control 2001-2010

Volume Units: ● MM ○ 1000 M3

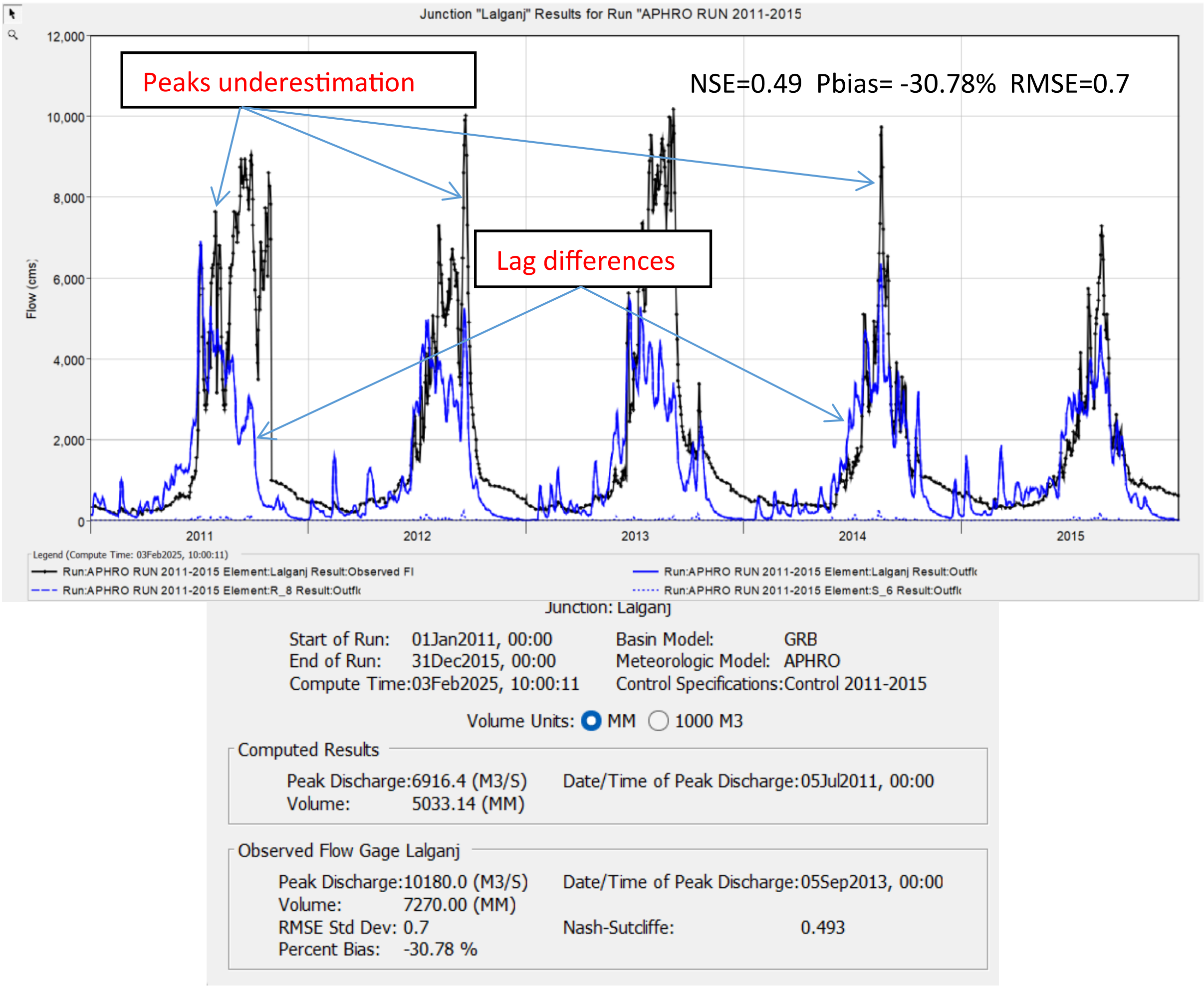
Computed Results

Peak Discharge: 7588.9 (M3/S)
Date/Time of Peak Discharge: 30Jul2007, 00:00
Volume: 10934.58 (MM)

Observed Flow Gage Lalganj

Peak Discharge: 15750.0 (M3/S)
Date/Time of Peak Discharge: 05Aug2001, 00:00
Volume: 11555.66 (MM)
RMSE Std Dev: 0.6
Nash-Sutcliffe: 0.654
Percent Bias: -5.38 %

Figure 30: HMS long term simulations performance matrix at Lalganj during calinration period (2001-2010) with APHRODITE precipitation. SMA loss method and Lag & K routing method



Junction: Lalganj

Start of Run: 01Jan2011, 00:00
End of Run: 31Dec2015, 00:00
Compute Time:03Feb2025, 10:00:11
Basin Model: GRB
Meteorologic Model: APHRO
Control Specifications:Control 2011-2015

Volume Units: ● MM ○ 1000 M3

Computed Results

Peak Discharge:6916.4 (M3/S)
Volume: 5033.14 (MM)
Date/Time of Peak Discharge:05Jul2011, 00:00

Observed Flow Gage Lalganj

Peak Discharge:10180.0 (M3/S)
Volume: 7270.00 (MM)
RMSE Std Dev: 0.7
Percent Bias: -30.78 %
Date/Time of Peak Discharge:05Sep2013, 00:00
Nash-Sutcliffe: 0.493

Figure 31: HMS long term simulations performance matrix at Lalganj during validation period (2011-2015) with APHRODITE precipitation. SMA loss method and Lag & K routing method

5.2.3 HEC-HMS model short term simulation

In long term simulations of hydrological models, the errors and uncertainties get accumulated. Also, the dynamic inputs captured more accurately in short term simulations. In order to capture the model performance simulations are performed during specific shorter periods for 2010-2012. Higher accuracy is found because short time frames reduce the accumulation of uncertainties and errors common in long-term predictions. Short-term modelling also describes dynamic hydrological processes such as runoff, infiltration, and evapotranspiration more accurately, which react quickly to rainfall events. Further, it is closely applicable to typical use such as flood forecasting, where urgency of forecasting is needed. It is because climate and land use are rather stable on the timescale of a few minutes, model assumptions stay nearer to reality and give optimal as well as efficient results. HEC-HMS model simulation results are summarized as follows:

Table 15: HEC-HMS virgin model simulation: Multisite calibration performance metrics for GRB (2010-2012)

GD Sites (2010-2012)	***NSE***	***Pbias***	***RMSE Std Dev***	***Overall Performance***
Dumariaghat	0.776	-9.83	0.5	Very Good
Lalganj	0.647 (0.65)	-12.67	0.6	Good

Table 16: HEC-HMS virgin model simulation: Multisite validation performance metrics for GRB (2013-2015)

GD Sites (2013-2015)	***NSE***	***Pbias***	***RMSE***	***Overall Performance***
Dumariaghat	0.671	12.69	0.6	Good
Lalganj	0.704	-5.78	0.5	Very Good

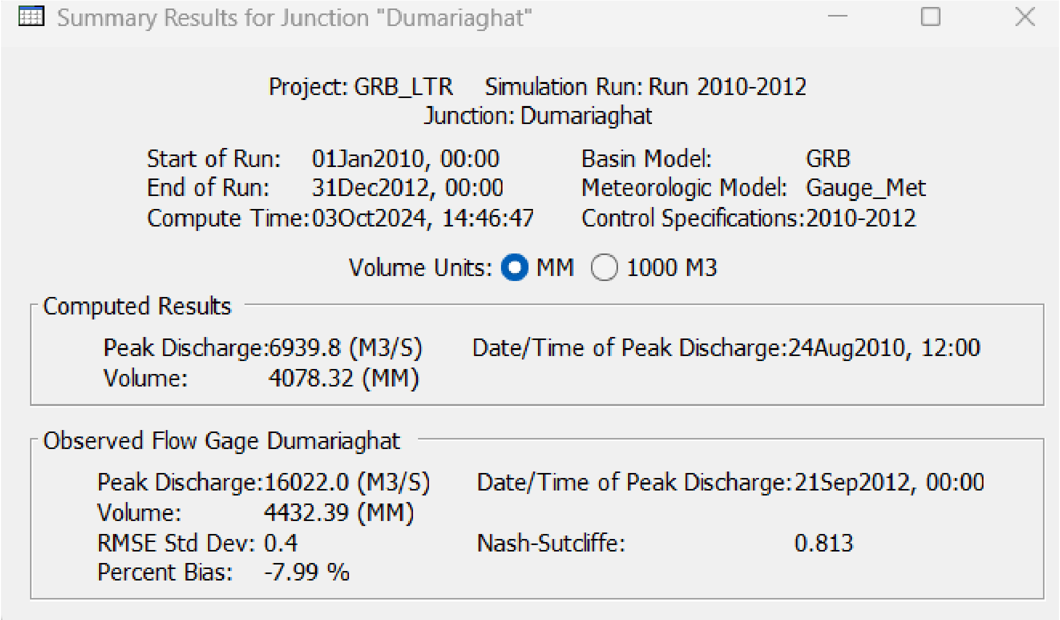
The above simulations were for the virgin flows i.e. without considering the diversions from Gandak Barrage to the Eastern Main Canal (Bihar) having designed capacity of 240.69 cumecs with 879 thousand hectares of culturable command area and Western Main Canal (Uttar Pradesh) with designed capacity of 263.34 cumecs and culturable command area about 395 thousand hectares. The details of the diversions are incorporated in the model and the results are discussed in the subsequent sections. For model simulation purpose details of canal diversion are collected from available information from CWC reports and WRD reports and India WRIS portal [17], [21],[22], [77], [93], [99].

Table 17: HEC-HMS model simulation using canal diversion: Multisite calibration performance metrics for GRB (2010-2012)

GD Sites (2010-2012)	***NSE***	***Pbias***	***RMSE Std Dev***	***Overall Performance***
Dumariaghat	0.813	-7.99	0.4	Very Good
Lalganj	0.648 (0.65)	-10.88	0.6	Good

Table 18: HEC-HMS model simulation using canal diversion: Multisite validation performance metrics for GRB (2013-2015)

GD Sites (2013-2015)	***NSE***	***Pbias***	***RMSE***	***Overall Performance***
Dumariaghat	0.706	14.97	0.5	Very Good
Lalganj	0.689	-3.87	0.6	Good


Summary Results for Junction "Dumariaghat"

Project: GRB_LTR Simulation Run: Run 2010-2012
Junction: Dumariaghat

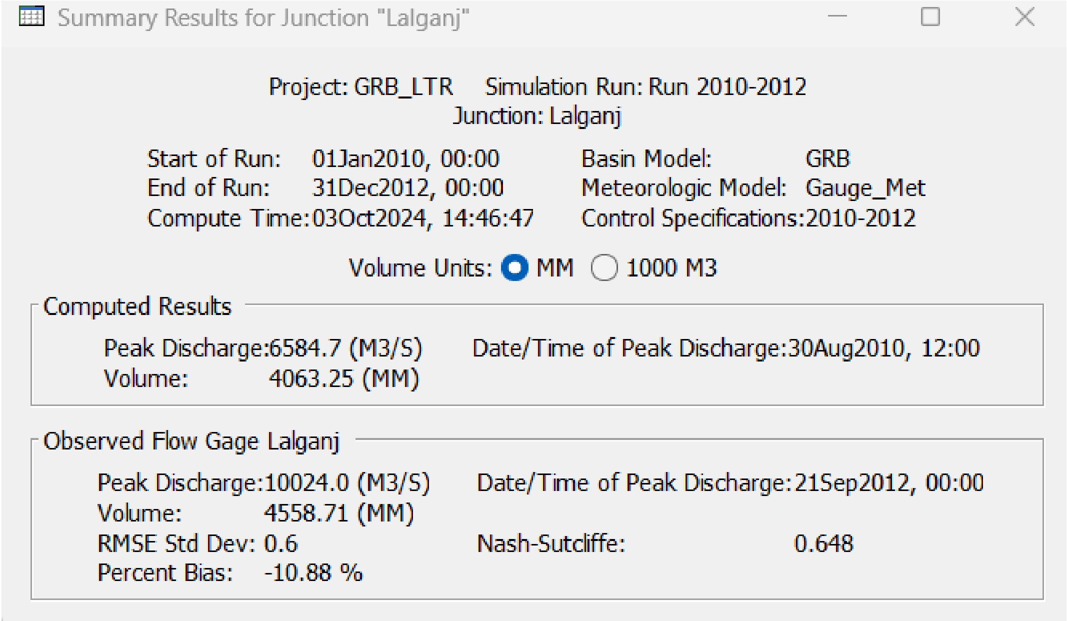
Start of Run: 01Jan2010, 00:00
End of Run: 31Dec2012, 00:00
Compute Time: 03Oct2024, 14:46:47
Basin Model: GRB
Meteorologic Model: Gauge_Met
Control Specifications: 2010-2012

Volume Units: ● MM ○ 1000 M3

Computed Results
Peak Discharge: 6939.8 (M3/S)
Date/Time of Peak Discharge: 24Aug2010, 12:00
Volume: 4078.32 (MM)

Observed Flow Gage Dumariaghat
Peak Discharge: 16022.0 (M3/S)
Date/Time of Peak Discharge: 21Sep2012, 00:00
Volume: 4432.39 (MM)
RMSE Std Dev: 0.4
Nash-Sutcliffe: 0.813
Percent Bias: -7.99 %

Figure 32: HMS simulations performance matrix with canal diversion at Dumariaghat during calibration period (2010-2012)


Summary Results for Junction "Lalganj"

Project: GRB_LTR Simulation Run: Run 2010-2012
Junction: Lalganj

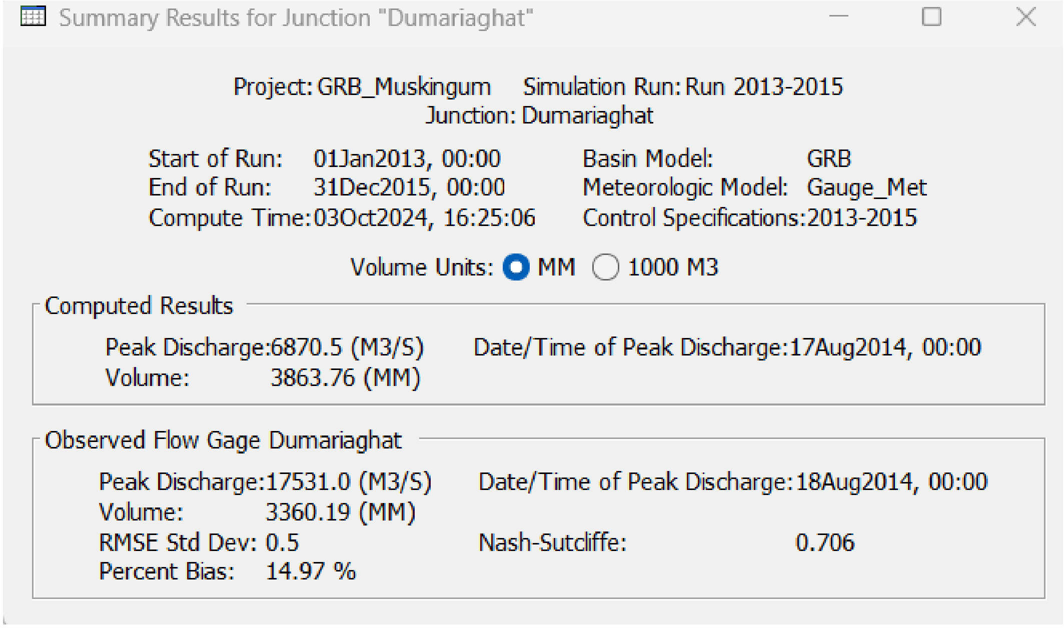
Start of Run: 01Jan2010, 00:00
End of Run: 31Dec2012, 00:00
Compute Time: 03Oct2024, 14:46:47
Basin Model: GRB
Meteorologic Model: Gauge_Met
Control Specifications: 2010-2012

Volume Units: ● MM ○ 1000 M3

Computed Results
Peak Discharge: 6584.7 (M3/S)
Date/Time of Peak Discharge: 30Aug2010, 12:00
Volume: 4063.25 (MM)

Observed Flow Gage Lalganj
Peak Discharge: 10024.0 (M3/S)
Date/Time of Peak Discharge: 21Sep2012, 00:00
Volume: 4558.71 (MM)
RMSE Std Dev: 0.6
Nash-Sutcliffe: 0.648
Percent Bias: -10.88 %

Figure 33: HMS simulations performance matrix with canal diversion at Lalganj during calibration period (2010-2012)



Summary Results for Junction "Dumariaghat"

Project: GRB_Muskingum Simulation Run: Run 2013-2015
Junction: Dumariaghat

Start of Run: 01Jan2013, 00:00 Basin Model: GRB
End of Run: 31Dec2015, 00:00 Meteorologic Model: Gauge_Met
Compute Time: 03Oct2024, 16:25:06 Control Specifications: 2013-2015

Volume Units: ● MM ○ 1000 M3

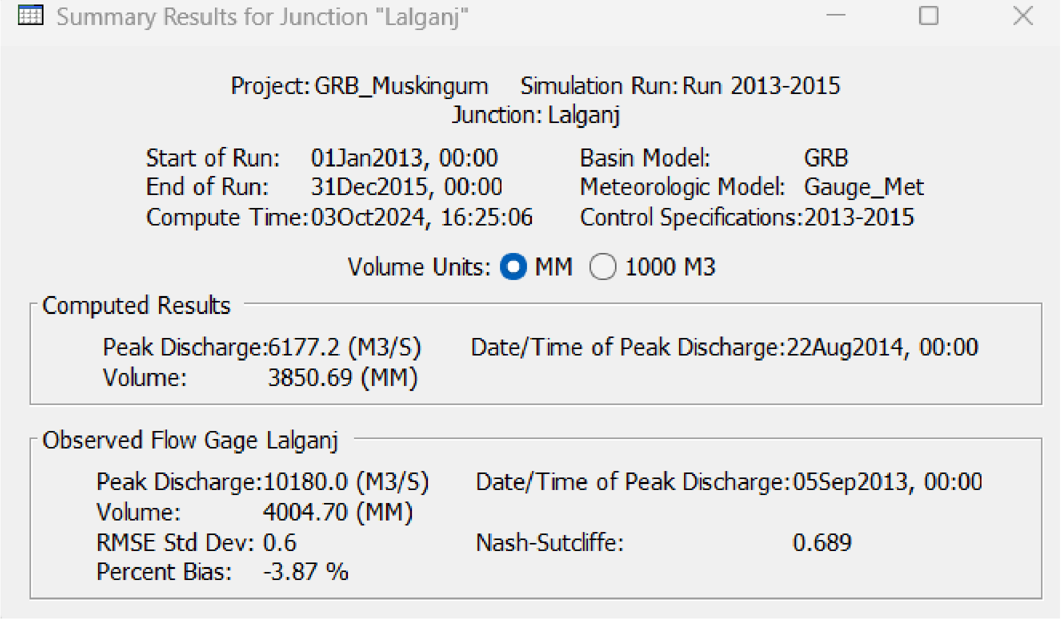
Computed Results

Peak Discharge: 6870.5 (M3/S) Date/Time of Peak Discharge: 17Aug2014, 00:00
Volume: 3863.76 (MM)

Observed Flow Gage Dumariaghat

Peak Discharge: 17531.0 (M3/S) Date/Time of Peak Discharge: 18Aug2014, 00:00
Volume: 3360.19 (MM)
RMSE Std Dev: 0.5 Nash-Sutcliffe: 0.706
Percent Bias: 14.97 %

Figure 34: HMS simulations performance matrix with canal diversion at Dumariaghat during validation period (2013-2015)



Summary Results for Junction "Lalganj"

Project: GRB_Muskingum Simulation Run: Run 2013-2015
Junction: Lalganj

Start of Run: 01Jan2013, 00:00 Basin Model: GRB
End of Run: 31Dec2015, 00:00 Meteorologic Model: Gauge_Met
Compute Time: 03Oct2024, 16:25:06 Control Specifications: 2013-2015

Volume Units: ● MM ○ 1000 M3

Computed Results

Peak Discharge: 6177.2 (M3/S) Date/Time of Peak Discharge: 22Aug2014, 00:00
Volume: 3850.69 (MM)

Observed Flow Gage Lalganj

Peak Discharge: 10180.0 (M3/S) Date/Time of Peak Discharge: 05Sep2013, 00:00
Volume: 4004.70 (MM)
RMSE Std Dev: 0.6 Nash-Sutcliffe: 0.689
Percent Bias: -3.87 %

Figure 35: HMS simulations performance matrix with canal diversion at Lalganj during validation period (2013-2015)

It is important to check the model performance in different combinations of simulation intervals to avoid the over-calibration of model. Also, the simulation period could be extended to check the model stability during long-term simulations. The overall HEC-HMS model performance was found to be satisfactory in short term runs, and the model is further simulated for long-term runs for calibration period 2001-2010 and validated for 2011-2015. Model performance is evaluated against the observed discharge values at both the sites as mentioned in fig. 28 to fig. 35. It has also been observed that the model was not predicting the peak flows accurately during calibration at the Lalganaj site lag difference is also observed during validation, due to which the NSE is reduced to 0.49 at this site.

5.3 Soil & Water Assessment Tool (SWAT+)

The Soil & Water Assessment Tool (SWAT+) is utilised for rainfall-runoff simulations over GRB. Short term calibration in SWAT does not provide good results and in order to capture behaviour of catchment long term simulations about 12 years is used for calibration. The model is setup for calibration period of 2001-2012 and validation period of 2013-2015. Sobol method is used for performing parameter sensitivity analysis as it is capable of handling linearity and captures interactions as well. The most sensitive parameters were found to be Saturated hydraulic conductivity (K), available water capacity of soil (awc), and percolation coefficient (perco). Figure 36 represents the model development in SWAT+. The details of SWAT+ model performance are showcased from fig. 37 to fig. 40.

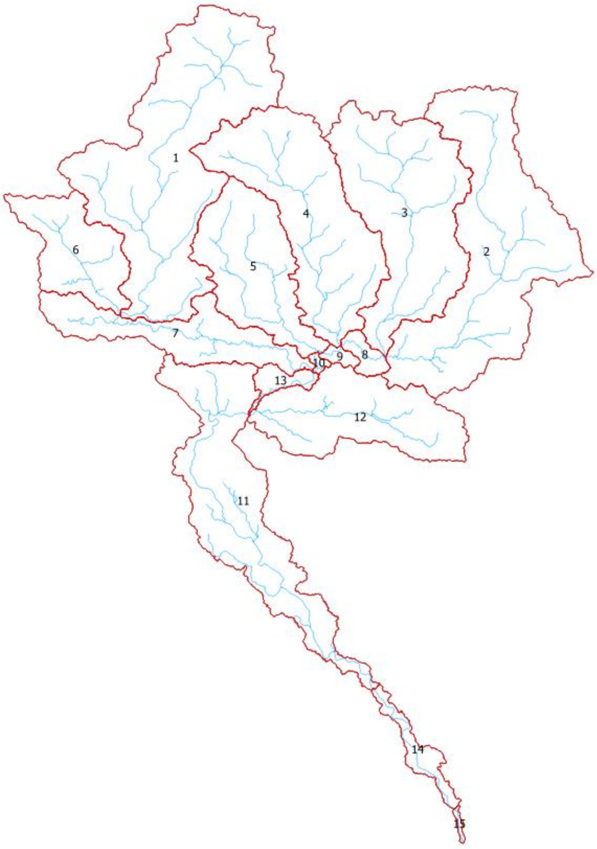


Figure 36: SWAT+ setup for Gandak River Basin

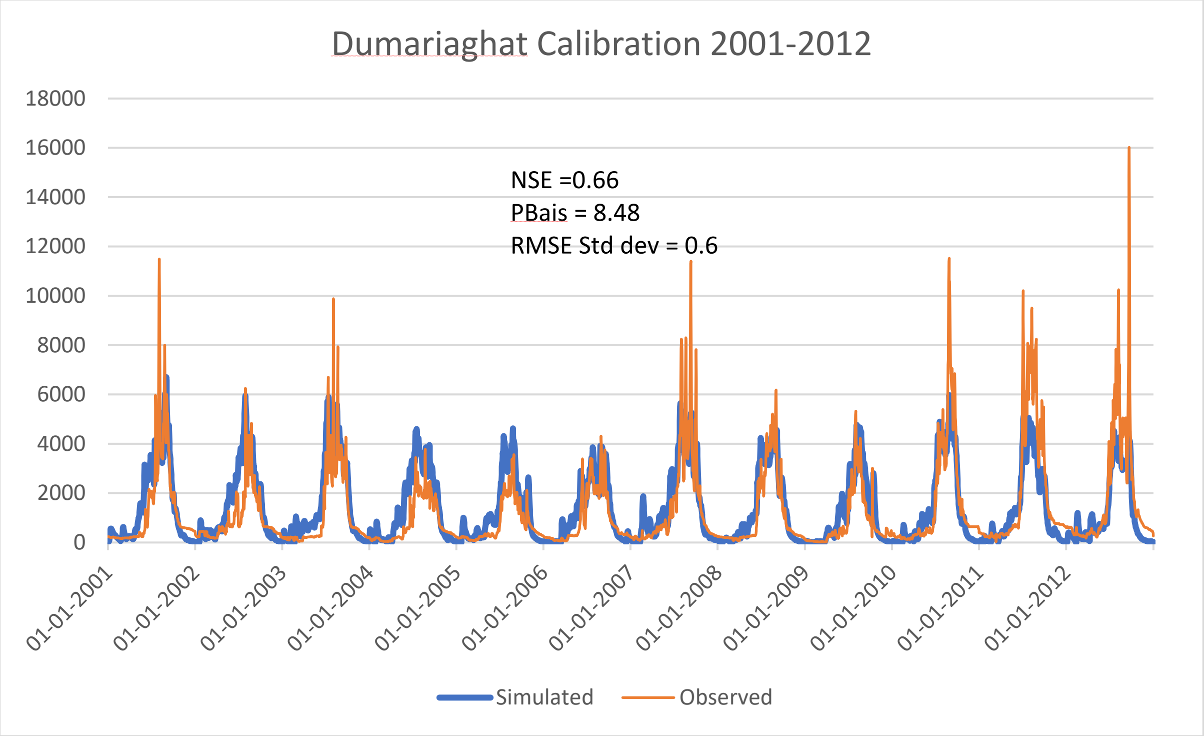


Figure 37: SWAT+ simulations performance matrix at Dumariaghat during calibration period (2001-2012)

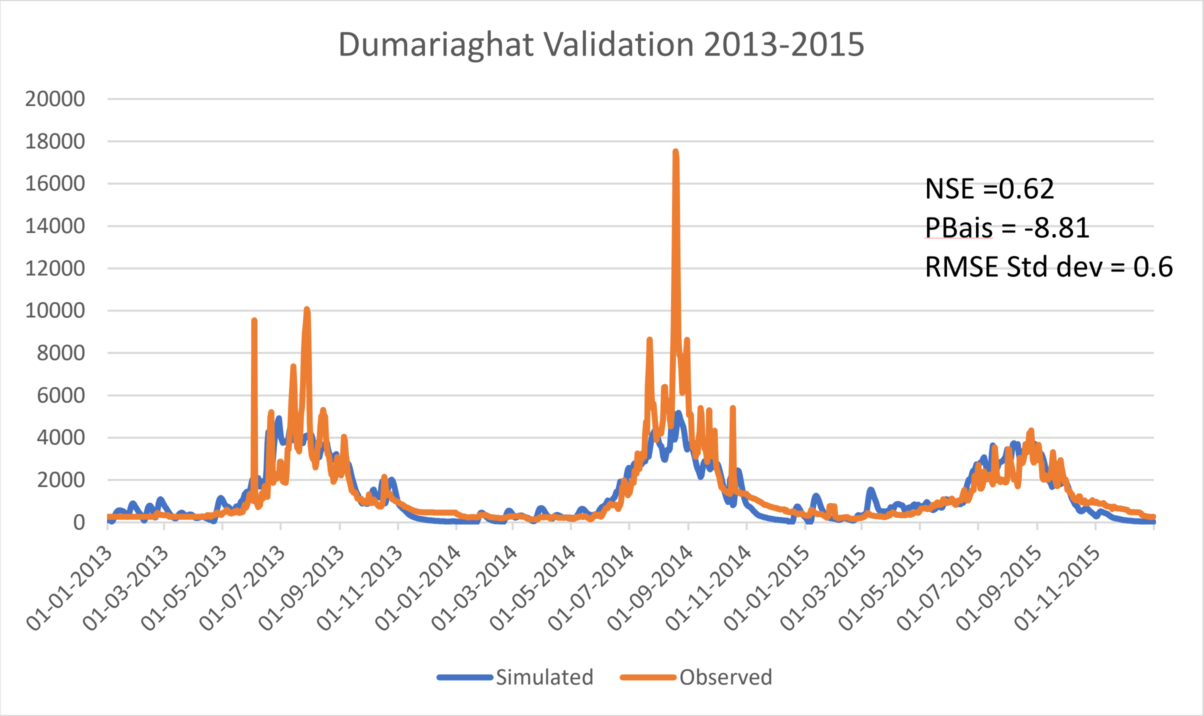


Figure 38: SWAT+ simulations performance matrix at Dumariaghat during validation period (2013-2015)

Although SWAT+ model is a robust hydrological and watershed simulation model, it has some constraints that need to be considered by users. One of the main constraints of the SWAT+ model is its requirement for high input data. SWAT+ demands large amounts of spatial and temporal datasets (e.g., weather, land use, soil, management practices), which may not always be readily available or uniform, especially in data-poor regions. While considering the model applications it has to be remembered the SWAT model was originally developed for prediction of impact of land management practices on the water, sediment and chemical yields of large agricultural watersheds. In our case the basin is highly irregular and slope is a predominating factor for runoff generation in mountainous regions. It requires specialized hydrology, GIS, and model parameterization expertise for getting quality output. But the major concern is model calibration and setup can be highly time-consuming (of the order of 3-4 days based upon the system configurations). SWAT+ also typically presumes lumped processes in Hydrological Response Units (HRUs) that may potentially reduce spatial process variability such as runoff and evapotranspiration. Computation demands can also become highly high for large or highly resolved basins. Ultimately, SWAT+ has the potential to exhibit limited accuracy for large river basins and highly complex terrain catchments since it was originally intended for agricultural and rural catchments and may not inherently account for large hydrological complexity without extreme customization.

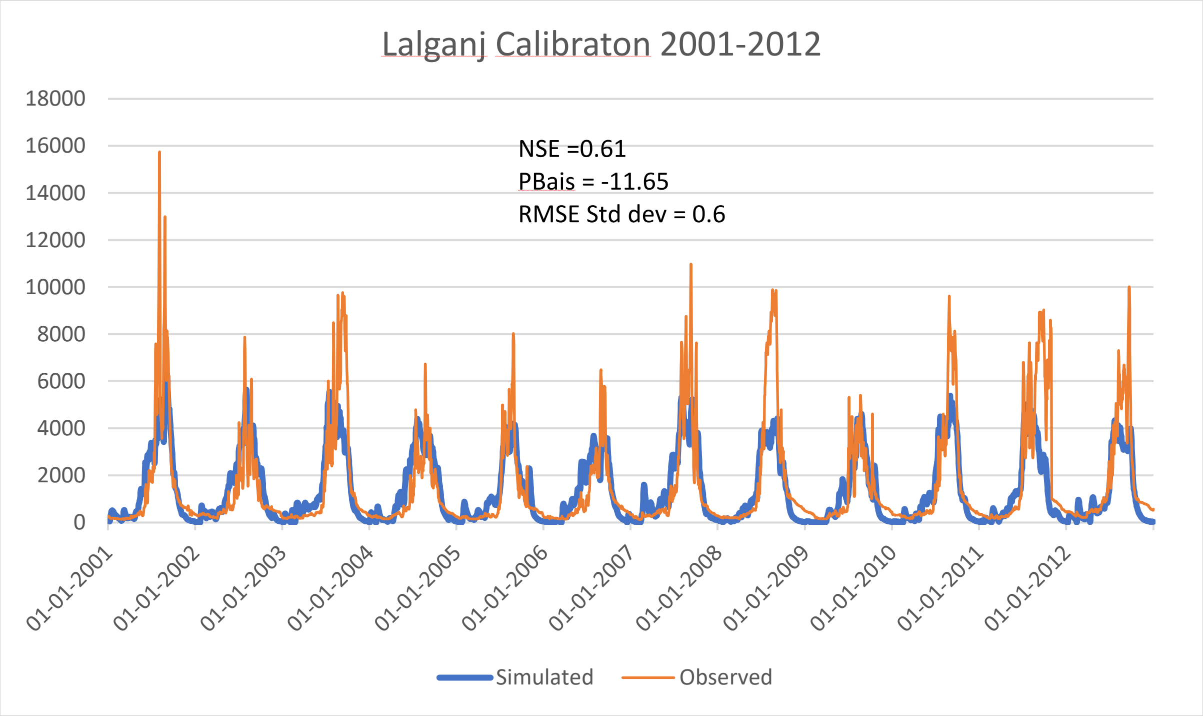


Figure 39: SWAT+ simulations performance matrix at Lalganj during calibration period (2001-2012)

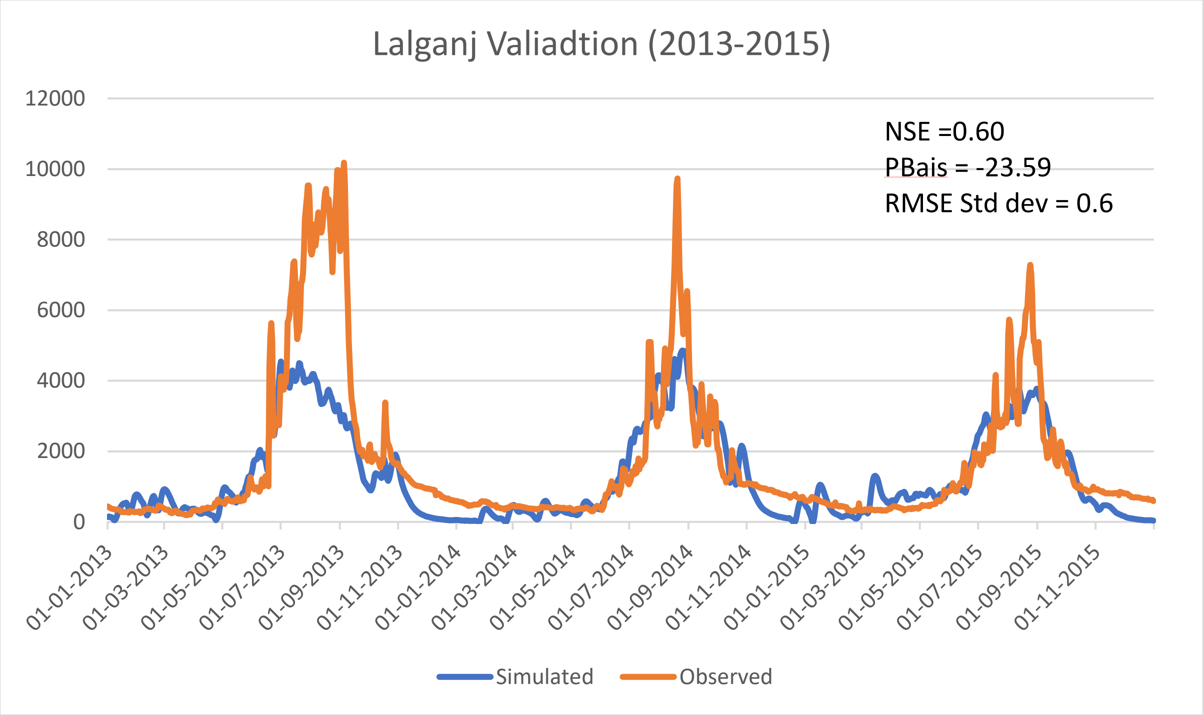


Figure 40: SWAT+ simulations performance matrix at Lalganj during validation period (2013-2015)

5.4 MIKE 11 NAM Results

MIKE 11 NAM (Rainfall-Runoff Model in English, short for Nedbør-Afstrømnings-Model, Rainfall-Runoff Model in Danish) was designed to simulate the rainfall-runoff processes in a catchment for hydrological forecasting and river flow modelling. It was initially developed by the Danish Hydraulic Institute (DHI) in an attempt to provide an easily utilized but effective conceptual tool that would be used together with hydraulic models like MIKE 11 for real-time flood forecasting, river basin management, and water resources planning. The goal was to achieve a balance between simplicity and precision: NAM uses a series of connected reservoirs to represent different parts of the hydrological cycle without the necessity of very detailed physical data. Since NAM is a conceptual lumped model, it models the whole catchment as one unit with uniform rainfall, soil characteristics, and land use throughout the basin. Such an assumption is not good for large or heterogeneous catchments where spatial variability is essential e.g., in basins with mountainous, forest, and urbanized zones. In these situations, the model can miss localized hydrological reactions, resulting in poor runoff predictions, particularly for severe events or areas of intense spatial rainfall gradients. The spatial plots mentioned in the previous section emphasised of existence of high rainfall patch in the Gandak River basin. Such areas are significantly important and to be captured under the modelling environment as well, where MIKE 11 NAM is ineffective.

NAM models fundamental processes such as surface runoff, interflow, and groundwater flow with the aid of several reservoirs. It does not, though, dynamically model advanced hydrologic processes such as snowmelt dynamics, dynamic evapotranspiration with different vegetation conditions, preferential flow through soils, etc. Hence, the model may lose essential process interactions in complex environments, making it less physically realistic and reliable outside the range it was parameterized for.

MIKE 11 NAM model is applied for Gandak River Basin. The model is lumped model and therefore it is set for Lalganj site as there is no additional meteorological grids between Dumariaghat and Lalganj. The model is calibrated over a period of 2013-2017 and validated for 2017-2019. The model shows NSE of 0.705 during calibration period and 0.673 during validation period. However, the peaks are underestimated in this model as well. On detailed investigation of model setup and results the reason for systematic underestimation of peak flows in all the hydrological models with different approaches viz., semi-distributed, gridded/HRUs based and lumped methods, it was found that the approximation of canal releases might be the major source of such underestimation. The values for the canal releases are being incorporated from the reports as design discharge, which is not the actual case. The releases are dynamic and a single design value throughout the period cause the drop of flow in the main river stream. To overcome this a novel approach is discussed in the subsequent section.

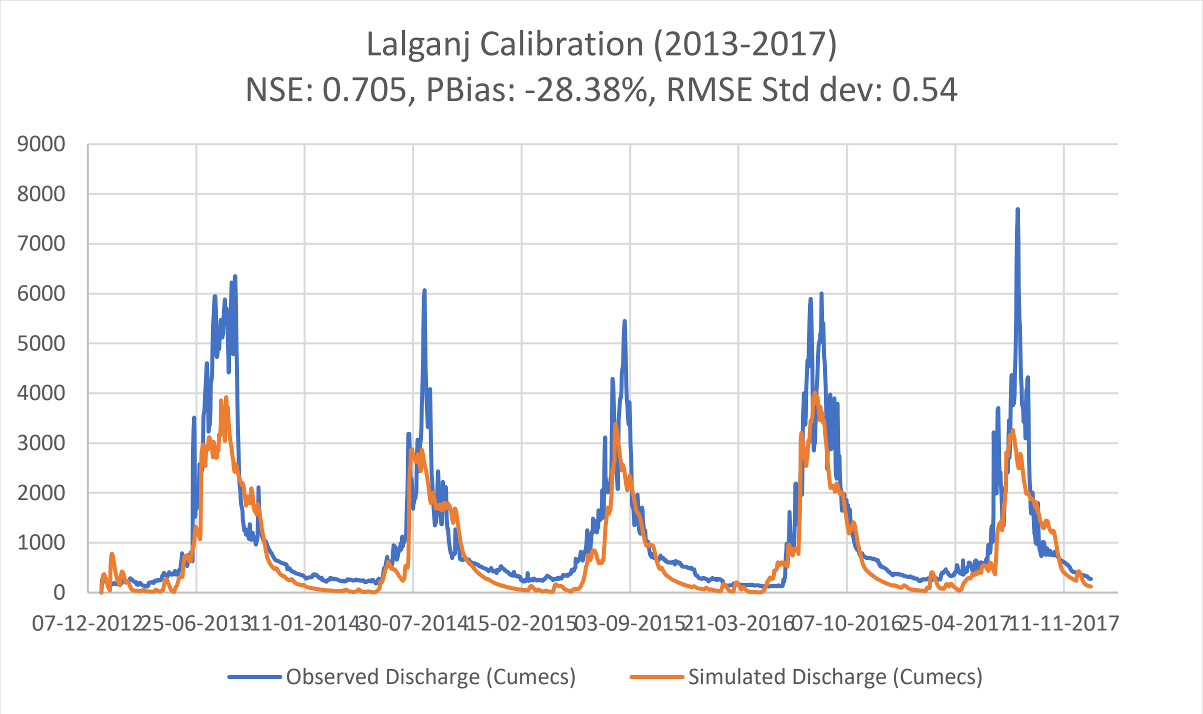


Figure 41: MIKE 11 NAM simulations performance matrix at Lalganj during calibration period (2013-2017)

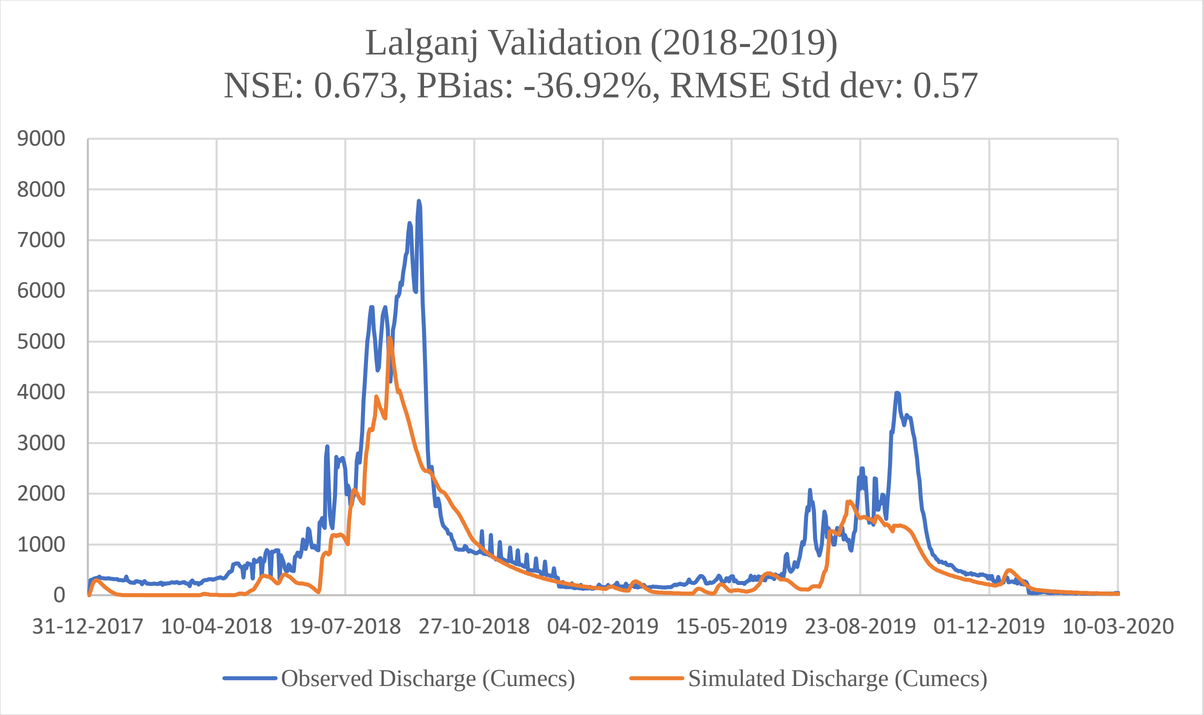


Figure 42: MIKE 11 NAM simulations performance matrix at Lalganj during validation period (2018-2019)

5.5 Novel approach to overcome missing dataset through Hybrid HEC-HMS-LSTM model for correction of peak flow underestimation

A data-driven LSTM model is developed to identify and learn systematic biases in HEC-HMS simulated discharges. The model was able to effectively correct underestimations in peak flows, demonstrating improved agreement with observed discharge and enhancing overall model performance. The physically-based rainfall-runoff models such as HEC-HMS are commonly used to simulate river discharge using meteorological inputs, basin characteristics, and parameter calibration. However, model often exhibit limitations when applied over long time periods or under complex basin conditions. A common challenge, in the form of unmodeled influences like availability of records for canal diversions, land-use changes, or evolving hydro-climatic patterns. Due to this a systematic underestimation of the observed peak discharges is observed for the modelled simulations in the Gandak River basin. Interestingly, on investigation it was observed that all the three model simulations underestimations are mainly due to unavailability of canal releases record during historical period. Recently, hybrid modelling approach with the fusion of physical based rainfall-runoff models with machine learning algorithms are developed. Also, the literature showcased a good reliability of the hybrid models in terms of improved model performance. The HEC-HMS model which is showing overall better accuracy as compared to the other models is considered for performing hybrid analysis for historic period i.e. 2001–2010. Non-stationarity of physical-based models causes underperformance in long-term simulations, even though no exceptional rainfall or discharge anomalies were recorded. While the HEC-HMS model was already calibrated using available data and Q_sim captured seasonal flow patterns reasonably well, the systematic underestimation pointed towards hidden processes or data non-stationarity not captured by the physical model.

To address this, a data-driven correction model using Long Short-Term Memory (LSTM), a deep learning approach capable of learning temporal dependencies and correcting systematic simulation errors is developed. The LSTM model was trained to learn the mapping between past sequences of simulated discharges and the actual observed discharges, effectively acting as a post-processor to the HEC-HMS model. The aim was to use this neural network to generate corrected discharge values that are closer to the observed values while leveraging the existing HEC-HMS outputs as the base.

The development process began with the preparation of a clean dataset combining daily Q_obs and Q_sim from 2001 to 2010. After removing missing values, the dataset was normalized using a MinMaxScaler to ensure all values lay between 0 and 1, which is essential for training neural networks. The input to the LSTM model consisted of time-windowed sequences of Q_sim values (length = 150 days), while the target output was the corresponding Q_obs value at the next timestep. This sliding-window approach allowed the model to learn how patterns in simulated flows lead to actual observed flows. A simple LSTM model architecture was constructed using TensorFlow/Keras, comprising a single LSTM layer with 50 units followed by a dense output layer. The model was compiled using the Mean Squared Error loss function and the Adam optimizer. It was trained over 50 epochs with a batch size of 16, using 70% of the data for training (calibration period) and 30% for testing (validation period).

In our application, we developed a customized LSTM-based model to improve the peak flow predictions of the HEC-HMS hydrological model, which showed consistent underestimation during certain high-flow periods. Our LSTM model was specifically trained to learn the systematic error between the simulated discharge (Q_sim) and observed discharge (Q_obs). The model was designed to take in the HEC-HMS simulated discharge as input and output the corrected streamflow that closely aligns with the observed data. We selected a look-back period of 150 days, meaning the model uses 150 previous values of Q_sim to predict the current Q_obs. This large context window helps the model understand the temporal dynamics that may influence flow behavior, such as seasonal changes, delayed runoff, or reservoir operations.

Once trained, the LSTM model was used to generate corrected discharge values across the entire simulation period. The predicted values were inverse-transformed back to the original discharge scale and compared visually and statistically with both the observed and simulated discharges. The results showed a clear improvement in accuracy and peak flow representation. Visual inspection of time-series plots revealed that the LSTM-corrected discharges better captured the timing and magnitude of high-flow events. To quantify performance, three widely accepted hydrological metrics were calculated: NSE (Nash-Sutcliffe Efficiency), RMSE (Root Mean Square Error), and PBIAS (Percent Bias). These were computed for both calibration and validation periods. The corrected model outperformed the original HEC-HMS simulations on all metrics, indicating that the LSTM was successfully able to learn and apply flow corrections based on historical discrepancies.

However, the LSTM-corrected values during the years 2008–2010 were found to be consistently lower than both observed and simulated discharges. This behavior was investigated and attributed primarily to non-stationarity in the underlying discharge patterns. Since the model was trained on patterns from earlier years, it could not generalize well to altered flow conditions in the later period, especially when unobserved influences like evolving land use, climate shifts, or operational changes (e.g., increased upstream withdrawals) were present. To improve model performance under such conditions, several strategies were identified, including reducing the look-back period to avoid excessive historical bias, adding additional input variables (e.g., rainfall, temperature, reservoir releases), retraining with more recent data, or using a hybrid approach that combines LSTM with error residual modelling.

In conclusion, the LSTM-based correction framework developed in this study provides an efficient and scalable post-processing tool for improving the accuracy of hydrological simulations. It is particularly useful in operational or data-limited contexts where physical models cannot capture all influencing factors. This hybrid modelling approach—leveraging the strengths of both physical simulation and machine learning—demonstrates the potential for significant performance improvements in long-term hydrological forecasting and river basin management.

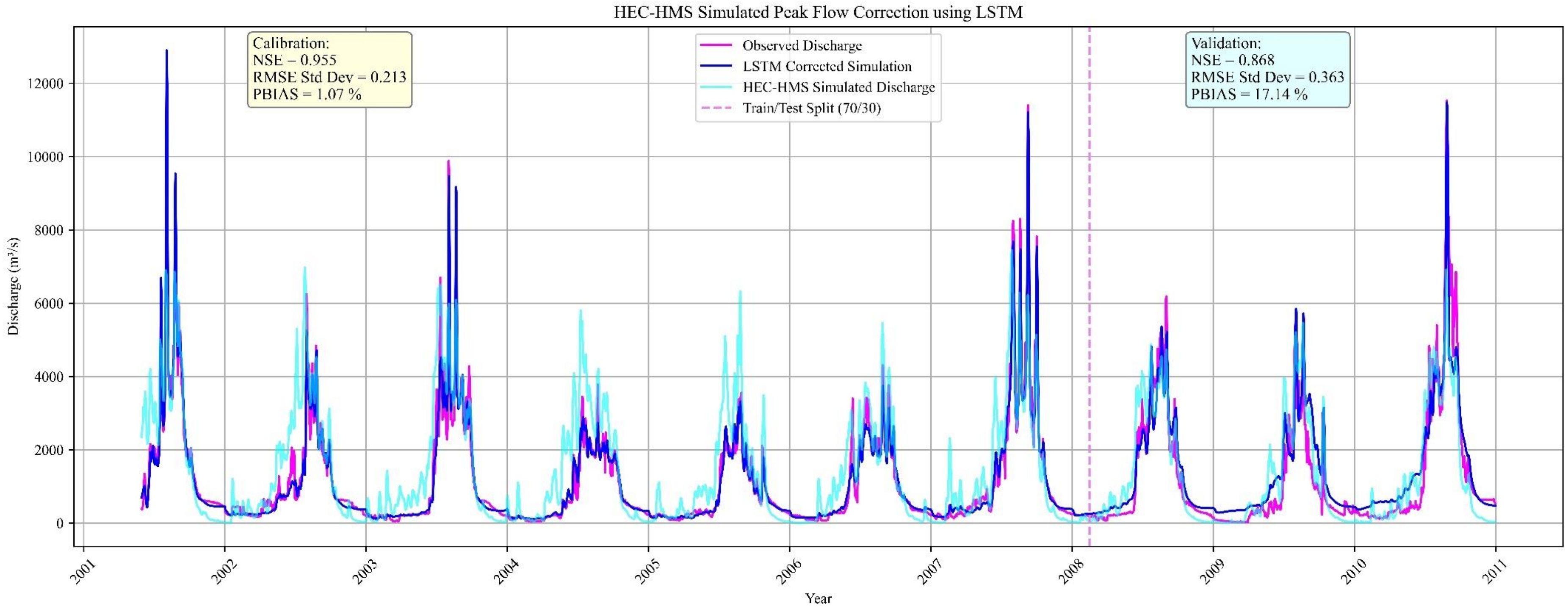


Figure 43: Peak flows correction for HEC-HMS simulated flows using Long Short-Term Memory model

5.6 Discussion

In comparing hydrological models, it is important to remember why they were originally developed, as the reason a model was developed is directly reflected in its structure, assumptions, complexity, and usefulness. Every model is designed to address specific types of problems e.g., SWAT was developed for long-term watershed management and land-use and climate impact analysis, MIKE 11 NAM was developed for river flow simulation and real-time flood forecasting, and HEC-HMS was primarily developed by the U.S. Army Corps of Engineers for simulation of rainfall-runoff processes for flood hydrology, water availability studies, and watershed response analysis. It is important to focus on the original purpose of model development as well, otherwise risk of misusing a model beyond its best range leading to bad estimates or wrong conclusions. A model that is specifically calibrated for flood simulations (like MIKE 11 NAM or HEC-HMS) will not perform best for land-use planning (where SWAT excels) and vice versa. Therefore, awareness of the underlying motives behind all models helps researchers and decision makers for selecting the right tool, respected to the limitations and assumptions of the model. Warmup period is also important for before the actual analysis period consideration for performance in order to stabilize the soil moisture and baseflow conditions. It is recommended for having 1 to 1.5 years of warm up period for HEC-HMS, whereas in can of SWAT+ it is recommended to have about 2 years as it has deeper soil/aquifer interactions which are more sensitive to initial conditions as compared to HEC-HMS. One year of warm up period is also suitable for MIKE 11 NAM model.

HEC-HMS was originally developed as an event-based model and employed primarily to simulate a single rainfall-runoff event, with major applications being flood hydrology, reservoir design storm, and flood hazard management. The first versions of HEC-HMS were designed particularly for computation of short-term simulations of one storm or collection of storms in a way that it became extremely popular for event-based analysis such as Probable Maximum Flood (PMF) estimation. Even though hydrologic study needs were growing such as on-going water supply appraisal, urban run-off simulation, climate impact estimation, and subsequently watershed management more recent releases of HEC-HMS featured with continuous simulation capabilities as well. Although HEC-HMS model was originally developed as event-based model but over the period of time with several upgrades it became robust and incorporated options for continuous hydrological modelling as well. Today, HEC-HMS can simulate months or years of continuous hydrology, using features like continuous soil moisture accounting, baseflow modelling, evapotranspiration losses, and snowmelt processes, making it much more versatile.

The model setup is done for the Gandak River basin with three models viz. HEC-HMS, SWAT+ and MIKE11 NAM. The overall performance of the HEC-HMS model is better as compared to SWAT+ and MIKE11 NAM. However, the HEC-HMS model itself has a wide number of options for different methods related to routing, baseflow, snow, and evaporation and it is not possible to try combination of each and every method for modelling. The selection of methods is based upon the available dataset and as per the reviewed literature. Also, the overall efficiency of HEC-HMS model is good but the peak flows are being underestimated in this model as well. The possible reason of this could be actual releases from the Gandak barrage to the right and left bank canals. In the model, constant values of design discharge from the reports are adopted, in which actual period i.e. date wise releases were not mentioned. The releases are available from 2020 onwards. In the upcoming studies this information could be incorporated for the period of 2020-2025. Another insight about these model's performance is about the spatio-temporal variability related to the basin. This reflects in terms of long term and short-term simulation periods. In order to address this issue short term simulations are also considered and model performance are analysed. The stationarity of parameters does not allows the dynamics of monsoon and non-monsoon periods, moisture conditions variations with in the monsoons and any LULC change over the decades. These are some of the concerns which should be taken care while addressing the extreme events like floods. However, the external inputs like precipitation, temperature and changes in LULC can be updated in the model and short-term simulation runs can be created for the updated conditions as well.

5.7 Key points:

1. In comparing three hydrological models for the Gandak River Basin, HEC-HMS gave the most satisfactory performance in terms of time to complete simulations, model performance and model structure.
2. It is crucial to consider why a model was originally developed before considering it for a specific purpose, as this greatly influences the model's structure, assumptions, complexity, and applicability. Lumped models are enough for getting a preliminary analysis of the basin. Semi-distributed models like SWAT+, which are originally developed for land/agriculture management applications, are good on monthly scales. In case of flood management applications where accuracy at a daily scale is required, simulations based on models which are actually developed as event-based models are more reliable.
3. HEC-HMS model can be used for a large river basin as the Gandak River Basin, with its robustness, reliability and overall performance.
4. Providing a warm-up period of 1-1.5 years will be suitable for the HEC-HMS model, 2 years for the SWAT+ model and 1 year for the MIKE 11 NAM model will allow these models to stabilise and perform better.
5. Models with a physical-based, semi-distributed modelling approach can be used for the large river basins as Gandak River Basin.
6. In future, as the fine resolution dataset related to soil moisture and evapotranspiration becomes available, a gridded modelling approach could be incorporated for the Gandak River basin.
7. Physical based hydrological models are subjected to parameter stationarity and heavily rely on detailed dataset in terms of both spatial and temporal scale. The systematic underestimation in peak flows due to approximation of canal diversions during historical period and model parameters stationarity consideration, can significantly improve when the simulated flows are post-processed with deep learning algorithms like LSTM model.

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References

1. Abdulkareem, J. H., et al. "Review of studies on hydrological modelling in Malaysia." *Modeling Earth Systems and Environment* 4 (2018): 1577-1605.
2. Ackerman, Cameron T., Matthew J. Fleming, and Gary W. Brunner. "Hydrologic and hydraulic models for performing dam break studies." *World Environmental and Water Resources Congress 2008: Ahupua'A*. 2008.
3. Adjei, Kwaku Amaning, et al. "Application of satellite-derived rainfall for hydrological modelling in the data-scarce Black Volta trans-boundary basin." *Hydrology Research* 46.5 (2015): 777-791.
4. Akoko, George, et al. "A review of SWAT model application in Africa." *Water* 13.9 (2021): 1313.
5. Alemayehu, Tadesse, et al. "Evaluation and application of alternative rainfall data sources for forcing hydrologic models in the Mara Basin." *Hydrology Research* 49.4 (2018): 1271-1282.
6. Al-Khudhairy, D. H. A., et al. "Hydrological modelling of a drained grazing marsh under agricultural land use and the simulation of restoration management scenarios." *Hydrological Sciences Journal* 44.6 (1999): 943-971.
7. Altaf, Yasir, Manzoor Ahangar, and Mohammad Fahimuddin. "Modelling snowmelt runoff in Lidder River Basin using coupled model." *International Journal of River Basin Management* 18.2 (2020): 167-175.
8. Andersen, Hans Estrup, et al. "Climate-change impacts on hydrology and nutrients in a Danish lowland river basin." *Science of the Total Environment* 365.1-3 (2006): 223-237.
9. Aqnouy, Mourad, et al. "Comparison of hydrological platforms in assessing rainfall-runoff behavior in a Mediterranean watershed of Northern Morocco." *Water* 15.3 (2023): 447.
10. Aredo, Mesfin Reta, Samuel Dagalo Hatiye, and Santosh Murlidhar Pingale. "Modeling the rainfall-runoff using MIKE 11 NAM model in Shaya catchment, Ethiopia." *Modeling Earth Systems and Environment* 7.4 (2021): 2545-2551.
11. Arnold, Jeffrey G., et al. "SWAT: Model use, calibration, and validation." *Transactions of the ASABE* 55.4 (2012): 1491-1508.
12. Arsenault, Richard, et al. "Continuous streamflow prediction in ungauged basins: long short-term memory neural networks clearly outperform traditional hydrological models." Hydrology and Earth System Sciences 27.1 (2023): 139-157.
13. Aryal, Anil, Sangam Shrestha, and Mukand S. Babel. "Quantifying the sources of uncertainty in an ensemble of hydrological climate-impact projections." *Theoretical and Applied Climatology* 135 (2019): 193-209.
14. Asadi, Arash, and Fardin Boostani. "Application of HEC-HMS for flood forecasting in Kabkian basin and Delibajak subbasin in Iran." *IOSR Journal of Engineering* 3.09 (2013): 10-16.
15. Bao, An-Ming, et al. "The effect of estimating areal rainfall using self-similarity topography method on the simulation accuracy of runoff prediction." *Hydrological Processes* 25.22 (2011): 3506-3512.
16. Bekele, Elias G., and John W. Nicklow. "Multi-objective automatic calibration of SWAT using NSGA-II." *Journal of Hydrology* 341.3-4 (2007): 165-176.
17. Bhuiyan, Hassan AKM, et al. "Application of HEC-HMS in a cold region watershed and use of RADARSAT-2 soil moisture in initializing the model." *Hydrology* 4.1 (2017): 9.
18. Bihar Water Resources Department. *Gandak Project Overview*. Government of Bihar. http://wrd.bih.nic.in/
19. Borah, D. K., and M. Bera. "Watershed-scale hydrologic and nonpoint-source pollution models: Review of mathematical bases." *Transactions of the ASAE* 46.6 (2003): 1553-1566.
20. Borah, Deva K., and Maitreyee Bera. "Watershed-scale hydrologic and nonpoint-source pollution models: Review of applications." *Transactions of the ASAE* 47.3 (2004): 789-803.
21. Broekhuizen, Ico, et al. "Urban drainage models for green areas: Structural differences and their effects on simulated runoff." *Journal of Hydrology X* 5 (2019): 100044.
22. Central Water Commission (CWC), 2014. *National Register of Large Dams (NRLD)*. Central Water Commission, Ministry of Water Resources, River Development & Ganga Rejuvenation, Government of India.
23. Central Water Commission (CWC), 2021. *Water and Related Statistics Report*. Water Planning and Projects Wing, Central Water Commission, Government of India.
24. Chathuranika, Imiya M., et al. "Comparison of two hydrological models, HEC-HMS and SWAT in runoff estimation: application to Huai Bang Sai Tropical Watershed, Thailand." *Fluids* 7.8 (2022): 267.

25. Cheng, Xu, et al. "Application of HEC-HMS parameter regionalization in small watershed of hilly area." *Water Resources Management* 35 (2021): 1961-1976.
26. Corkery, Aisling, et al. "Dublin Bay Water Quality Modelling from Catchment to Coast." *EGU General Assembly Conference Abstracts*. 2020.
27. Crăciun, Ioan, et al. "Modelling of the hydrological parameters in the experimental and representative Ciurea-Tinoasa hydrographical basin." *Lucrările Seminarului Geografic" Dimitrie Cantemir"* 37 (2014): 13-22.
28. Darbandsari, Pedram, and Paulin Coulibaly. "Inter-comparison of lumped hydrological models in data-scarce watersheds using different precipitation forcing data sets: Case study of Northern Ontario, Canada." *Journal of Hydrology: Regional Studies* 31 (2020): 100730.
29. Das, S. K., A. W. M. Ng, and B. J. C. Perera. "Sensitivity analysis of SWAT model in the Yarra River catchment." *20th International Congress on modelling and simulation, Adelaide*. 2013.
30. Deulkar, Aparna M., et al. "Comparative Assessment of Artificial Neural Networks (ANNs), Long Short-Term Memory Network (LSTM) and Hydrologic Engineering Centre-Hydrologic Modelling System (HEC-HMS) for Runoff Modelling." Water Resources Management (2025): 1-20.
31. Devia, Gayathri K., B. Pa Ganasri, and G. Sa Dwarakish. "A review on hydrological models." *Aquatic procedia* 4 (2015): 1001-1007.
32. DHI, 2009. Mike 11: A Modelling System for Rivers and Channel. Reference Manual.
33. Dile, Yihun Taddele, and Raghavan Srinivasan. "Evaluation of CFSR climate data for hydrologic prediction in data-scarce watersheds: an application in the Blue Nile River Basin." *JAWRA Journal of the American Water Resources Association* 50.5 (2014): 1226-1241.
34. Doulgeris, Ch, et al. "Evaluating three different model setups in the MIKE 11 NAM model." *Advances in the Research of Aquatic Environment: Volume 1*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011. 241-249.
35. Du, Jinkang, et al. "Hydrological simulation by SWAT model with fixed and varied parameterization approaches under land use change." *Water resources management* 27 (2013): 2823-2838.
36. El Khalki, El Mahdi, et al. "Challenges in flood modeling over data-scarce regions: how to exploit globally available soil moisture products to estimate antecedent soil wetness conditions in Morocco." *Natural Hazards and Earth System Sciences* 20.10 (2020): 2591-2607.
37. El-Nasr, Ahmed Abu, et al. "Modelling the hydrology of a catchment using a distributed and a semi-distributed model." *Hydrological Processes: An International Journal* 19.3 (2005): 573-587.
38. Filianoti, Pasquale, et al. "An evaluation matrix to compare computer hydrological models for flood predictions." *Hydrology* 7.3 (2020): 42.
39. Fleming, Matt, and Vincent Neary. "Continuous hydrologic modeling study with the hydrologic modeling system." *Journal of hydrologic engineering* 9.3 (2004): 175-183.
40. Fuchs, Mike, Sebastian Gebler, and Andreas Lorke. "Modelling landscape-level pesticide concentrations with SWAT+-an uncertainty assessment of application timing." *EGU General Assembly Conference Abstracts*. 2021.
41. Gauch, Martin, et al. "Rainfall–runoff prediction at multiple timescales with a single Long Short-Term Memory network." Hydrology and Earth System Sciences 25.4 (2021): 2045-2062.
42. Gebre, Sintayehu Legesse. "Application of the HEC-HMS model for runoff simulation of Upper Blue Nile River Basin." *Hydrology: Current Research* 6.2 (2015): 1.
43. Gitau, Margaret W., and Indrajeet Chaubey. "Regionalization of SWAT model parameters for use in ungauged watersheds." *Water* 2.4 (2010): 849-871.
44. Gumindoga, Webster, et al. "Ungauged runoff simulation in Upper Manyame Catchment, Zimbabwe: Application of the HEC-HMS model." *Physics and Chemistry of the Earth, Parts A/B/C* 100 (2017): 371-382.
45. Guo, Yanrong, et al. "Modelling the impacts of climate and land use changes on soil water erosion: Model applications, limitations and future challenges." *Journal of environmental management* 250 (2019): 109403.
46. Gupta, Hoshin V., et al. "Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling." *Journal of hydrology* 377.1-2 (2009): 80-91.
47. Gupta, Hoshin Vijai, Soroosh Sorooshian, and Patrice Ogou Yapo. "Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration." *Journal of hydrologic engineering* 4.2 (1999): 135-143.

48. Haas, Henrique, et al. "Improving the representation of forests in hydrological models." *Science of The Total Environment* 812 (2022): 151425.
49. Haas, Henrique, Latif Kalin, and Puneet Srivastava. "Improved forest dynamics leads to better hydrological predictions in watershed modeling." *Science of The Total Environment* 821 (2022): 153180.
50. Hafezparast, Maryam, et al. "A conceptual rainfall-runoff model using the auto calibrated NAM models in the Sarisoo River." *Hydrology: current research* 4.1 (2013).
51. Halwatura, D., and M. M. M. Najim. "Application of the HEC-HMS model for runoff simulation in a tropical catchment." *Environmental modelling & software* 46 (2013): 155-162.
52. Hashem, Ahmed A., et al. "Evaluation of SWAT soil water estimation accuracy using data from Indiana, Colorado, and Texas." *Transactions of the ASABE* 63.6 (2020): 1827-1843.
53. Hashemi, Reyhaneh, et al. "How can we benefit from regime information to make more effective use of long short-term memory (LSTM) runoff models?." Hydrology and Earth System Sciences 26.22 (2022): 5793-5816.
54. Huffman, George J., et al. "Integrated Multi-satellitE Retrievals for GPM (IMERG) technical documentation." *Nasa/Gsfc Code* 612.47 (2015): 2019.
55. Hunt, Kieran MR, et al. "Using a long short-term memory (LSTM) neural network to boost river streamflow forecasts over the western United States." Hydrology and Earth System Sciences 26.21 (2022): 5449-5472.
56. Ibrahim-Bathis, K., and S. A. Ahmed. "Rainfall-runoff modelling of Doddahalla watershed—an application of HEC-HMS and SCN-CN in ungauged agricultural watershed." *Arabian Journal of Geosciences* 9.3 (2016): 170.
57. Jakada, Hamza, and Zhihua Chen. "An approach to runoff modelling in small karst watersheds using the SWAT model." *Arabian Journal of Geosciences* 13 (2020): 1-18.
58. James, Wesley P., John Warinner, and Michael Reedy. "APPLICATION OF THE GREEN-AMPT INFILTRATION EQUATION TO WATERSHED MODELING 1." *JAWRA Journal of the American Water Resources Association* 28.3 (1992): 623-635.
59. Janjić, Josip, and Lidija Tadić. "Fields of application of SWAT hydrological model—a review." *Earth* 4.2 (2023): 331-344.
60. Jayakrishnan, R. S. R. S., et al. "Advances in the application of the SWAT model for water resources management." *Hydrological Processes: An International Journal* 19.3 (2005): 749-762.
61. Kannan, N., et al. "Sensitivity analysis and identification of the best evapotranspiration and runoff options for hydrological modelling in SWAT-2000." *Journal of Hydrology* 332.3-4 (2007): 456-466.
62. Karim, Fazlul, et al. "Assessing the impacts of climate change and dams on floodplain inundation and wetland connectivity in the wet–dry tropics of northern Australia." *Journal of Hydrology* 522 (2015): 80-94.
63. Keller, Arturo A., et al. "Hydrological models for climate-based assessments at the watershed scale: A critical review of existing hydrologic and water quality models." *Science of the Total Environment* 867 (2023): 161209.
64. Khaniya, Bhabishya, S. S. Wanniarachchi, and Upaka Rathnayake. "Importance of hydrologic simulation for lids and BMPs design using HEC-HMS: a case demonstration." (2017).
65. Koshuma, Abera Ermias, et al. "Application of Different Modelling Methods to Arbitrate Various Hydrological Attributes Using CMORPH and TRMM Satellite Data in Upper Omo-Gibe Basin of Ethiopia." *Mathematical Problems in Engineering* 2021.1 (2021): 4143958.
66. Koutsovili, Eleni-Ioanna, et al. "Early flood monitoring and forecasting system using a hybrid machine learning-based approach." ISPRS International Journal of Geo-Information 12.11 (2023): 464.
67. Kratzert, Frederik, et al. "Neural Hydrology–interpreting LSTMs in hydrology." Explainable AI: Interpreting, explaining and visualizing deep learning (2019): 347-362.
68. Kratzert, Frederik, et al. "Rainfall–runoff modelling using long short-term memory (LSTM) networks." Hydrology and Earth System Sciences 22.11 (2018): 6005-6022.
69. Kratzert, Frederik, et al. "Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets." Hydrology and Earth System Sciences 23.12 (2019): 5089-5110.
70. Krause, Peter, D. P. Boyle, and Frank Bäse. "Comparison of different efficiency criteria for hydrological model assessment." *Advances in geosciences* 5 (2005): 89-97.
71. Kumar, Dilip, and Rajib Kumar Bhattacharjya. "Evaluating two GIS-based semi-distributed hydrological models in the Bhagirathi-Alkhnanda River catchment in India." *Water Policy* 22.6 (2020): 991-1014.

72. Kumar, K. Satish, R. V. Galkate, and H. L. Tiwari. "River basin modelling for Shipra River using MIKE BASIN." *ISH Journal of Hydraulic Engineering* 27.2 (2021): 188-199.
73. Kumar, Sanjiv, and Venkatesh Merwade. "Impact of watershed subdivision and soil data resolution on SWAT model calibration and parameter uncertainty 1." *JAWRA Journal of the American Water Resources Association* 45.5 (2009): 1179-1196.
74. Lee, Daeeop, et al. "Future runoff analysis in the Mekong river basin under a climate change scenario using deep learning." *Water* 12.6 (2020): 1556.
75. Lees, Thomas, et al. "Hydrological concept formation inside long short-term memory (LSTM) networks." Hydrology and Earth System Sciences Discussions 2021 (2021): 1-37.
76. Legates, David R., and Gregory J. McCabe Jr. "Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation." *Water resources research* 35.1 (1999): 233-241.
77. Ma, Qiang, and Philippe Gourbesville. "Modelling Strategy of Deterministic Distributed Hydrological Model Development at Catchment Scale." *Advances in Hydroinformatics: SimHydro 2019-Models for Extreme Situations and Crisis Management*. Springer Singapore, 2020.
78. Madsen, Henrik. "Automatic calibration and uncertainty assessment in rainfall-runoff modelling." *Building Partnerships*. 2000. 1-10.
79. Manguerra, H. B., and B. A. Engel. "HYDROLOGIC PARAMETERIZATION OF WATERSHEDS FOR RUNOFF PREDICTION USING SWAT 1." *JAWRA Journal of the American Water Resources Association* 34.5 (1998): 1149-1162.
80. Martins, Magda Stella de Melo, et al. "Potential impacts of land use changes on water resources in a tropical headwater catchment." *Water* 13.22 (2021): 3249.
81. McCuen, Richard H., Zachary Knight, and A. Gillian Cutter. "Evaluation of the Nash–Sutcliffe efficiency index." *Journal of hydrologic engineering* 11.6 (2006): 597-602.
82. Mirzaei, Majid, et al. "A novel stacked long short-term memory approach of deep learning for streamflow simulation." *Sustainability* 13.23 (2021): 13384.
83. Mishra, Srikanta. "Uncertainty and sensitivity analysis techniques for hydrologic modeling." *Journal of hydroinformatics* 11.3-4 (2009): 282-296.
84. Moriasi, Daniel N., et al. "Model evaluation guidelines for systematic quantification of accuracy in watershed simulations." *Transactions of the ASABE* 50.3 (2007): 885-900.
85. Moriasi, Daniel N., et al. "SWAT-LUT: A desktop graphical user interface for updating land use in SWAT." *JAWRA Journal of the American Water Resources Association* 55.5 (2019): 1102-1115.
86. Mureithi, Kivuti, et al. "Runoff estimation using satellite images in sparsely gauged basins: a case of Nzoia River Basin, Kenya." *Water Practice & Technology* 17.8 (2022): 1758-1768.
87. National Water Development Agency (NWDA), 2018. *Gandak Basin Report*. Government of India, Ministry of Jal Shakti. Available at: http://nwda.gov.in
88. Ngangbam, Romeji, Amaljit Bharali, and Sonamani Kangjam. "Urban Flood Scaling Using Hydrologic and Hydraulic Models with Inception for Early Warning." *International Journal of Engineering and Technology* 11.6 (2019).
89. Odiyo, J. O., J. I. Phangisa, and R. Makungo. "Rainfall–runoff modelling for estimating Latonyanda River flow contributions to Luvuvhu River downstream of Albasini Dam." *Physics and Chemistry of the Earth, Parts a/b/c* 50 (2012): 5-13.
90. Oleyiblo, James Oloche, and Zhi-jia Li. "Application of HEC-HMS for flood forecasting in Misai and Wan'an catchments in China." *Water Science and Engineering* 3.1 (2010): 14-22.
91. Panagopoulos, Y., et al. "SWAT parameterization for the identification of critical diffuse pollution source areas under data limitations." *Ecological modelling* 222.19 (2011): 3500-3512.
92. Pareta, Kuldeep. "Hydrological modelling of largest braided river of India using MIKE Hydro River software with rainfall runoff, hydrodynamic and snowmelt modules." *Journal of Water and Climate Change* 14.4 (2023): 1314-1338.
93. Pareta, Kuldeep. "Hydrological modelling of largest braided river of India using MIKE Hydro River software with rainfall runoff, hydrodynamic and snowmelt modules." *Journal of Water and Climate Change* 14.4 (2023): 1314-1338.
94. Plesca, I., et al. "Model intercomparison to explore catchment functioning: Results from a remote montane tropical rainforest." *Ecological Modelling* 239 (2012): 3-13.
95. Pushpalatha, Raji, et al. "A review of efficiency criteria suitable for evaluating low-flow simulations." *Journal of Hydrology* 420 (2012): 171-182.

96. Romanowicz, Agnieszka A., et al. "Sensitivity of the SWAT model to the soil and land use data parametrisation: a case study in the Thyle catchment, Belgium." *Ecological modelling* 187.1 (2005): 27-39.
97. Sabzipour, Behmard, et al. "Comparing a long short-term memory (LSTM) neural network with a physically-based hydrological model for streamflow forecasting over a Canadian catchment." Journal of Hydrology 627 (2023): 130380.
98. Sahu, Mukul Kumar, Hassan R. Shwetha, and Gowdagere S. Dwarakish. "State-of-the-art hydrological models and application of the HEC-HMS model: a review." *Modeling Earth Systems and Environment* 9.3 (2023): 3029-3051.
99. Salele, Badiya, et al. "Run-off modelling of pervious and impervious areas using couple SWAT and a novel machine learning model in cross-rivers state Nigeria." *Water Science & Technology* 88.7 (2023): 1893-1909.
100. Singh, Ashutosh, et al. "Rainfall-runoff modeling using MIKE 11 NAM model for Vinayakpur intercepted catchment, Chhattisgarh." *Indian Journal of Dryland Agricultural Research and Development* 29.2 (2014): 1-4.
101. Spruill, Crystal A., Stephen R. Workman, and Joseph L. Taraba. "Simulation of daily and monthly stream discharge from small watersheds using the SWAT model." *Transactions of the ASAE* 43.6 (2000): 1431-1439.
102. Tassew, Bitew G., Mulugeta A. Belete, and K. Miegel. "Application of HEC-HMS model for flow simulation in the Lake Tana basin: The case of Gilgel Abay catchment, upper Blue Nile basin, Ethiopia." *Hydrology* 6.1 (2019): 21.
103. Teshome, Fitsum T., et al. "Verification of the MIKE11-NAM model for simulating streamflow." *Journal of Environmental Protection* 11.02 (2020): 152.
104. Uttar Pradesh Irrigation Department. *Gandak Canal System Overview*. Government of Uttar Pradesh. Available at: http://irrigation.up.nic.in/
105. Vansteenkiste, Thomas, et al. "Intercomparison of hydrological model structures and calibration approaches in climate scenario impact projections." *Journal of Hydrology* 519 (2014): 743-755.
106. Veith, T. L., et al. "Parameter sensitivity and uncertainty in SWAT: A comparison across five USDA-ARS watersheds." *Transactions of the ASABE* 53.5 (2010): 1477-1486.
107. Verma, S. K., A. D. Prasad, and M. K. Verma. "An assessment of ongoing developments in water resources management incorporating SWAT model: Overview and perspectives." *Nature Environment and Pollution Technology* 21.4 (2022): 1963-1970.
108. Visescu, Mircea, Erika Beilicci, and Robert Beilicci. "Integrated Hydrographical Basin Management. Study Case–Crasna River Basin." *IOP Conference Series: Materials Science and Engineering*. Vol. 245. No. 3. IOP Publishing, 2017.
109. Wagener, Thorsten, Howard Wheater, and Hoshin Vijai Gupta. *Rainfall-runoff modelling in gauged and ungauged catchments*. World Scientific, 2004.
110. Wang, Wei, et al. "A hybrid rainfall-runoff model: integrating initial loss and LSTM for improved forecasting." Frontiers in Environmental Science 11 (2023): 1261239.
111. Water and Power Consultancy Services (WAPCOS), 2015. *Water Resource Assessment and Development of Gandak Basin*. Ministry of Water Resources, Government of India.
112. Winchell, Michael F., et al. "Soil and Water Assessment Tool model predictions of annual maximum pesticide concentrations in high vulnerability watersheds." *Integrated Environmental Assessment and Management* 14.3 (2018): 358-368.
113. Worku, Gebrekidan, et al. "Modelling hydrological processes under climate change scenarios in the Jemma sub-basin of upper Blue Nile Basin, Ethiopia." *Climate Risk Management* 31 (2021): 100272.
114. Yeditha, Pavan Kumar, et al. "Investigation of satellite precipitation product driven rainfall-runoff model using deep learning approaches in two different catchments of India." *Journal of Hydroinformatics* 24.1 (2022): 16-37.
115. Yonaba, Roland, et al. "A dynamic land use/land cover input helps in picturing the Sahelian paradox: Assessing variability and attribution of changes in surface runoff in a Sahelian watershed." *Science of the Total Environment* 757 (2021): 143792.
116. Yuan, Yongping, and Lydia Koropeckyj-Cox. "SWAT model application for evaluating agricultural conservation practice effectiveness in reducing phosphorous loss from the Western Lake Erie Basin." *Journal of environmental management* 302 (2022): 114000.

117. Yusop, Z., C. H. Chan, and A. Katimon. "Runoff characteristics and application of HEC-HMS for modelling stormflow hydrograph in an oil palm catchment." *Water Science and Technology* 56.8 (2007): 41-48.
118. Zarei, Erfan, Farzin Nasiri Saleh, and Afsaneh Nobakht Dalir. "Comparing the hybrid-lumped-LSTM model with a semi-distributed model for improved hydrological modeling." Journal of Water and Climate Change 15.8 (2024): 4099-4113.
119. Zhang, Bing, et al. "Emission estimation and fate modelling of three typical pesticides in Dongjiang River basin, China." *Environmental pollution* 258 (2020): 113660.
120. Zhao, Fubo, et al. "Parameter uncertainty analysis of the SWAT model in a mountain-loess transitional watershed on the Chinese Loess Plateau." *Water* 10.6 (2018): 690.

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