NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF CIVIL ENGINEERING

HYBRID PHYSICAL-ARTIFICIAL INTELLIGENCE-BASED MODELING FOR RAINFALL-RUNOFF-SEDIMENT PROCESS, CASE OF KATAR CATCHMENT, ETHIOPIA

PhD THESIS

Gebre Gelete KEBEDE

Nicosia

June, 2022

GEBRE GELETE KEBEDE
HYBRID PHYSICAL-ARTIFICIAL INTELLIGENCE-BASED MODELING FOR RAINFALL-RUNOFF-SEDIMENT PROCESS, CASE OF KATAR CATCHMENT, ETHIOPIA
PhD THESIS
2022

NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF CIVIL ENGINEERING

HYBRID PHYSICAL-ARTIFICIAL INTELLIGENCE-BASED MODELING FOR RAINFALL-RUNOFF-SEDIMENT PROCESS, CASE OF KATAR CATCHMENT, ETHIOPIA

PhD THESIS

Gebre Gelete KEBEDE

Supervisors

Prof. Dr. Hüseyin GÖKÇEKUŞ (Supervisor)

Prof. Dr. Vahid NOURANI (co-supervisor)

Nicosia

June, 2022

Approval

We certify that we have read the thesis submitted by Gebre Gelete Kebede titled **"Hybrid Physical-artificial Intelligence-based Modeling for Rainfall-Runoff-Sediment Process, case of Katar Catchment, Ethiopia"** and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree Doctor of Philosophy in Civil Engineering.

Examining Committee	Name-Surname	Signature
Head of the Committee:	Prof. Dr. Mustafa Ergil	……ni buraya yazın
Committee Member*:	Assist. Prof. Dr Elnaz Sharghi	……………………
Committee Member*:	Assoc. Prof. Dr. Anoosheh Iravanian	……………………
Committee Member*:	Assoc. Prof. Dr.Fidan Aslanova	……………………
Committee Member*:	Assoc. Prof. Dr. Youssef Kassem	……………………
Supervisor :	Prof. Dr. Hüseyin Gökçekuş	……………………
Cosupervisor:	Prof. Dr. Vahid Nourani	……………………

Approved by the Head of the Department

.21./.09../2022

……………………………

Prof. Dr. Kabir Sadeghi

Head of Department

Approved by the Institute of Graduate Studies

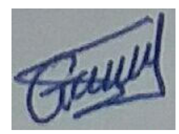
…../…../20…

Prof. Dr. Kemal Hüsnü Can Başer

Head of the Institute

Declaration

I hereby declare that all information, documents, analysis, and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of the Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.



Gebre Gelete Kebede

11/07/2022

Acknowledgments

Above all, glory to God for giving me the strength throughout my studies and to complete my Ph.D. thesis work successfully. I would like to thank my supervisors Prof. Dr. Huseyin Gokcekus (Supervisor), and Prof. Dr. Vahid Nourani (Co-Supervisor), for their motivation, patience and enormous contribution, toward achieving this success.

Also, I would like to thank the rest of my thesis committee members for their encouragement and knowledgeable comments.

I am very grateful to my family for their endless support throughout my life and academic years.

My profound gratitude goes to all my friends, and colleagues who have always been the source of strength and encouragement.

I would like to thank the Ethiopian National meteorological agency and the Ministry of Water and Energy – Ethiopia for giving me all the required information.

Gebre Gelete Kebede

Abstract

Hybrid Physical-artificial Intelligence-based Modeling for Rainfall-runoff-sediment Process, Case of Katar Catchment, Ethiopia

Gebre Gelete Kebede

PhD, Department of Civil Engineering

Supervisors: Prof. Dr. Hüseyin Gökçekuş (supervisor)

Prof. Dr. Vahid Nourani (Co-supervisor)

June, 2022, 146 pages

The study aimed to develop a hybrid physically-artificial intelligence (AI)-based ensemble model for modeling the rainfall-runoff-sediment process of Katar catchment, Ethiopia. The study used an adaptive neuro-fuzzy inference system (ANFIS), Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS), Hydrologiska Byråns Vattenbalansavdelning (HBV), soil and water assessment tool (SWAT), support vector machine (SVM) and Feedforward neural network (FFNN). The study used ten years of climate and hydrological data. Five steps were followed in this study. In the first step of the study, sensitivity analysis was performed to identify the dominant inputs that have a significant influence on the output. In the second step, the rainfall-runoff and suspended sediment load (SSL) were simulated using single models. In this step, rainfall-runoff was modeled via SWAT, HEC-HMS, HBV, ANFIS, ANN and SVM. Also, SSL estimation (strategy 1) was conducted via ANFIS, SVM, FFNN and multilinear regression (MLR) using different combinations of lagged SSL and discharge as input. In the third step, the runoff result of each physically-based and AI-based model was combined using a simple average ensemble (SE), weighted average ensemble (WE), neural network ensemble (NE) and ANFIS ensemble (AE) (for SSL only) technique in three scenarios. In step four of the study, strategy 2 of SSL modeling, the runoff values of the best ensemble technique from the third step together with lagged runoff were used as input for the AI-based and MLR model. Finally, the SSL output from the fourth step was ensembled using SE, WE, AE and NE (separately for each scenario) to boost the overall accuracy of the simulation. The performances of the individual and ensemble techniques applied for rainfall-runoff and SSL modeling were evaluated using root means square error (RMSE), Nash-Sutcliffe efficiency (NSE) and mean absolute error (MAE). According to the result, the ANFIS model provided better performance (NSE=0.913/0.884/0.88/0.92, RMSE=6.018m^3/s/1943.67ton/day/1628.259 ton/day and MAE= 2.847m^3/s/ 897.37 t/day/1018.312 t/day) in rainfall-runoff/SSL (strategy 1)/hybrid SSL (strategy 2), respectively in the validation period. From the three ensemble techniques, NE provided more accurate results in modeling rainfall-runoff and improved the individual models by 5.8%-27.6%. From the four ensemble techniques in SSL modeling, AE produced better results and improved the individual models by 9.73% to 37% for the first strategy of SSL modeling and by 3.59%-41.8% for hybrid SLL modeling (strategy 2) in the validation phase. In general, the finding of this research showed that the employed ensemble technique especially nonlinear ensemble techniques provided the most accurate result in both rainfall-runoff and SSL modeling.

Keywords: rainfall-runoff-sediment, AI-based, physically-based, ensemble technique, Katar catchment

Table of content

List of Tables

List of Figures

List of Abbreviations

AI	Artificial Intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial Neural Network
BP	Back-Propagation algorithm
CN	Soil Curve Number
DEM	Digital Elevation Mode
FC	Field Capacity
FIS	Fuzzy Inference System
GA	Genetic Algorithm
GEP	Gene expression programming
GP	Genetic Programming
GWDELAY	Groundwater delay time
HBV	Hydrologiska Byråns Vattenbalansavdelning
HEC-HMS	Hydrologic Engineering Center's Hydraulic Modeling System
HRU	Hydrologic Response Units
IHECRAS	Identification of Unit Hydrograph Components from Rainfall, Evaporation, and Streamflow
LM	Levenberg-Marquardt algorithm
LP	Limit of Potential Evaporation
LULC	Land Use Land Cover
MAE	Mean Absolute Error
MAXBAS	Length of Weighing Function
MF	Membership Function
MLP	Multi-layer Perceptron
MLR	Multi-linear Regression
NE	Neural Network Ensemble
NSE	Nash-Sutcliffe Coefficient of Efficiency
P	Rainfall

PED	Parameter Efficient Distributed
POS	Particle Swarm Optimization
Q	Discharge
RBFNN	Radial basis function neural network
RMSE	Root Mean Square Error
SE	Simple Average Ensemble
SCS	Soil Conservation Service
SCS-CN	Soil Conservation Service Soil Curve Number
SSL	Suspended sediment load
SURLAG	Surface runoff lag coefficient
SVM	Support Vector Machine
SVR	Support Vector Regression
SWAT-CUP	SWAT Calibration Uncertainty Program
SWAT	Soil and Water Assessment Tool
T	Temperature
TT	Threshold Temperature
UZL	Reservoir threshold
WE	Weighted Average Ensemble

CHAPTER I

Introduction

Hydrology is the study of the cycle and movements of water between the atmosphere, hydrosphere and earth surface (Hadi and Tombul, 2018). Surface runoff occurs when the rate of precipitation is greater than the rate of infiltration of the soil. A higher runoff rate results in accelerated soil erosion and transport of eroded soil to downstream rivers (Chen et al., 2011). The rainfall-runoff-sediment process is characterized by their highly complex and degree of spatial and temporal variability. Therefore, hydrologists are always dealing with the problem of determining these nonlinear, complex, dynamics and nonstationary relationships of the hydrological process (Nourani, 2017). Accurate modeling of rainfall-runoff and SSL is therefore a very crucial issue in designing, management, and planning of water resource (Anusree and Varghese, 2016; Kisi et al., 2013), in mitigating drought, designing and planning flood control work (Nourani and Komasi, 2013). Thus, for the last couple of decades modeling of the rainfall-runoff and suspended sediment load has gotten great attention and becomes the main hydrological research areas. Thus, accuracy in runoff and SSL modeling have a direct influence on water resource management decision making (Noori and Kalin, 2016). The relationship between rainfall-runoff and SSL is very complex due to the spatial and temporal variation in precipitation and watershed characteristics as well as the number of parameters included in the modeling process (Rezaeianzadeh et al., 2013). There have been many hydrological models that are being still developed to model these complex and stochastic hydrological process (Rajurkara et al, 2005; Shoaib et al., 2014). These models include AI, physically-based and statistical hydrological models.

Statistical methods (e.g., linear regression models) are too simplistic and are limited to a functional form between the input and response parameters before analysis (Noori and Kalin, 2016). These models work based on the assumption that a linear relationship exists between the input and output. Consequently, poor result is obtained from these models as there exist a strong nonlinear relationship in the rainfall-runoff process (Adnan et al., 2019). Semi-distributed physical models, on the other hand, can better simulate rainfall-runoff in a watershed because they take into account various spatial and hydro climatological inputs through mathematical formulations. Physically-based models used mathematical equations and construct simplified watershed system and have mechanisms to represent the actual physics of the process (Young et al., 2017). These models account for the contribution of groundwater, the effect of non-uniform distribution of evapotranspiration, rainfall and watershed characteristics such as land use, soil characteristics and slope (Kisi, 2012). To date, various physically-based, semi-distributed models such as SWAT, HEC-HMS and HBV have been used in modeling rainfall-runoff process.

The SWAT model is a physically based hydrological model (Arnold et al., 1998), developed to predict land use impacts on agricultural chemical yield, sediment and water in a complex and large catchment with different land use and soil for a long period of time (Eckhardt et al., 2005). In this model, the watershed is divided into sub-watersheds which are further subdivided into units with distinct land use, soil type and slope called hydrological response units (HRUs). Surface runoff is then estimated for each sub-watershed and routed to compute the watersheds' total runoff. The SWAT model was used for rainfall-runoff modeling and gave acceptable results in different studies (e.g., Iskender and Sajikumar, 2016; Jeong et al., 2010; Noori and Kalin, 2016; Vilaysane et al., 2015; Zhang et al., 2008).

HEC-HMS is another semi-distributed physically-based model which is extensively used in modeling rainfall-runoff process. It was originally developed for rainfall-runoff simulation of dendritic watersheds and later its applicability was expanded to address a variety of problems related to flood hydrograph and natural watersheds runoff (Shekar and Vinay, 2021). This model has successfully been used for rainfall-runoff modeling in different catchments (e.g., Abushandi and Merkel, 2013; Gebre, 2015; Gumindoga et al., 2017; Halwatura and Najim, 2013; Verma et al. 2010).

The third model, HBV, is a semi-distributed conceptual rainfall-runoff model in which the catchment is divided into a maximum of twenty elevation zone and three vegetation zone. HBV model was used for simulation of rainfall-runoff and gave suitable results (Bizuneh et al., 2021; Esmaeili-gisavandani et al., 2021; Ouatiki. et al., 2020).

Physically-based models requires large temporal and spatial data as well as long time to run. As it becomes difficult to consider all the physical parameters in the modelling (Nourani and Komasi, 2013) and limitation of physically based models to achieve the required accuracy, artificial intelligence (AI) which converts the inputs to output values is lately found applicable in accurate modeling of rainfall-runoff and SSL process (Kisi et al., 2012). AI-based models provide more accurate modeling result in rainfall-runoff and SSL modeling because they are able to handle spatial and temporal irregularities and the nonlinearity of rainfall-runoff-sediment process. These models detect the hidden relationship between the inputs and response variables from the historical data without prior knowledge of the underlying physics of the phenomena (Yang et al., 2020). AI models such as adaptive neuro-fuzzy inference system (ANFIS) support vector machine (SVM) and artificial neural networks (ANNs) such as FFNN are commonly used for modeling of complex hydrological processes such as rainfall-runoff-sediment from historical data due to their simplicity, efficiency and popularity (Kisi et al., 2013; Kumar et al., 2011).

FFNN , a black-box AI-based model, is extensively used in water resource and hydrology studies as a forecasting tool (Nourani et al., 2011). In recent decades, FFNN become popular and has been successfully used in modeling different hydrologic process. This is due to its ability in solving the complex nonlinear hydrological problems by identifying the relationship from a given pattern (Sahoo et al., 2017). This model imitates the human brain, learns rules naturally by training using large historical observed data without prior knowledge of the characteristics of the catchment (Young et al., 2017). A detailed review of the application and theories of ANNs in hydrological modeling are provided by Govindaraju and Rao (2000). The modeling accuracy of FFNN depends on the selection of suitable network structure and its internal parameters which is solved by using a simple trial-and-error method (Young et al., 2017). So far, many research have been done and published on the applicability of FFNN in modeling rainfall-runoff (e.g., (Dounia et al., 2014; Melesse et al., 2011)) and SSL (e.g., Kalteh, 2013; Khan et al., 2018; Nourani, 2017; Shoaib et al., 2014).

ANFIS, another AI model, developed by Jang (1993) is a hybrid of neural network and fuzzy inference system (FIS). Complex and dynamic process such as rainfall-runoff and SSL can be accurately modeled by ANFIS due to advantage of combining the learning features of neural network and approximation ability of a fuzzy inference system (Tahmoures et al., 2015). Due to this reason it has been successfully used in the area of hydrology and water resource management specifically in rainfall-runoff process modeling (Kwin et al, 2018; Nawaz et al. , 2016; Nourani and Komasi, 2013; Kisi and Shiri, 2013) and SSL (Cobaner et al., 2009; Kaveh et al., 2017) because of handling of uncertainties by fuzzy theory.

SVM which was developed by Vapnik (2013) is a supervised learning method from structural risk minimization and machine learning theory. It is relatively recent artificial intelligence-based model has been widely used for time series modeling as alternative to ANFIS and FFNN. This method can be applied both in regression and classification. It is basically derived from the concept of the hypothesis of risk minimization and thus it helps in producing good generalization. In recent years SVR are widely used in modeling of hydrological process (Mirabbasi et al., 2018; Okkan and Serbes, 2012; Raghavendra and Deka, 2014; Sharma et al., 2015 Yu et al., 2018).

Although the mentioned physical and AI based models can give reliable results, it is clear that one of the models performs better than the others for a given data set and when different data sets are used the result may entirely be opposite (Nourani et al., 2019). No single model is superior in providing rainfall-runoff and suspended sediment load modeling for all kind of catchment under all conditions than those of other competing models. This could be due to the fact that a given hydrological process evolves exclusively over time, whereas modeling methods based on time series and finite data sets are variable in structure and governed by parametric forms that vary from one model to another. In past few decades different attempts have been made to achieve better accurate rainfall-runoff and SSL modeling in catchment. Their key objective was to develop more efficient model by combining the single models because different models capture specific features of the phenomena. According to Fenicia et al. (2007), the accuracy of rainfall-runoff and SSL modeling can be improved by modifying the existing models by combining the output of different models instead of using a single model. Ensemble approach has increasingly gained popularity in hydrological modeling as an alternative for improving the reliability and accuracy of individual models (Fernando et al., 2012). For example, Young et al. (2017) improved the performance of rainfall-runoff modeling using HEC-HMS in conjunction with SVM and ANN. Esmaeili-gisavandani et al. (2021) used the gene expression programming method to combine the outputs of five different models to get improved runoff prediction. Therefore, it is important to develop an ensemble technique to benefit from the high predictive efficiency of AI-based and physically-based models that incorporate the effect of catchment characteristics in the modeling of the rainfall-runoff-SSL process. It is noteworthy that the physically-based and AI-based models in the ensemble unit, which have different philosophies, complement each other with regard to their inherent drawbacks and strengths. The weak simulation accuracy of physically-based models can be mitigated by powerful AI-based models, specifically for poorly gauged watersheds. Thus, ensemble techniques is believed to improve the modeling performance by combining the strength of the individual in the rainfall-runoff-SSL modeling.

Statement of the problem

Even though water is essential for all life forms, it can also be destructive when it is too much and create a problem when it is too low. Water can trigger and cause soil erosion, landslide, flooding, and sediment flow when it is excess (Badrzadeh et al., 2015). Nowadays many countries are vulnerable to disasters and damage related to water and the causalities are on the increase (Badrzadeh et al., 2015; Bates et al., 2008). Thus, the number of people affected by the increased water related disaster such as flooding and drought is increasing (Bates et al., 2008). Reliable information on rainfall-runoff-sediment is critical to water resources management and planning. Anthropogenic and natural water-related environmental hazards, especially droughts, floods and sedimentation of reservoir are becoming more frequent. Rapid population growth is increasing the need for agricultural land, and associated deforestation is causing soil erosion and sedimentation problems. As a result of these, environmental problems, deterioration of water quantity and quality, health problems and food insecurity are exacerbated.

The current study is conducted in Katar catchment, Ethiopia. The catchment contains Katar River and its tributaries draining into Lake Ziway. This lake serves as the source of water supply for Ziway town, irrigation and income source for the fishing community and hence contributes to food security and economic development (Desta and Fetene, 2020). Inside the catchment soil erosion, sedimentation, land degradations soil fertility loss is common due to erosive rainfall, poor land management system and marginal land cultivation (Aliye et al., 2020). These causes sedimentation of the Lake and flood plain along the bank of the river and siltation of the irrigation canal (Aga et al., 2018). Katar catchment was chosen as a case study because of the above-mentioned problems and availability of data. This catchment is a good case study to evaluate the performances of the applied models in the rainfall-runoff-sediment modeling.

Objective

The general objective of this study is to model the rainfall-runoff-sediment process of Katar catchment using combined artificial intelligence and physically-based models.

Specific objectives

The specific objectives of this study are:

- To compare the performance of AI-based (ANFIS, FFNN and SVM) and physically based models (SWAT, HEC-HMS and HBV) in modeling the rainfall-runoff process in Katar catchment.
- To develop an ensemble model for the prediction of runoff-rainfall process using the outputs of AI-based and physically-based models in Katar catchment
- SSL modeling by AI-based (FFNN, ANFIS and SVM) and MLR models
- To develop AI-based ensemble models for the estimation of SSL in Katar catchment
- To estimate the suspended sediment load in Katar catchment by a hybrid Physically–AI based models

Significant of the study

Accurate modeling of suspended sediment load and rainfall-runoff in a catchment could be a good tool for water management, planning and policy making. Runoff and suspended sediment are therefore the two most important factors for water resources planning (Kumar et al., 2019). Thus, rainfall-runoff and SSL modeling using reliable model is necessary for operation and optimization of water resources (Noori and Kalin, 2016) and essential for managing water resources such as dam operation, flood control, irrigation, water quality and water supply (Chen et al., 2011; Doroudi et al., 2021). Moreover, reliable SSL modeling in a catchment is important to hydrology as it affects water management and hydraulic structure. It is fundamental for various water management classifications, such as reservoir sedimentation and capacity reduction, river morphology, water quality demonstration and increasing maintenance costs of dams and irrigation canals (Kumar et al., 2019). Therefore, the capabilities and accuracy of runoff and SSL simulation can have a direct impact on water resource management decisions (Noori and Kalin, 2016). In this regard, this study used a hybrid physical and AI-based models for rainfall-runoff-sediment process modeling. To further improve the modeling accuracy ensemble techniques were applied by combining the output of single models applied for rainfall-runoff and SSL modeling. Therefore, the results of this study could provide valuable information for water management, flood protection and drought, design and operation of hydraulic structure.

Limitation of the study

Financial constraints, travel restrictions due to COVID-19 and the associated time constraints were the limitations encountered in this study.

CHAPTER II

Literature review

This part provides a literature review related to the study presented in this thesis. Firstly, it introduces the background of different modeling approach which is relevant in the field of rainfall-runoff-suspended sediment modelling. Secondly, it introduces background about ensemble approaches which is applied in the context of rainfall runoff and suspended sediment modeling.

Hydrological models

In the land and surface systems evapotranspiration, precipitation, surface runoff and suspended sediment load are the dominant processes (Singh, 1989). Therefore, the main aims of hydrological models are to quantify and model these processes that govern the transfer of moisture through different systems. From many hydrological processes, modeling of rainfall-runoff-sediment process are highly important from a different perspective.

There have been many efforts made to better understand and model the complex rainfall-runoff and SSL during the past decades. Researchers developed various models and these hydrological models are generally categorized in two groups as: data-driven (e.g., AI models) and physical-based models (Bourdin et al, 2012; Solomatine and Dulal, 2003). Physicaly-based models can highly enhance better understanding of the factors affecting the process of hydrological systems, but they are time consuming and require large input data that covers diverse aspects of the system including hydro-meteorological and spatial data. These data are not easily available and the model requires high computing power to prepare and process the input data.

To overcome this drawback, data driven artificial intelligence (AI) approaches such as fuzzy logic (FL), ANNs, SVM, genetic programming, ANFIS, ant colony optimization, and other hybrid methods are developed which are more feasible and accurate for a hydrological process like rainfall-runoff and SSL (Yaseen et al., 2015). These AI models has the capacity to accurately model the complex and nonlinear rainfall-runoff-sediment process without requiring prior knowledge of the underlying physical process of the system (Kwin et al., 2018; Mehr and Nourani, 2018). AI models are preferable in modelling of the complex and nonlinear hydrological process (e.g., rainfall-runoff and SSl) as it discovers the complex relationship between input and output data's even under the condition when the users do not have a complete understanding and knowledge of the underlying physical process (Asadi et al., 2013; Sudheer et al., 2010). However, this type of model are black-box, they ignore the underyling physics of the phenomena.

Artificial intelligence

Over the last couples of decades, there has been an increasing tendency of using different AI models in time series forecasting and hydrological modeling. Many researchers used various types artificial techniques such as SVM, ANN, ANFIS, and regression model (e., MLR) for rainfall-runoff modeling. Rainfall-runoff and SSL have a nonlinear and complicated relationship. Moreover, the process by which rainfall changed in to runoff and causing sediment transport is dependent on various catchment characteristics such as soil type, temperature, soil moisture, topography, slope evaporation, shape, etc. Physically-based models usually consider all these parameters and needs prior knowledge about them. Whereas, black box models like AI-based models have a great ability to find a complex relation between rainfall and runoff from historical data. Some of the commonly used artificial intelligence models used in rainfall-runoff and SSL modeling's are presented as follows.

ANN in Rainfall-runoff and SSL modeling

ANN is a model usually designed to mimic the function of the human brain (Abba and Elkiran, 2017). ANN models are nonlinear statistical and mathematical modeling tool which is very useful in solving several engineering and hydrological problems. This model contains a large number of high processors and neurons which can solve the problem of a highly complex and large amount of spatially and temporal variable data (Dogan et al., 2008). In hydrological modeling diffrent ANNs such as multilayer perceptron (MLP) and radial basis function neural network (RBFNN) and feed forward neural network (FFNN) are commonly used (Kumar et al., 2005). Many studies compare these models based on their capability in simulating nonlinear process (Singh et al., 2013). Generally, based on many studies all ANNs model performs well in any hydrological process even though it depends on network type and number of input variables (Mutlu et al. , 2008).

ANN models have numerous advantages although they have some drawback such as over training, getting trapped in local minima, subjectivity in model parameter determination and the components of its structure (Okkan and Serbes, 2012). Regardless of some drawbacks, ANN is one of the most widely used soft computing techniques which contains interconnected dense nodes (Alp and Cigizoglu, 2007; Kalteh, 2013). ANN has the ability to store and extract information from the few data during training by learning. It has gained great recognition especially in the modeling of sediment load, rainfall-runoff, precipitation and ground water modeling (Sharma et al. , 2015).

Wu Chau (2011) studied the rainfall-runoff relation in the two basins of china using ANN coupled with singular spectrum analysis (SSA). This study has eliminated the lag effect in predicting runoff by using singular spectrum analysis and modular artificial neural network for data processing. They used daily collected data for training and testing of the model. The result of this study showed that ANN provides better performance in runoff prediction when it is coupled with singular spectrum analysis.

Melesse et al. (2011) used ANN for modeling the SSL of three major rivers in the USA and compare the result with multiple linear regression (MLR), autoregressive integrated moving average (RIMA) and multiple nonlinear regression (MNLR). They used precipitation, current-day discharge, antecedent discharge and antecedent SSL values to predict the current-day SSL. They used R^2 model efficiency (E) and mean absolute percent error (MAPE) to evaluate the performance of the models. The result showed the superiority of the ANN model over the other models. Kisi et al. (2012) compared ANN, SVM, GP and ANFIS in modeling suspended sediment in Cumberland River ,U.SA using different combination of antecedent suspended sediment load and discharge as an input. Rajaee et al. (2011) applied a ANN, combined Wavelet–ANN(WANN), sediment rating curve and multilinear regression (MLR) method for estimating the river suspended sediment load and found that WANN showed a good fit between observed and predicted data.

Afan et al. (2014) two different ANNs (FFNN and RBF) to predict SSL using sediment and flow data of Johor River, Malaysia. A good result was obtained from both models, but FFNN performed better than the RBF. Nourani et al. (2012) used geomorphology ANN and multi-station data trained ANN for simulation of suspended sediment concentration of the Eel River, California and concluded that the geomorphological ANN approach led to a better result than the integrated model.

Aytek et al. (2008) apply the ANNs (both feeds forward back propagation and generalized regression neural network) and compared it with gene expression programming (GEP) in rainfall-runoff. They have used daily hydro meteorological data from three rainfall stations as input for the models Juniata River basin, USA. The determination coefficient (R^2) and root mean square error (RMSE) was used to evaluate the performance of these models. The result of this study showed that ANN gave very good result but not as good as GEP and GEP was proposed as an alternative to ANN models.

Dounia et al.(2014) used ANN for rainfall-runoff process modeling and compare the result with GR2M model by using monthly rainfall and runoff data. The result of this study revealed that ANN gave better performance with NSE value of 0.955 compared to GR2M (NSE=0.873). Kumar et al. (2005) applied the two commonly used ANNs multilayer perceptron (MLP) and radial basis function neural network (RBFNN) for rainfall-runoff modeling of Malaprabha catchment, India. The study investigated about 18 different combinations of lag rainfall and discharge values. The study found that RBFNN provided an accurate prediction with R^2 value of 0.99 than that of the MLP model. Many studies compare these two forms of ANN based on their capability in simulating rainfall-runoff and SSL modeling. Generally, based on many studies both model performs good in any hydrological process even though it depends on network type and number of input variable (Singh et al., 2013).

ANFIS for rainfall-runoff and SSL modeling

The ANFIS model, developed by Jang (1993), is a hybrid of neural network and fuzzy logic. According to Jang et al. (1997), ANFIS model being as a combination of

ANN and FIS, can provide reasonable solutions while providing qualitative and heuristic information about the obtained solution. Fuzzy logic (FL) is used to change the linguistic concepts to mathematical and computational architecture. The if-then rule in the FL could provide a better understanding of the nonlinear relationships that may exist between rainfall-runoff-suspended sediment load. FL is to the methods of solving and computing complex problems based on the reasoning ability of human brain (Chandwani et al., 2015). In Fuzzy logic problems are defined without fixed boundaries or unique numbers and uses a set of logical values from sets of numbers ranging from 0 (completely false) to 1 (completely true) called membership functions (MFs) on which the numbers are represented. In ANFIS model, different MFs are available. Among them trapezoidal, Gaussian, triangular and sigmodal functions are the most widely used in hydrological modeling. Fuzzy logic uses the logical operation functions AND /OR and IF-THEN fuzzy rules, each of which has its own definition based on membership concepts. However, it learns physical procedures imprecisely and affecting boundary circumstances. ANFIS, as a combination of ANN and fuzzy inference system improves the learning procedure and detection capacity and known to handle nonlinear and complex phenomenon. ANFIS has been used extensively to solve nonlinear and nonstationary hydrologic such as rainfall-runoff and suspended sediment load modeling.

Babanezhad et al. (2021) applied ANFIS model for prediction of the SSL of different rivers in US. The study applied ANFIS with different membership function and compared with the ant colony optimization technique. They used different statistical indices such as R^2, RMSE, MSE and correlation coefficient (r) to compare the performance of the models. The result revealed that the ANFIS model with trimf gave best result with R^2 value of 0.981.

Bartoletti et al. (2018) studied the rainfall-runoff process with a combination of ANFIS and principal component analysis (PCA). The model used historical rainfall and runoff data as input to produce effective and simplified runoff prediction in the catchment. In this study, a combination of PCA and ANFIS was also used for modeling of the rainfall-runoff process. The study found out that the combined ANFIS-PCA model gives a more accurate prediction of runoff compared to traditional ANFIS model.

Folorunsho et al. (2012) modeled the stream flow of Kuduna River using ANFIS model. The study used 30 years of climatic and discharge data on monthly step. They used 70% of the data for model calibration and 30% for mode verification testing. The performance of the model was assessed using RMSE and correlation coefficient (r). The result of this study revealed that ANFIS-based model performs with high accuracy (r value of 0.86) for predicting the river discharge. (Zakhrouf et al., 2014)also compare ANFIS, ANN and MLR for modeling the rainfall-runoff process in Algerian costal basin. The study used 10 years daily precipitation and discharge data for. The performances of the applied model were evaluated using NSE and MSE and r. The result of this study showed that ANFIS performs better than the other models by giving the highest NSE (0.9364) and r and lowest MSE.

Cobaner et al. (2009) also used ANFIS model for estimation river suspended sediment load in Mad River catchment, USA. The study used historical daily SSL, discharge and precipitation data as input variable to estimate the current day sediment load. The study compares the performance of ANFIS with MLP, GRNN and different sediment rating curve. They concluded that ANFIS model outperforms the other models estimating daily SSL for the particular data they used in the study.

Kaveh et al. (2017) tested different learning algorism of ANFIS model such as hybrid, Levenberg-Marquardt (LM) and backpropagation for SSL prediction using different combination of discharge and previous day SSL. The obtained result of this study showed that the all the training algorithm gave good result however network trained with Levenberg-Marquardt algorism gives better accuracy in prediction sediment.

Kottuvayal et al. (2014) applied ANFIS and ANN for rainfall-runoff modeling of Vamanapuram river basin. The accuracy of the models was compared using RMSE and DC. The result of this study showed that the ANFIS model provides more accurate prediction than ANN by providing lower RMSE and higher DC. The performance of ANN and ANFIS was also compared by Panchal et al. (2016) in modeling rainfall-runoff process in Dharoi sub basin, India. The study used 10 years of monthly precipitation and discharge data for validation and calibration. The result revealed that the ANFIS model provided more accurate in rainfall-runoff prediction compared to ANN.

SVM for rainfall-runoff and SSL modeling

In recent years engineering research had directed towards intelligent system development that can automatically model a complex hydrological process. This process has high dimensional nature, non-uniform and data for them are limited. This problem had resulted in the literature to use machine learning techniques for building models. SVM is one of AI model developed by (Vapnik, 1995) which is gaining popularity due to its promising performance and attractive features.

In recent years SVM has extensively used in modeling of many hydrological processes and water management. Okkan and Serbes (2012) applied least square support vector machine (LSSVM) and ANN for forecasting runoff process in Tahtali and Gordes watersheds, Turkey. They also compared the accuracy of SVM and ANN with other autoregressive moving average and multiple linear regression models. The result of this study indicated that LSSVM and ANN give better prediction performance than the conventional statistical models. LSSVM also provided better performance compared with ANN.

Kisi et al. (2012)used Genetic programming (GP), ANFIS, SVM and ANN in estimating suspended sediment load. According to this study, SVM gives a good modeling result. Kişi and Çimen (2009) also applied SVM in the modeling of reference evapotranspiration. In this study, the accuracy of SVM was compared with ANN and many other empirical models. The result revealed that SVM out performs and can be successfully used in modeling of reference evapotranspiration. Another study by Tabari et al.(2013) used ANFIS and SVM for modeling crop evapotranspiration and compared them with various empirical models. The result showed that SVM and ANFIS give better forecasting performance than the empirical model.

Sedighi et al. (2016) compared the performance of SVM and ANN to simulate the rainfall-runoff process in snow watershed in Iran. They used temperature, discharge, rainfall and snow water equivalent (SWE) data as input to predict runoff. The study used RMSE and R^2 to evaluate the performance of the applied model. The study concluded that the ANN model performed better than the SMV.

Wang et al. (2013) estimated the SSL process using SVM, FFNN and particle swarm optimization (PSO) in Yellow River, China. To enhance the performance of the model, they proposed ensemble empirical mode decomposition (EEMD) to decompose the annual the annual rainfall in rainfall runoff modeling based on SVM. The result of the study showed that the proposed PSO–SVM–EEMD model enhanced the overall rainfall-runoff forecasting performance.

Kakaei et al. (2013) used SVM (using four kernels) and ANN to predict the daily SSL of Doiraj River, Iran. The study used 11 years of rainfall and discharge as input to predict SSL. The best input identification was conducted using a combination of genetic programing and Gamma test and compared with the result of Pearson correlation analysis. The performance of SVM and ANN in SSL estimation was evaluated using NSE, R^2, MAE and Efficiency Index (E). The result showed that ANN model led the best result and among different SVM model, radial basis function (RBF) give the best estimation performance.

Meshram et al. (2020) applied SVM, FFNN, RBF, and multi-model ANNs for sediment yield modeling in the Manot and Shakkar watersheds in India. The study used 10 and 25 years of rainfall, runoff, and sediment data for the Manot and Shakkar watersheds, respectively. The study evaluated the performance of the developed models based on the lowest relative absolute error (LARE), NSE, RMSE and correlation coefficient (r). Among the applied models, the multi-model ANN provided better prediction with LARE = 0.344 and 0.36, r= 0.883 and 0.921, RMSE= 269,671.5 and 23,609.5 , NSE= 0.763 and 0.744 in testing period for Manot and Shakkar, respectively.

Kumar et al. (2022) uses wavelet-based SVM (WSVM) and SVM and compares their results with other three data-driven models, namely MLR, wavelet-based ANN (WANN) and ANN for suspended sediment concentration (SSC) prediction in the Subernrekha catchment, India. For this purpose, 10 years of daily water levels (h), SSC and discharge (Q) were used for the analysis. They used different input combinations and sensitivity analysis was performed using gamma test. The performances of the models used were evaluated with RMSE, NSE, r and Wilmot index (WI). The result of the study showed that the WSVM model with NSE, RMSE, r and WI value of 0.861 and 0.541, 0.117 g/l and 0.095 g/l, 0.928 and 0.751, 0.962 and 0.859, respectively, led to a better result in the calibration and verification phase.

Misra et al. (2009) also applied SVM and ANN were used to estimate SSL and runoff on a daily, weekly, and monthly basis. Multilinear regression pattern recognition (MLRPR) was also tested for modeling runoff. The result showed that SVM gave a better result than ANN for both SSL and runoff modeling. It also showed that MLRPR performed worse than the other models in runoff modeling.

The SVM, random forest (RF) and ANN model were used by Al-Mukhtar (2019) to estimate suspended sediment load in Tigris river, Baghdad. The study used 10 years of SSL and runoff data for model calibration and verification. In this study the data was divided as 75% and 25% for calibration and verification, respectively. Based on the RMSE, NSE and R^2 values, RF provided the most accurate result than the other models.

Linear regression models

Linear regression models (LRM) is empirical model that is applicable in solving linear problem. One of the big problems in the statistical analysis is to find a suitable relationship between a dependent variable and a set of independent variables. Regression analysis is thus used to describe the quantitative relationship between dependent variable and one or more independent variables (Tabari et al., 2010; Tabari et al., 2011). Regression models have been applied in hydrology in forecasting time series hydrological process such as in evapotranspiration (Tabari et al., 2012), rainfall-runoff modeling (Lateef Ahmad, 2017) and reservoir operation. The physically-based models (e.g SWAT, HBV and HEC-HMS) can incorporate simple linear laws and assume time varying, non-linear and deterministic parameters in modeling. Therefore, in this study MLR is applied only for SSL modeling.

Physical model

The physic-based or water balance model uses equations to simulate the movement of water throughout the system until it leaves. There are many physically based hydrological models used in forecasting of the rainfall-runoff process. Among them, a semi-distributed physically based hydrological model such as SWAT, HBV and HEC-HMS were selected for this particular study.

SWAT for rainfall-runoff modeling

SWAT model is a semi-distributed physical model that operates on a daily time step (Arnold et al., 1998). This model was first developed by the United states department of agriculture to simulate land management impacts on water, agricultural chemical and sediment yield of complex catchment over a long period of time. This days SWAT model has extensively been applied in hydrological study (Iskender and Sajikumar, 2016; Jeong et al., 2010; Noori and Kalin, 2016; Vilaysane et al., 2015; Zhang et al., 2008). In SWAT model the watershed is divided into subwaterseds and which is then devided into HRUs based on the soil type, land use and slope. Dividing the catchment into sub-watersheds enables the SWAT model to reflect the effect of hetrogenity of catchment characterstics and nonuniform distribution of climatic variables on the output.

Ahmadi et al. (2019) compared IHACRES, SWAT and ANN for rainfall-runoff simulation of Kan watershed, Iran, on an annual, monthly and daily basis. The result of the study confirmed that three of the considered models are suitable for simulation of the rainfall-runoff process even though the ANN model outperformed the other two models. Hallouz et al. (2018) also used SWAT for a small agricultural watershed (Wadi Harraza's), Algeria. Good result was obtained based on model evaluation criterias.

SWAT model was also used for hydrological characterization and assessment of Lake Ziway sub-watersheds, Ethiopia. Brighenti et al. (2019) also applied the SWAT model for runoff and sediment simulation with two different calibrations (simultaneous and sequential techniques. The result suggested that good result was obtained from the modes even though the simultaneous calibration method shows superiority over the other method.

Bizuneh et al. (2021) used SWAT and HBV models to simulate the runoff from three watersheds in the upper Blue Nile basin, Ethiopia. The study used Nash-Sutcliffe Error (NSE) as a performance evaluation criterion and found that the two models used produced acceptable results in both calibration and validation phases. Biru and Kumar,

(2018) applied the SWAT model for runoff and suspended sediment load simulation of Mojo watershed, Ethiopia. They concluded that the model showed a good simulation performance of runoff with NSE of 0.7 in the verification phase. Melaku and Wang, (2019) applied a modified SWAT model to estimate the groundwater table of two locations (Barons and Lethbridge), Canada. The result showed the modified SWAT showed an improvement of modeling accuracy in the groundwater table.

Ahmadi et al. (2019) compared IHACRES, SWAT and ANN for rainfall-runoff simulation of Kan watershed, Iran, on an annual, monthly and daily basis. The result of the study confirmed that three of the considered models are suitable for simulation of the rainfall-runoff process even though the ANN model outperformed the other two models.

Hallouz et al. (2018) also used SWAT for a small agricultural watershed (Wadi Harraza's), Algeria. SWAT model was also used for hydrological characterization and assessment of Lake Ziway sub-watersheds, Ethiopia. Brighenti et al. (2019) also applied the SWAT model for runoff and sediment simulation with two different calibrations (simultaneous and sequential techniques. The result suggested that good result was obtained from the modes even though the simultaneous calibration method shows superiority over the other method.

HEC-HMS for rainfall-runoff modeling

HEC-HMS hydrological model was developed by the US Army Corps of Engineers (Feldman, 2000) for simulating many hydrological process. HECH-HMS model was origionaly developed for modeling rainfall-runoff process for dendric watershed in time and space. Latter,the applicability of this model was expanded and have been applied to model many hydrological studies due to its ability of providing acceptable runoff simulation, operational simplicity and use of commen methods (Tassew et al., 2019). Generally, different hydrological parameters can be simulated using HEC-HMS such as runoff, evapotranspiration, precipitation and groundwater discharge in which simulation of each parameter is done using separate method. In this model, the spatial and temporal distribution of the rainfall can be evaluated using different methods such as soil conservation service, grided precipitation, specified hyetograph etc.

HEC-HMS model comprises different components such as terrain data manager, basin model, control specification, meteorological model and time series data manager. This model is becoming increasingly popular because it is user friendly, can successfully simulate both continuous and event-based runoff. Also, it can be used to solve various hydrological problems such as rainfall-runoff modeling, flood prediction and warning, project planning and watershed management irrespective of the size of the catchment. For rainfall-runoff the model uses different inputs such as temperature LULC, precipitation, runoff and evapotranspiration.

Previous studies on the use of HEC-HMS on simulation and forcasting of runoff proved its ability to give acceptable result on different catchment type and datasets. Those studies indicated that the simulation result of the model were location specific, in that runoff transform method, loss method and baseflow separation methods were found to be variable (Tassew et al., 2019).

The tudy conducted by Abushandi and Merkel (2013) on the Dhuliel arid catchment, Jourdan used Hec-Hms and IHACRES to model rainfall-runoff process. The result of this study revealed that HEC-HMS model can give more accurate result.

Aliye et al. (2020) evaluated the performance of HEC-HMS model and compared it with the SWAT model for rainfall-runoff simulation in data scarce region of Ethiopian rift valley lake basin. The result obtained in this study, using R2 and NSE, indicated that the rainfall-runoff simulation ability of the HEC-HMS model was better than the SWAT model for that specific catchment.

Zelelew and Melesse (2018) applied HEC-HMS model runoff estimation at Angereb catchment, Upper Blue Nile, Ethiopia. The objective of the study was to compare different loss method and transfer method and test it for ungauged catchment. For this they used two loss methods namely initial and constant method and soil conservation service methods and two transfer methods namely Clark unit hydrograph and SCS-unit hydrograph. The result of the study showed that constant and initial loss method with SCS unit hydrograph transform method gave best result.

HBV for rainfall-runoff modeling

The HBV, developed by the Swedish Meteorological and Hydrological Institute, is a conceptual semi-distributed rainfall-runoff model. This model is simple and requires small number of inputs such as daily temperature, rainfall and evapotranspiration. It gives relatively good result and its structure is flexible in which the watershed is subdivided on different land use, elevation band and vegetation zones (Lindstrom et al., 1997). In last previous decades, this model has been widely used applied in rainfall-runoff simulation of ungauged watershed, design flood computation and water quality modeling. The HBV model for rainfall-runoff modeling has hydrologic routines namely snow routine, response routine, soil routine and routing routine. The threshold temperature (TT) in the snow routine defines the range of temperature at which the snow starts melting. The main routine, soil routine, controls the transformation of rainfall or snow melt to runoff. The transformation function in the response routine converts the excess flow in the soil routine to runoff. At the outlet point, the runoff hydrograph can be obtained in the routing routine by transforming the runoff from the response routine. This model has been used for various hydrologic modeling and has demonstrated the best modeling capability in modeling climate change (Kazemi et al., 2019), runoff simulation (Esmaeili-gisavandani et al., 2021) and water level prediction (Pervin et al., 2021).

Bizuneh et al. (2021) applied HBV model to simulate the stream flow of three watersheds in Blue Nile River basin. Based on the NSE value, the model gave acceptable result even though it shows unfactored result in the extreme too dry and too wet conditions. Also Esmaeili-gisavandani et al. (2021) used HBV model for rainfall-runoff modeling in Iran and compare the result with other models. They used NSE, RMSE and KGE to evaluate the performance of the models. The result of this model showed that HBV model gave acceptable result (NSE=0.55), but not as good as the SWAT model.

Uhlenbrook et al. (2010) applied the HBV model for stream flow characterization of Koga and Upper Gilgel Abay catchments. They analyzed the model’s response for stream flow in lumped, lumped with various vegetation zone and semi-distributed with various elevation and vegetation zone condition. The study found that the HBV model applied for semi-distributed catchment gave very good result with NSE value of 0.8. Ren et al. (2018) used combined HBV model and Bayesian neural network (BNN) for prediction of stream flow in Alpine region. In this study, in the first step, the stream flow was modeled by HBV and BNN. Then, a hybrid of the two models was then developed to further improve the stream flow prediction. The result of this study revealed that more accurate result was obtained from the hybrid model than the single models.

Ensemble techniques rainfall-runoff and SSL modeling

Ensemble technique is a kind of machine lernean in which the results of single models are combined using different technique to improve the overall modeling performance. To date, various ensemble methods have been applied in the field engineering. The methods employed in previous studies are either linear or non-linear ensemble methods. The linear ensemble methods include the weighted average ensemble (WE) and simple average ensemble (SE) whereas the non-linear combination methods include artificial neural network (NE), gene expression programming (GEP), symbolic regression, Bayesian model averaging method, and fuzzy based methods. Generally, linear ensemble methods; namely SE and WE are most commonly applied for stream flow forecasting. These methods are also used as a benchmark for comparing the results with other ensemble techniques (e.g. ANN methods and regression methods). Many published studies showed that SAM ensemble method can provide forecasts that are better than those obtained by single models (Makridakis and Winkler, 2008; Nourani et al., 2019; Sharghi et al., 2018; Timmermann, 2005)

The application of model combination techniques was first published by Bates and Grange (1969) in the field of economic forecasting. This study used the weighted average method of combining the results from a different set of forecasting models. The result of this study revealed that the ensemble technique performs better than the individual forcasting models. Since then the advantage of ensemble technique has been demonstrated in different field of studies (Armstrong, 2001; Deutsch et al., 1994; Palm and Zellner, 1992). The result from these studies showed that the ensemble technique could lead to significantly increased performance by reducing forecasting error as compared with the result of single models.

The first model combination methods in the field of hydrology were investigated by Cavadias and Morin (1986). They used ten hydrological models for simulating the discharge and combined the result of these models using three different combination methods. The result of this study showed that ensemble the simulated discharge improved the performance by 80% more than the individual model results. In rainfall-runoff forecasting, Shamseldin et al. (1997) compared three ensemble methods: WE, NE and SE to combine the obtained results from five different rainfall-runoff models. The result revealed that the ensemble output was more accurate than the best single model and the NE ensemble method outperforms as compared with another ensemble method. Later, a real-time model output combination method was developed and tested by Shamseldin and O'connor (1999) using three different rainfall-runoff models on five watersheds. Their result indicated that the ensemble streamflow output was better than that of the single outputs. Coulibaly et al. (2005) found that using WE for combining three different models can significantly improve the accuracy of the daily reservoir inflow forecast.

Another study by See and Openshaw (2000) forecasted Ouse river's flow in northern England by applying a hybrid multi-model approach. The study developed four different conventional and AI-based approaches namely: the ARIMA model, hybrid neural network, naïve prediction and simple rule-based fuzzy logic models to give a hybridized solution for flood and river level problem. These individual models were then combined through four approaches: Bayesian approaches, simple average, and two fuzzy logic models (fuzzification of crisp Bayesian method, and based current and past river flow condition). The result indicated that the proposed combined model provides better output than the individual models and crisp Bayesian model yielded results superior to other integrated(combined) methods.

Xiong et al. (2001) introduced and applied a novel combination method of first-order Takagi-Sugeno fuzzy system (besides the neural network ensemble (NNM), weighted average method (WAM) and simple average method (SAE) to combine the output from five different rainfall-runoff models on eleven watersheds. The result showed that the output of the combined model was more accurate than the individual single models and the first-order Takagi-Sugeno fuzzy system as an efficient result as WAM and NN₀.

Fernando et al. (2012) also applied Gene expression programing (GEP) to combine the output from four different conventional (two black boxes and two conceptual) rainfall-runoff models on four different catchments. They found that GEP combination gives an improvement in forecasting rainfall-runoff process compared to an individual single model. They concluded that GEP can be used as an alternative to combine multi-models in rainfall-runoff modeling.

The applicability of ensemble techniques for SSL estimation has not been reported in literature. Thus, this study was the first study which applied the two nonlinear (AE and NE) and two linear ensemble techniques (WE and SE) for SSL modeling in Katar catchment.

CHAPTER III

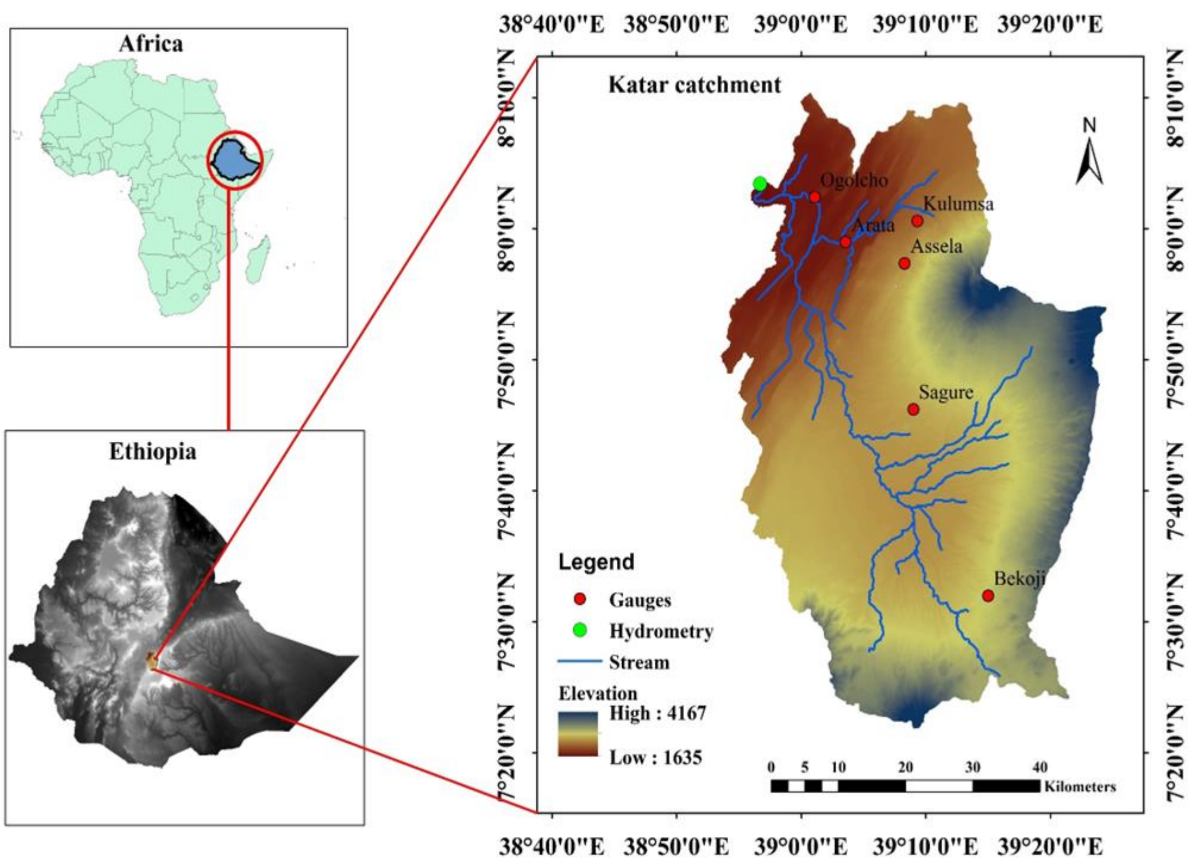
Methodology

Description of the study area

The study was conducted in the Katar catchment, a sub-catchment of Ethiopian central rift valley basin. The catchment is located at latitude 7.359° to 8.165°N and longitude 38.899° to 39.41°E (see Fig. 1), covering an area of 3350 Km^2. In the study area, the main river (Katar River) and its tributaries originating from the eastern parts of Chilalo, Lalema and Kakka mountains drains to Lake Ziway. The catchment is characterized by complex topography where elevations vary between 1635 m to 4167 m above mean sea level.

Figure 1

Map of Katar catchment



Climate and hydrology of the study area

Semiarid to sub-humid climates are the main characteristics of Katar catchment with average annual temperature of 16-20 °C. The minimum and maximum annual rainfall of the area is 729.6 mm and 1231.7 mm, respectively. The dry period of the year extends from October - May and the wet season occurs from June to September (contribute about 70% of the rainfall). In the catchment, six meteorological stations are available namely, Sagure, Assela, Bekoji, Arata, Kulumsa and Ogolcho (see Figure 1). The area has one stream gauging station (Abura), at the catchment outlet, which gets a maximum flow in August (152.033 m^3/s) and a minimum flow in January (0.106 m^3/s).

Soil and land use

The study area comprises six dominant soil types namely luvisols, andosols, fluvisols, cambisols, nitisols and vertisols (Aga et al., 2018). The common land use type of the catchment is agriculture where both rainfed and irrigated crops are grown. In addition to agriculture, other land use type includes afro-alpine, wetland, waterbody, shrublands and settlement (urban area).

Methodology

Data type and source

In this work, 12 years (2006-2017) of daily rainfall, minimum and maximum temperature, runoff, and 2 years (2016-2017) of SSL data (due to data shortage) were used for rainfall-runoff-sediment modeling. For rainfall-runoff modeling, the first two years of data (2006-2007) were used for the warming period (for SWAT and HBV model), seven years of data (2008-2014) were used for calibration, and the remaining three years (2015-2017) of data were used for validation. Due to data scarcity, only two years (2016-2017) SSL and runoff data were used for modeling SSL. In SSL modeling, from the two years of data, 70% was used for calibration and the remaining 30% of the data was used for validation. The climate data such as minimum temperature, daily rainfall, and maximum temperature from six meteorological stations were collected from the Ethiopian National Meteorological Agency. The runoff data recorded at the Abura gauging station were obtained from the Ethiopian Ministry of Water, Irrigation and Energy. The descriptive statistics of Thiessen polygon average rainfall, SSL, and runoff are shown in Table 1.

Table 1

Statistics of Runoff, SSL and Rainfall Data

Data type	Period	Statistical parameters				
		Minimum	Average	Maximum	Standard deviation	Coefficient of variation
Discharge (m^3/s)	Calibration	0.106	11.848	152.033	19.043	1.6073
	Validation	0.115	12.995	126.779	20.4354	1.57255
	Whole	0.106	12.192	152.033	19.47834	1.5976
Rainfall (mm)	Calibration	0	71.2	2.1277	4.658	2.1891
	Validation	0	2.6243	52.4	5.2445	1.9984
	Whole	0	2.2767	71.2	4.8467	2.1288
SSL (ton/day)	Calibration	0	1760.29	57335.524	5102.626	2.899
	Validation	0	3391.36	52947.35	5850.01	1.725
	Whole	0	2248.94	57335.52	5389.566	2.397

Physically-based models require not only climatic and hydrological data, but also spatial data such as soil maps, land use maps, and digital elevation models (DEM). The soil map was prepared by downloading global soil map from the Food and Agriculture Organization (FAO) database and clipped it to the size of the Katar catchment. The other basic input for physically- based models to get terrain information, DEM with a 30m x 30m resolution was obtained from the Shuttle Radar Topography Mission (SRTM) of https://earthexplorer.usgs.gov/. In the catchment, different process such as flow rate, evapotranspiration, infiltration rate and soil erosion are highly influenced by land use type. Therefore, Landsat image was downloaded from the United States Geological Survey website to prepare the land use map of the study area. Then, the satellite image was processed using ArcGIS 10.3 to generate the required land use information.

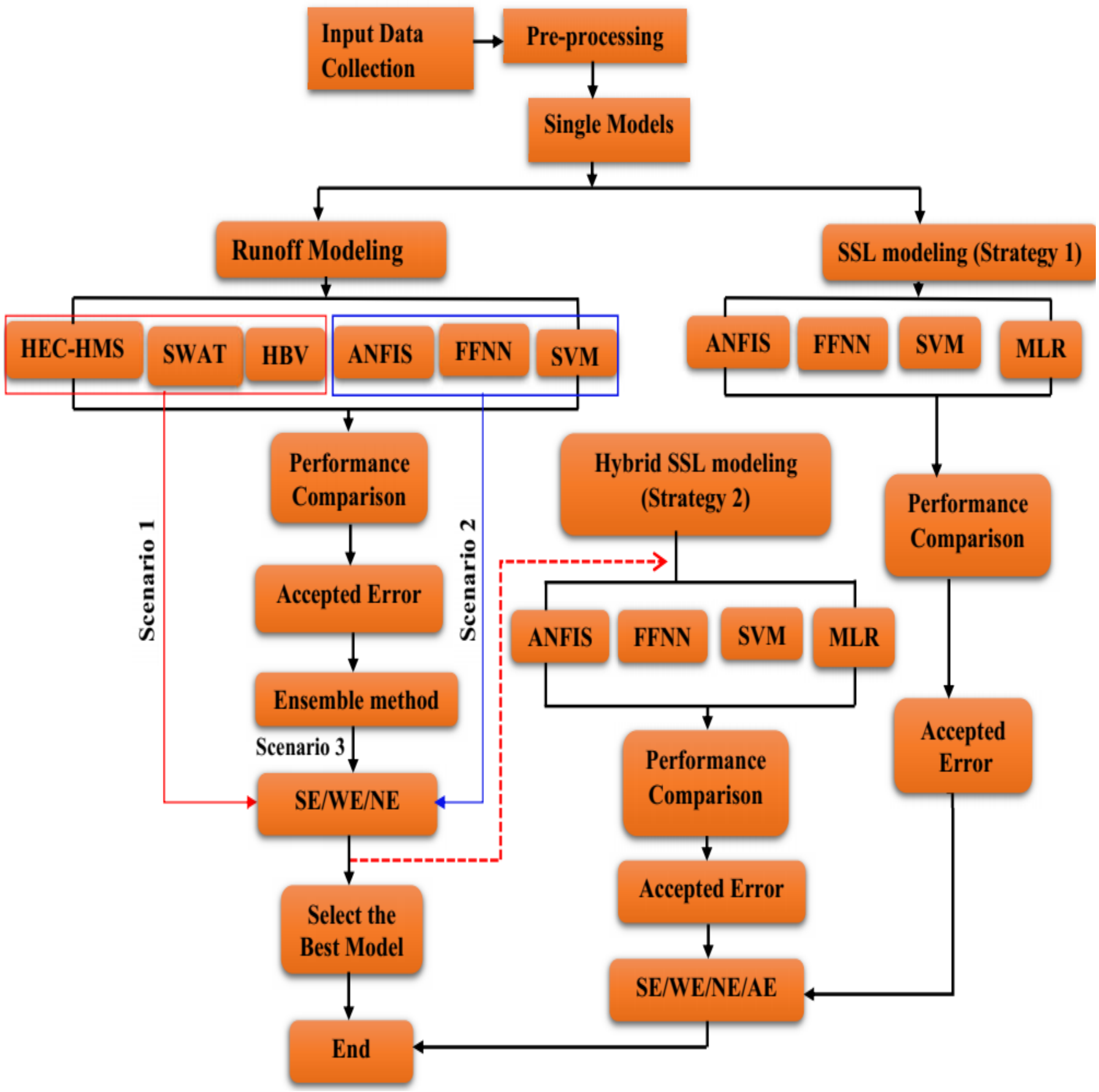
Proposed models

For this study two physically based model (SWAT and HEC-HMS), one conceptual semi-distributed (HBV) model and three AI models (SVM, ANFIS and FFNN,) was used for the rainfall-runoff modeling in the Katar catchment. Similarly, three AI-based (SVM ANFIS and FFNN) and multilinear regression (MLR) models was employed for SSL modeling. For AI-based models, the input data used was first normalized and partitioned in to training and validation sets in order to model the rainfall-runoff-sediment process. Moreover, for this study three ensemble techniques such as neural network ensemble (NE), weighted average ensemble (WE), simple average ensemble (SE) and ANFIS ensemble (AE) (for SLL only) was used to improve the overall modeling efficiency. A combination of different AI models (ANFIS, FFNN, and SVM), conceptual model (HBV) and physically model (SWAT, HEC-HMS) was examined in the modeling framework.

The study was conducted in five steps. In the first step, a sensitivity analysis was performed to identify the most important inputs in modeling rainfall-runoff and SSL. Secondly, rainfall-runoff and SSL modeling was conducted via single models. In this step, three AI based (ANFIS, SVM, and FFNN) and three physical based models (SWAT, HBV and HEC-HMS) were used for rainfall-runoff modeling. For SSL modeling, only the AI-based (ANFIS, SVM, and FFNN) and MLR models were used due to the complexity of the process and data scarcity. In the third step, the runoff results of each model from second step were combined using three ensemble techniques (SE, WE and NE) in three scenarios. In the first scenario, only the result of the three physically based models were combined using the proposed ensemble techniques. In the second scenario, only the outputs of the three AI-based models were considered in the ensemble unit. In the third scenario, all six models (both physically-based and AI-based models) were ensembled using the WE, SE and NE technique. Similarly the SSL value obtained by the AI-based and MLR models in the second step was ensembled via SE, WE, AE and NE. In the fourth step, the runoff results obtained by the best ensemble technique in step three (from each scenario) with lagged discharge were used as input for SSL modeling via ANFIS, SVM, FFNN and MLR. Finally, the SSL value obtained from each individual model in step four was ensembled via AE, NE, WE and SE. The results of each model and ensemble techniques were compared. The general procedure of the proposed methodology is shown in Figure 2.

Figure 2

Schematic Representation of the Proposed Methodology

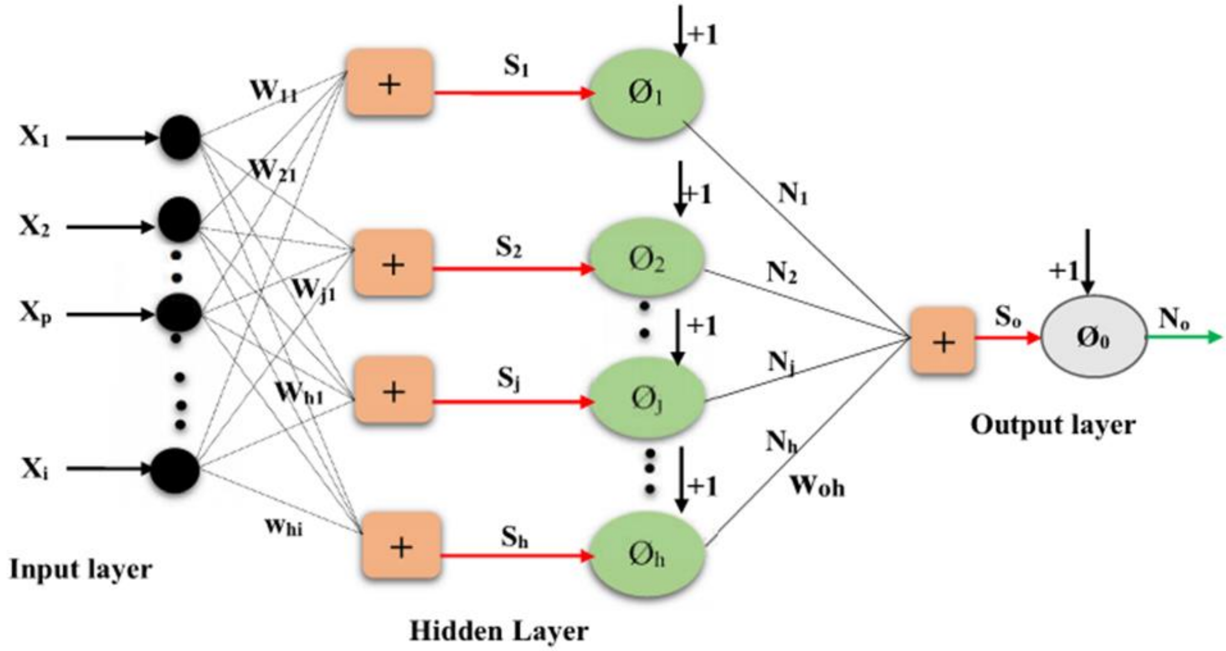


FFNN

ANN is one of the most widely used AI-based model which mimics the simulation and learning ability biological neural network operation performance. This model provides an outstanding methodology in handling with nonlinearity, nonstationary and noisy data particularly when the physical relationships are not fully understood. Its ability to learn from training data makes ANN applicable and robust in areas of mathematics, engineering, science and business (Kumar et al., 2014). Among the different forms of ANN, the FFNN trained by BP is the most widely applied because of its simplicity and convergence time. The name FFNN is derived from the way information is transmitted. In this method information flows only in forward direction (Umar et al., 2021). The structure of FFNN is shown in Figure 3. The FFNN structure consists of nodes, a interconnected processing element having unique properties such as learning, nonlinearity, tolerance, and other data processing capabilities (Kumar et al., 2014). FFNN have different layer such as input, hidden and output layer as shown in Figure 3. In this model, weights connect progressing layers and neurons. The backpropagation algorithm was used for the learning phase. For this particular study, FFNN was chosen because it has the unique advantage of providing exceptional solutions to various problems without the need to know the mathematical calculations of the parameters. In this model adjusted weight is applied to each input and transfer function is used to pass it in order to provide output for that node. Among transfer functions, sigmoid function, the most widely applied function, is then acts on sum of weight of input neuron (Ghaffari et al., 2006). The neural network establishes the relationship between the data by iteratively adjusting the weight.

Figure 3

The Structure of ANN Model (Tanty and Desmukh 2015)



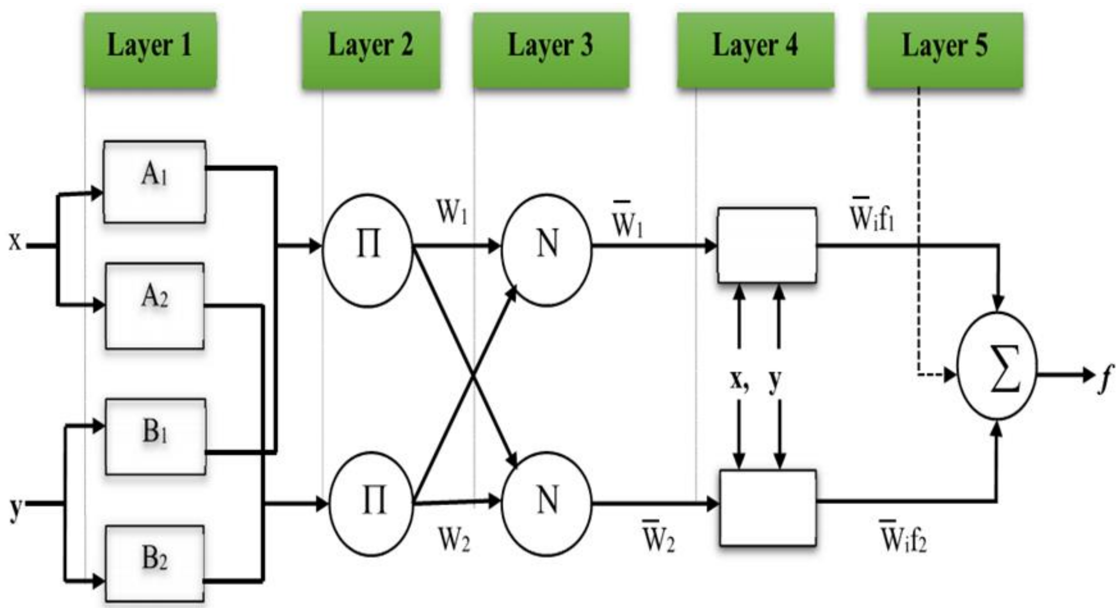
ANFIS

ANFIS, the other important model, is universal approximator first developed by Jang (1993) as a hybrid of ANN and FIS to solve the limitations of ANN and FIS. As a hybrid model, ANFIS combines the advantage of ANN learning ability and reasoning ability of rule-based FIS that can include past observation in to classification process. In this model, fuzzy logic definition is used to built the system and neural network automatically optimizes the system parameters as opposed to manual optimization in building system in FIS (Rai et al., 2015). The flexibility and adaptability of ANFIS model makes it a proven approach in processing the uncertainty in the data that is as well as its high ability to handle large noisy data from dynamic and complex systems (Nourani et al., 2020).

According to Nourani and Komasi(2013) fuzzy database fuzzifier and defuzzfier are the three parts of fuzzy system. Also, the inference engine and fuzzy rule are the two parts of the fuzzy database. As result most operational analysis is performed via Fuzzy inference engine. Among different FIS, in the present study, the Sugeno first-order fuzzy model was used. In ANFIS, model calibration requires definition of fuzzy language rules. In this model, calibration of MF can be made using least square and or BP. The ANFIS structure consists of five layers each named after their operational functions with layer 1, layer 2, layer 3, layer 4 and layer 5 representing the input, input MF, the rule, the output MF and the output, respectively as shown in Figure 4.

Figure 4

Structure of ANFIS Model (Nourani et al., 2017)



After building the fuzzy system, if-then rule is used to establish the relationship between input and output variables. A Siguro system assuming a FIS containing only wo inputs (x and y) and one output (f), has the following rules (Eq. 1 and 2).

$$\text{Rule (1): if } \mu(x) \text{ is A1 and } \mu(y) \text{ is B1: then f1} = \text{p1x} + \text{q1y} + \text{r1} \qquad (1)$$

$$\text{Rule (2): if } \mu(x) \text{ is A2 and } \mu(y) \text{ is B2: then f2} = \text{p2x} + \text{q2y} + \text{r2} \qquad (2)$$

Where A_1, A_2, B_1 and B_2 are MFs parameters for input x and y. Whereas, p_1, q_1, r_1, p_2, q_2, r_2, are outlet functions' parameters of *f*.

The description and structural formula of each five layers of ANFIS are as follow:

Layer 1: Every node i is an adaptive node in this layer, which has a node function as Eq. (3).

$$Q_i^1 = \mu Ai(x) \text{for } i = 1,2 \text{ or } Q_i^1 = \mu Bi(x) for\ i = 3,4 \quad (3)$$

Where Q_i^1 is membership grade for x or y.

Layer 2: in this layer, T-norm operator connects each rule between inputs with "AND" operator as in Eq. (4).

$$Q_i^2 = \text{wi} = \mu Ai(x).\, \mu Bi(y) \text{ for i} = 1,2 \quad (4)$$

Layer 3: Normalized firing strength is the output in this layer and calculated as:

$$Q_i^3 = \bar{w} = \frac{w_i}{w_1+w_2}\ for\ i = 1,2 \quad (5)$$

Where $\bar{w}$ is the output

Layer 4: Each node i in this layer calculates the consequence of the rules on the output of the model:

$$Q_i^4 = \bar{w}\ (p_i x + q_i y + r_i) = \bar{w} f_i \quad (6)$$

Layer 5: The total output of the model is computed by adding all incoming signals to this layer as:

$$Q_i^5 = \bar{w}(pix\ +\ qiy\ +\ ri) = \Sigma w_i f_i = \frac{\Sigma w_i f_i}{\Sigma w_i} \quad (7)$$

SVM

Support vector machine (SVM) , one of the AI-based model which is a proven solution for acceptable regression, prediction, and classification tasks (Kalteh, 2013). Statistical learning and structural risk minimization theory are the two important features that makes SVM different from other AI models such as ANN. Among different SVM-based models, Support vector regression (SVR) is used for regression and employs structural risk minimization. SVR is a comparatively new model that can be used to successfully model complex, daynamic and nonlinear processes. As with other SVM-based models, minimizing operational risk is the main goal of SVR. This distinguishes them from other AI models, where the main objective is to minimize the difference between observed and calculated values. The SVR consists of two stages in which the data is first fitted to a linear regression and then the output goes through a nonlinear kernel to capture nonlinearity of the data (Umar et al., 2021). For a given data set, $\{(x_i, d_i)\}\overset{n}{i}$

($x_i, d_i$and n denotes the actual value, input vector and number of data respectively), the general SVR function is given by Wang et al. (2013) as:

$y = f(x) = \omega\phi(xi) + b$ (8)

Where ϕ, ω and b are nonlinear mapping function, weight vector and bias term, respectively. The value of ω and b can be computed by giving positive values for the slack parameters of ξ and ξ*and minimizing objective function as:

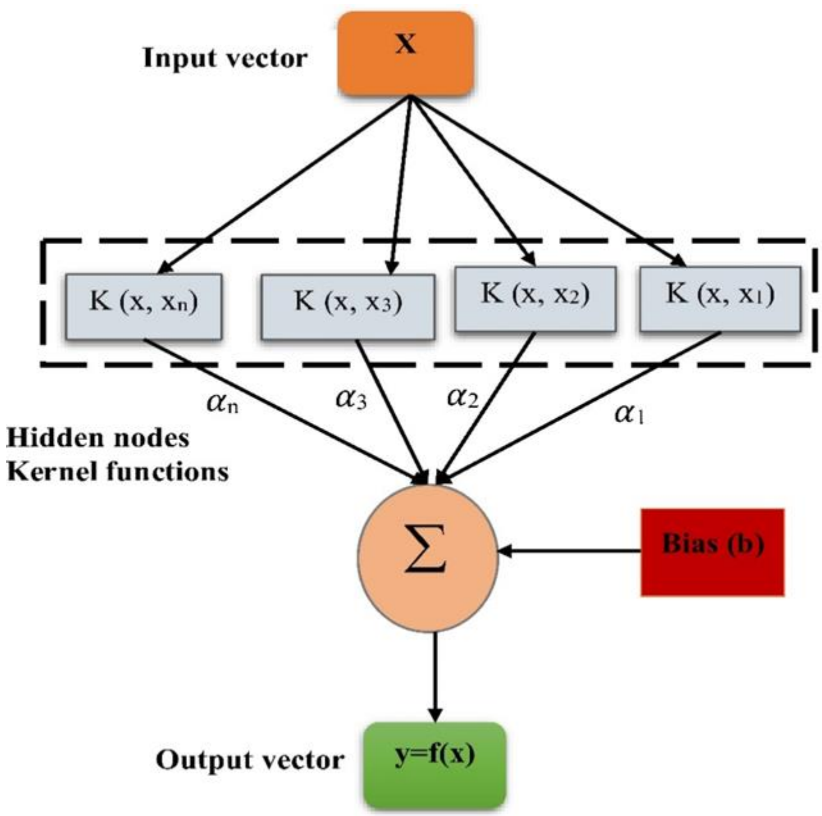
Minimize: $\frac{1}{2} \| w \|^2 + c\left(\sum_{i}^{n} \left(\xi_i + \xi_i * \right) \right)$

Subjected to: $\begin{cases} w_i\varphi(x_i) + b_i - d_i \leq \varepsilon + \xi_i *, i = 1,2, \ldots\ldots, n \\ d_i - w_i\varphi(x_i) + b_i \leq \varepsilon + \xi_i * i = 1,2, \ldots\ldots\ldots, n \\ \xi_i\xi_i *, i = 1,2, \ldots\ldots\ldots, n \end{cases}$

Where: $\frac{1}{2}||w||^2$, c and ε are the weights vector norm, regularized constant and tube size, respectively. The general SVM model structure is given in Figure 5.

Figure 5

The General Structure of SVM



A dual quadratic optimization problem is developed from the optimization problem indicated above by introducing $\alpha_i and\ \alpha_i *$ (langrage multipliers). This quadratic optimization problem is solved using inequality constant and weight vector (ω) can be computed as Wang et al. (2013).

$$w *= \sum_{i}^{n}(\alpha_i - \alpha_i *)\varphi(xi) \quad (9)$$

Thus, the final SVM regression formula is express as:

$$f(x, \alpha_i, \alpha_i *) = \sum_{i=1}^{n}(\alpha_i - \alpha_i *)K(x, x_i) + b \quad (10)$$

Where $k(x_1, x_2)$ is the kernel function.

Among various kernel functions, gaussian radial basis is the most extensively used and is expressed as:

$$k(x_1, x_2) = exp(-\gamma||x_1 - x_2||^2) \quad (11)$$

Where: γ is the kernel parmeter

SWAT

SWAT is a semi-distributed physical-based model that works on a daily time step (Arnold et al., 1998). In the last decades SWAT model has extensively been applied in simulation simulate erosion, infiltration, evapotranspiration, surface runoff, and groundwater flow, and to estimate storage in reservoirs over a long-term period (Iskender and Sajikumar, 2016; Vilaysane et al., 2015). This model requires climate and spatial input data including rainfall, temperature, soil map, terrain data (DEM) and land use and land cover (LULC) map. Although it requires large number of input parameters, SAWT model can provide accurate estimation of runoff on seasonal, monthly and daily time scale (Demirel et al. 2014)

In SWAT model the catchment is divid ed into multiple sub-catchments which are then further subdivided into hydrological response units (HRUs) depending on the soil, land use and slope of the catchment. Surface runoff is then estimated separately for each sub-basin and routed to quantify the total surface runoff of the catchment. This mode comprises different components such as crop growth, sedimentation, hydrology, pesticide, agriculture management and nutrient. A good description of these components is presented by Srinivasan et al. (1998).

The hydrologic cycle (hydrologic component) is expressed in terms of the water balance as:

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{lat} - Q_{gw}\right) \quad (12)$$

Where: SWt is the final water content (mm), SWo is the initial soil water content on day i (mm), t is time in days, R_{day} is amount of precipitation on day i (mm), Q_{surf} is the amount of surface runoff on day i (mm), Ea is the amount of evapotranspiration on day i (mm), Q_{lat} is lateral flow from soil to channel, W_{seep} is the amount of water entering the vadose zone from the soil profile on day i and Q_{gw} is the amount of ground water flow on day i (mm)

Surface runoff is computed using Green–ampt infiltration equation or soil conservation service (SCS) curve number (CN). For this particular study, the SCS curve number method was used to calculate surface runoff as:

$$Q = \frac{(R-0.2S)^2}{R+0.8S}, R > 0.2S \quad (13)$$

$$Q = 0, R \leq 0.2S$$

Where: Q, S, R represents daily runoff (m^3/s), retention papameter (mm) and rainfall (mm), respectively

The value of S is calculated using CN as:

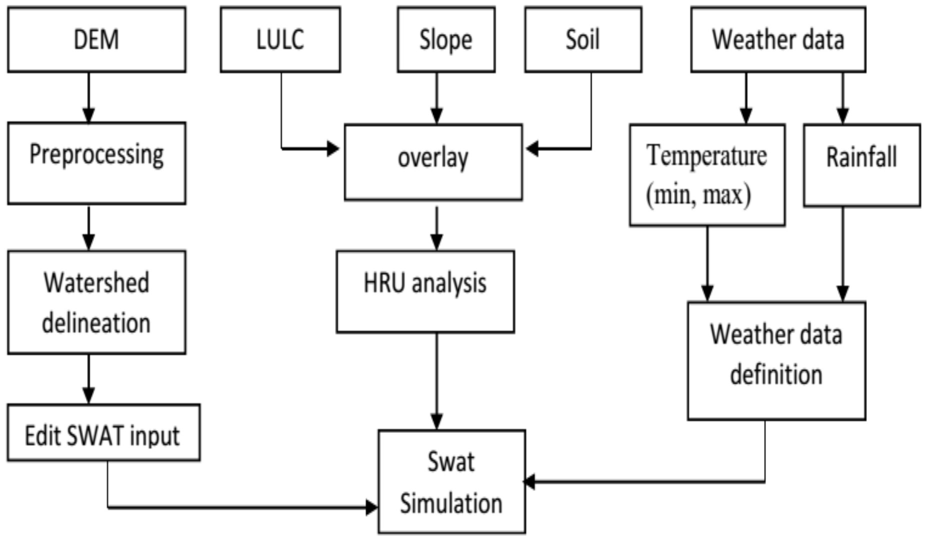
$$S = 254\left(\frac{100}{CN} - 1\right) \quad (14)$$

Where: CN is curve number(ranging between 1 and 100)

In SWATmodel penman monteith or Hargreaves method will be used to calculate the potential evaporation in the catchment (Arnold et al., 1998). The stream flows are adjusted for evaporation diversions, transmission losses, and return flow. A complete description of all the procedure and components in SWAT can be found in the literatures (Arnold et al., 1998; Neitsch et al., 2011) as shown in Figure 6.

Figure 6

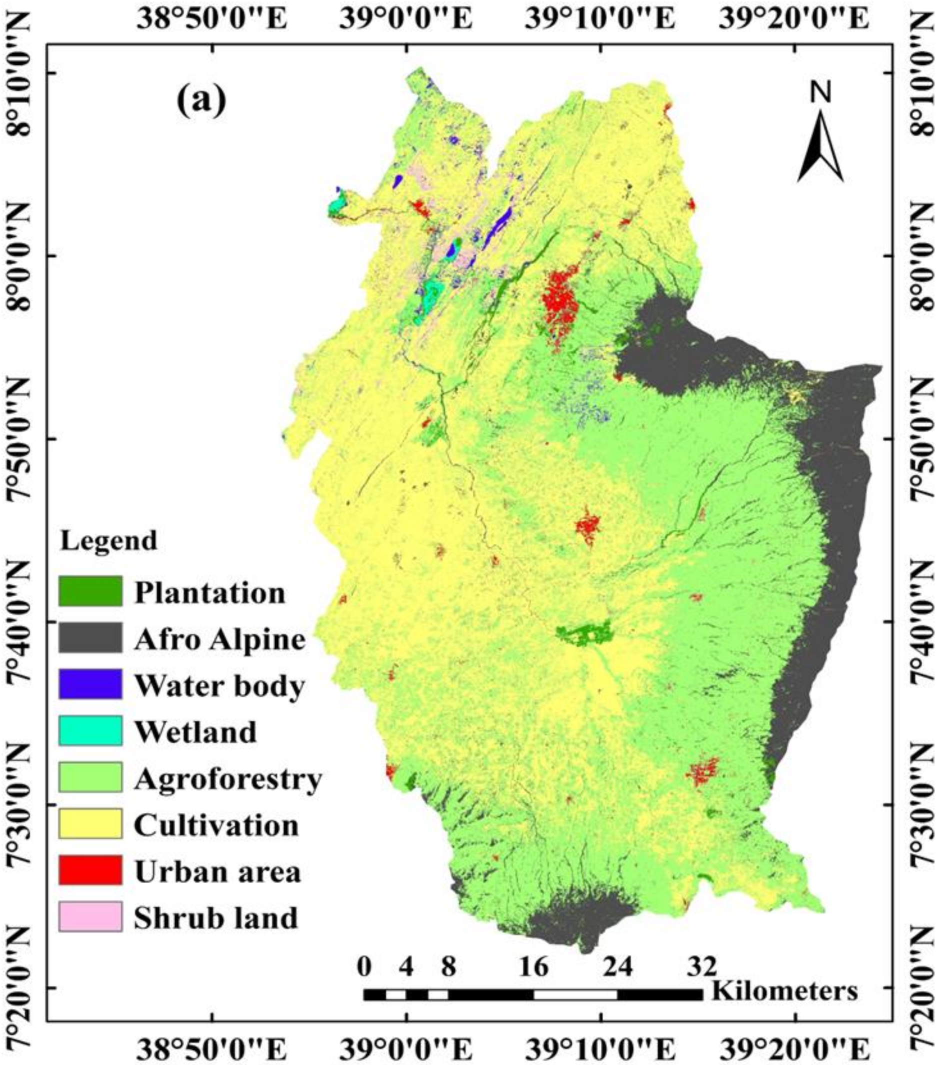
Schematic of SWAT Model Simulation



In the catchment, rate of infiltration, soil erosion, evaporation and runoff all affected by soil type and LULC. Thus, LULC information is one of the required inputs for SWAT model. For this purpose, a Landsat image was downloaded from the United States Geological Survey website and then processed and clipped to fit the size of the study area using ArcGIS as shown in Figure 7.

Figure 7

Land Use Map of the Study Area



The other required input for SWAT model, the soil data in which global soil map was downloaded from the database of FAO. Then the downloaded global soil map was processed and clipped to the size of Katar catchment using ArcGIS, as shown in Figure 8.

Figure 8

Soil map of Katar catchment

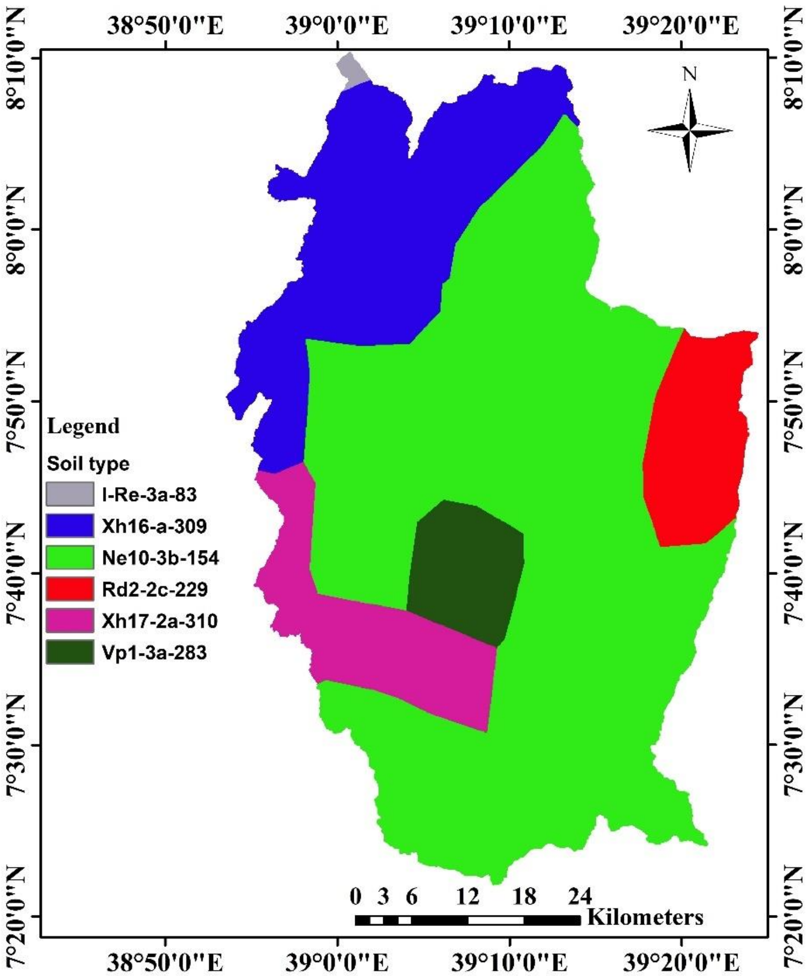


Figure 9

The Slope Classification of Katar Catchment

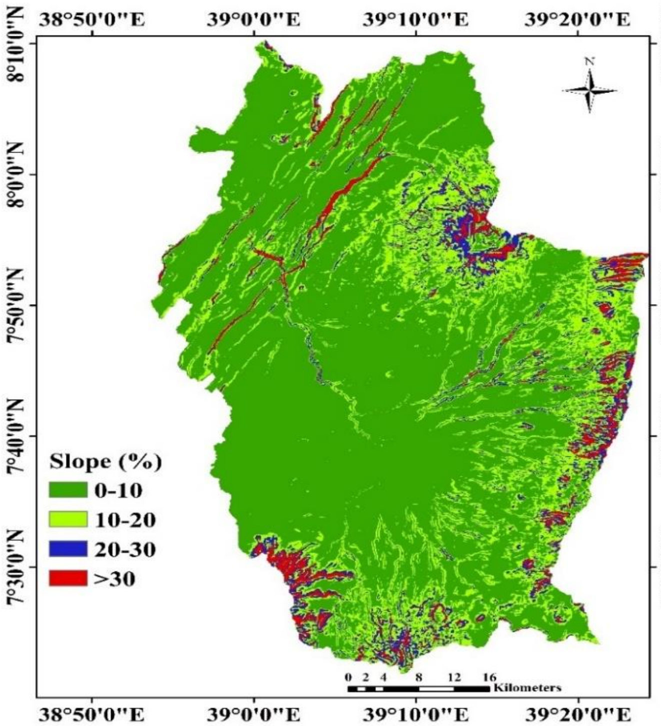
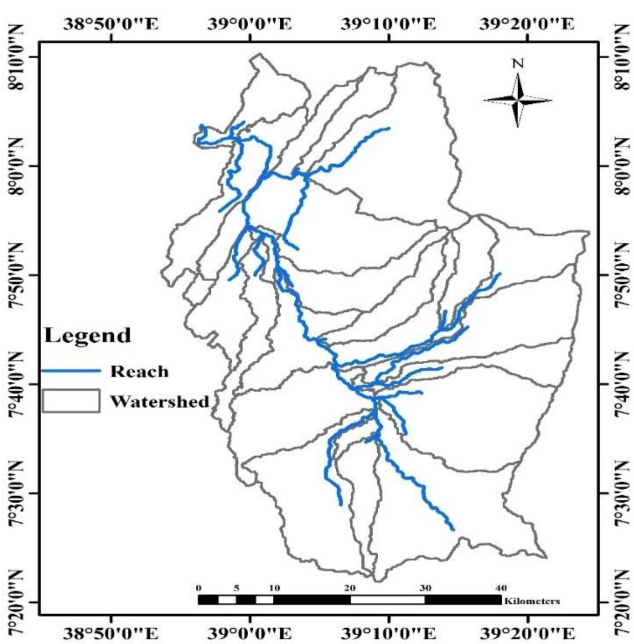


Figure 10

Sub-watershed Delineated by the SWAT Model for Katar Catchment



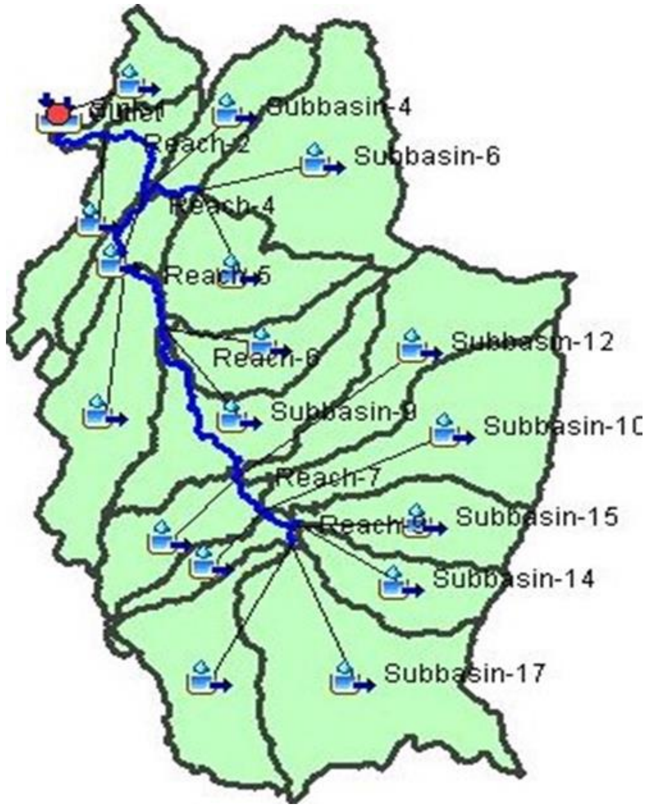
HEC-HMS

This model is a semi-distributed physically-based model which has been extensively applied for different watersheds using different dataset for streamflow simulation. The model was initially developed for simulation of the rainfall-runoff in dendric watershed. Later, its applicability is expanded to solve problems such as flood hydrograph, large drainage basin water distribution and runoff in small catchment (Shekar and Vinay, 2021). Like other physically-based hydrological models, HEC-HMS model can simulate rainfall-runoff process with acceptable accuracy (Abushandi and Merkel, 2013). In this model, the excess rainfall in the catchment is computed by considering pervious characteristics of the connected surfaces. The direct runoff in the stream is then formed by the combination of overland flow and near-surface flow (Young et al., 2017).

The input data for HEC-HMS in rainfall-runoff modeling includes DEM, weather data, discharge, soil type and LULC (Scharffenberg and Fleming, 2010). Like other semi-distributed physically based models, HEC-HMS divides the catchment into different sub-catchments connected by channels to represent the effects of spatial variability of the input data in the output. In the current study the catchment was divided in 17 sub basins (see Figure 11).

Figure 11

Sub-basins for HEC-HMS Model



In this study, HEC-HMS 4.7.1 was used and it has several components such as the basin model manager, terrain data manager, time series manager, and control specification manager. The DEM prepared using ArcGIS was imported into the HEC-HMS model for terrain processing and create basin model. In the HEC-HMS model, the GIS component is available and is used for drainage processing, sink preprocessing, stream identification and element delineation. In element identification, an outlet is selected and the model automatically delineates and divides the catchment in to sub-basines. Although the HEC-HMS model has been tested and calibrated on a global scale, few efforts have been made in the context of Katar catchments.

Runoff, in this model, is computed by deducting the interception, evapotranspiration, storage and infiltration from total rainfall. Different loss methods are available in this model, some of which are used for event simulation and others are appropriate for continuous process simulation. In addition, some of these methods are complex and require multiple inputs that are not readily available. Therefore, in this study, the SCS-CN loss method was used for direct runoff estimation because it is efficiency reported and tested in different environment, simple, data, require limited input and is well supported by empirical data. According to Tassew et al. (2019), SCS-CN method calculates that the accumulated rainfall-excess depends on soil type, land use and cumulative rainfall as shown in eq..

$$P_e = \frac{(P - I_a)^2}{P + I_a + S} \quad (15)$$

Where Pe and P are the accumulated excess rainfall and accumulated rainfall depth, respectively both at time t (mm). The maximum retention (S) can be computed from curve number (see Eq. 14).

HEC-HMS model computes the direct runoff from the watershed by transforming excess precipitation to point runoff using a variety of methods Tassew et al. (2019). In this study, the SCS Unit hydrograph transfer method was used to convert the excess precipitation to runoff. This method was preferred over the other methods because it requires only one input (lag time). The lag time (T_{lag}) is the time from the center of the excess precipitation to the peak of the hydrograph and is calculated for each sub-basine using the concentration time (Tc) as:

$$T_{lag} = 0.6T_c \quad (16)$$

Where T_{lag} and T_c are in minutes.

Tc is calculated based on each sub-basin characteristics as:

$$T_c = 0.0078\left(\frac{L^{0.77}}{S^{0.385}}\right) \quad (17)$$

Where L and S are the length of reach (feet) and slope, respectively

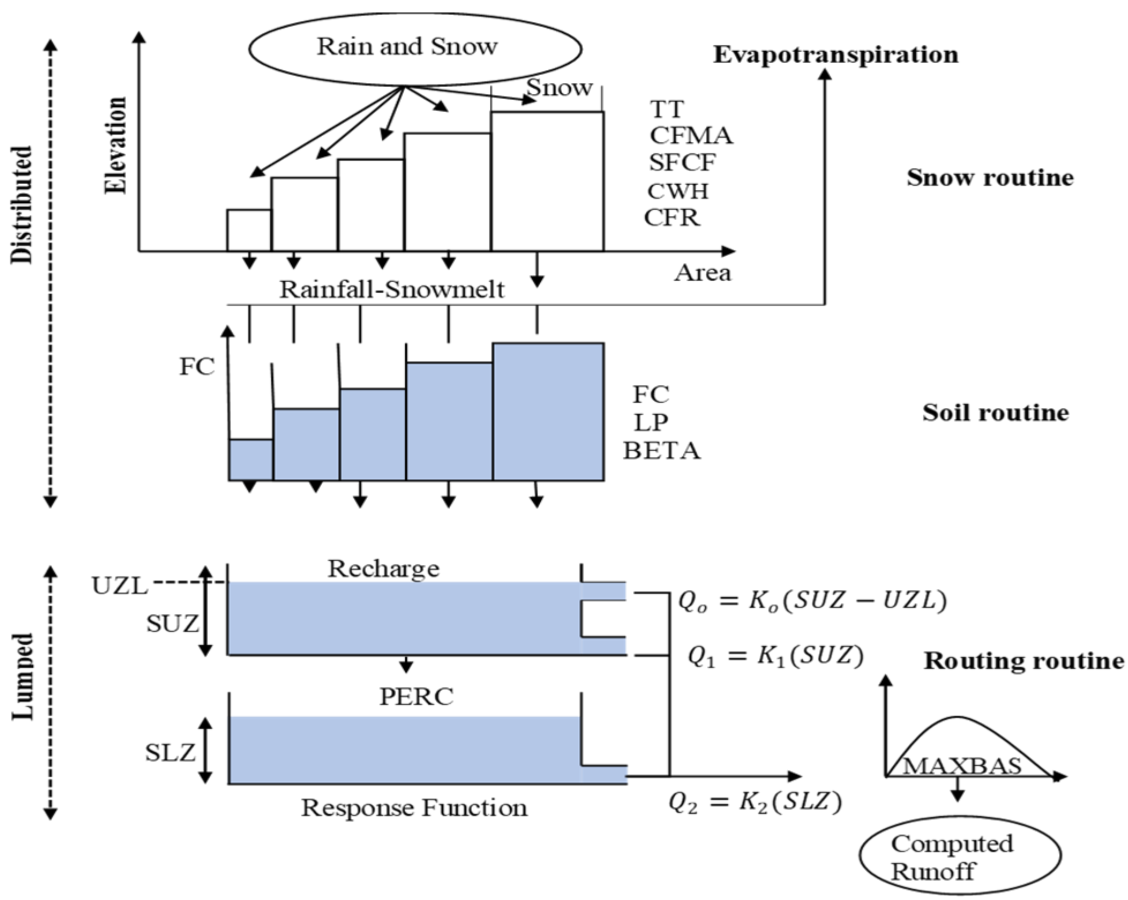
As water flows through a river, it is attenuated due to storage effects in the river channel. HEC-HMS model has several routing methods in rainfall-runoff modeling to account for the effect of this attenuation. Among different methods, this study used Muskingum routing approach. This method is preferred over the others because it is straightforward, simple and successfully tested in many areas of river engineering (Tewolde and Smithers, 2006). It requires only two parameters: dimensionless weight (X) and travel time (K).

HBV

HBV model is a semi-distributed conceptual model. In this method the whole catchment is divided in to sub catchments based on different vegetation and elevation zones. The structure of this model is simple and requires small input for rainfall-runoff of the catchment. The input for this method includes rainfall, runoff, air temperature and estimated evaporation on daily step. In this study, HBV light, an updated version of the original model, was used because considers the contribution of groundwater in rainfall-runoff modeling process. The general structure of the HBV model is shown in Figure 12.

Figure 12

Schematic of the HBV Model



HBV model consists of four subroutines such as snow routine, response routine (K0, UZL, K_1, PERC, and K_2), soil routine (FC, LP and BETA) and routing routine (MAXBAS). The snow component represents the contribution of snow melt to runoff generation and it is not relevant in this study as there is no snow available on the Katar catchment. Soil routine measures the contribution of groundwater and soil moisture (SM) variation based on the amount of flow coming from the earlier routine (P) and field capacity (FC) as:

$$\frac{recharge}{P_t} = \left[\frac{SM_t}{FC}\right]^{\beta} \quad (18)$$

If the ratio of SM to FC is greater than the value of LP, the actual evapotranspiration (ET_{act}) and potential evapotranspiration (ET_{pot}) are equal. Otherwise, AET is could be minimized as:

$$ET_{act} = ET_{pot}\ x\ min\left(\frac{SM_t}{FCxLP}, 1\right) \quad (19)$$

In HBV model, two reservoir model is considered for the study catchment and surface runoff is computed by subtracting losses from the precipitation which represents the flows in to the first reservoir. The outflow of the first reservoir are direct flow (Q_0) and intermediate flow (Q_1) while groundwater flow (Q_2) is the outflow of the second reservoir. Therefore, the groundwater flow (Q_{gw}) flow is computed by the summation of the two or three flows, based on upper zone storing (SUZ) is located above or below the threshold zone (UZL) as:

$$Q_{gw} = K_2\ x\ SLZ\ x\ K_1\ x\ SUZ\ x\ \ K_0\ x \max(SUZ - UZL, 1) \quad (20)$$

Where K_0, K_1, and K_2 are the recession coefficients for Q_0, Q_1 and Q_2, respectively.

Then runoff is simulated using the MAXBAS parameter and triangular weighting function as:

$$Q_{sim}(t) = \sum_{i=1}^{MAXBAS} C(i)\ x\ Q_{gw}(t - i + 1) \quad (21)$$

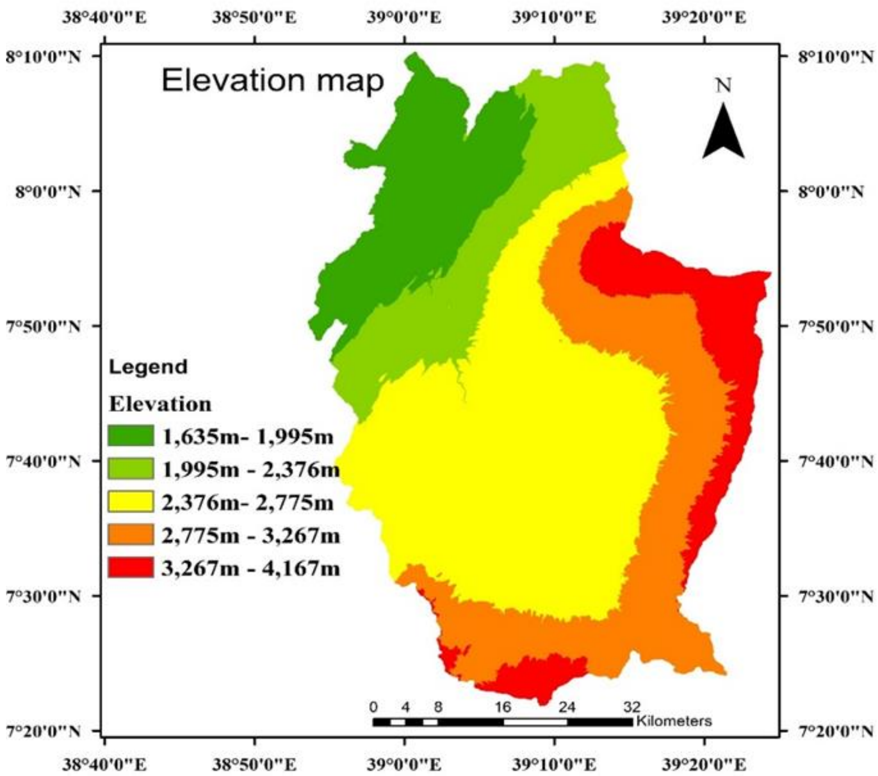
Where Q_{sim} is simulated runoff and C(i) can be calculated as:

$$C(i) = \int_{i-1}^{i} \frac{2}{\mathrm{MAXBAS}} - \left|U - \frac{MAXBAS}{2}\right|\ x\ \frac{4}{MAXBAS^{\ 2}} dU \quad (22)$$

In order to incorporate the influence of heterogeneity of watershed characteristics on run off, HBV accepts a maximum of three vegetation and twenty elevation zones. For this study, the Katar catchment was divided into three vegetation zones and five elevation zones (see Figure 13).

Figure 13

Elevation Map of the Study Area



Sensitivity analysis, calibration and validation

The first step in hydrologic modeling is identification the most important parameters having significant effect on the output. According Ouatiki. et al. (2020), sensitivity analysis allows to identify the significant of each parameter in the final model output. In SWAT, the SUFI-2 algorithm using SWAT-CUP software was used for sensitivity analysis and calibration. In the process global sensitivity analysis using trial and error method is applied to automatically adjust different parameters until the best agreement between measured and predicted runoff is achieved. Likewise, in HEC-HMS model, sensitivity analysis was carried out using one-at-a-time method in which the value of one parameter was repeatedly varied at a time while other parameters were held constant. Then, the change in RMSE value between the measure and computed runoff value at the outlet is then compared. Thus, in this study, the identification of sensitive parameters was performed by changing the range of the parameters between ±25% intervals until the best match between observed and simulated data was achieved. The parameters used for sensitivity analysis include CN, initial abstraction, the Muskingum k and x coefficient. In HBV model, Monte Carlo technique was used for sensitivity analysis and calibration. In this method, by setting the objective function the optimal value of the parameters was automatically provided within the predefined value range.

Similarly, the accuracy of black-box AI-based models is highly influenced by the quality of input and its relevance with respect to the output. This is because too many inputs may cause overfitting problem, make the modeling complex and may give unrealistic results. An insufficient number of inputs, on the other hand, can reduce the accuracy of the modeling. Therefore, it is very important to select optimum number of inputs to get good result. So far different methods have been used for identification of sensitive parameters such as partial derivative (PaD), neural network and Pearson correlation. The sensitivity analysis using linear technique (e.g., PaD and Pearson correlation) may not capture the nonlinearity of complex process such as rainfall-runoff and SSL and also inappropriate for high-dimensional data. Nonlinear methods (e.g., neural network), on the other hand, are known in their ability in capturing the nonlinear relationship between input and output of a complex and nonlinear problem. Therefore, in this study FFNN was used to identify the key inputs to the AI-based models. This method is a single-input single-output sensitivity analysis technique in which each input variable was fed independently into the FFNN model to simulate runoff and SSL. In this way, the relationship between the input variable and the output was determined without considering the other input variable's influence.

Data normalization and Model evaluation criteria

In AI-based modeling, data should be normalized to avoid dimensions and ensure that all variables receive equal attention. Thus, both the output and input variables was normalized before training the modelt to bring the data in a range between 0 to 1 using the following equation:

$$X = \frac{X_i - Xmin}{X\,max - Xmin}; \;\; i= 1,2,3\ldots.n \qquad (23)$$

Where: X, Xi, X_{min} and X_{max} represents the normalized, actual(measure), minimum and maximum values respectively

The predictive performance of hydrological models needs to be evaluated in both calibration and validation phase (Sharghi et al, 2018). According to Nourani (2017) and Nourani et al. (2018) , at least one goodness of fit and one absolute error measure should be included to have a good model performance evaluation. The accuracy of the ensemble technique and individual models used were compared using three performance indicators such as mean squared error (MAE), Nash-Sutcliffe efficiency (NSE) and root mean square error (RMSE). These performance measure methods have been widely used for evaluating accuracy of hydrologic modeling (Jimeno-Sáez et al., 2021; Young et al., 2017)

$$NSE = 1 - \frac{\sum_{i=1}^{N}\left(X_{ob}-X_{pr}\right)^2}{\sum_{i=1}^{N}\left(X_{ob}-\bar{X}_{ob}\right)^2} \qquad -\infty < \text{NSE} \le 1 \tag{24}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{ob} - X_{pr}\right)^2} \qquad 0 \le \text{RMSE} < \infty \tag{25}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|X_{Ob} - X_{pr}\right| \qquad 0 \le \text{MAE} < \infty \tag{26}$$

Where X_{Ob}, $\bar{X}_{ob}$, X_{pr} and N are Observed, average observed, predicted values and number of observations, respectively

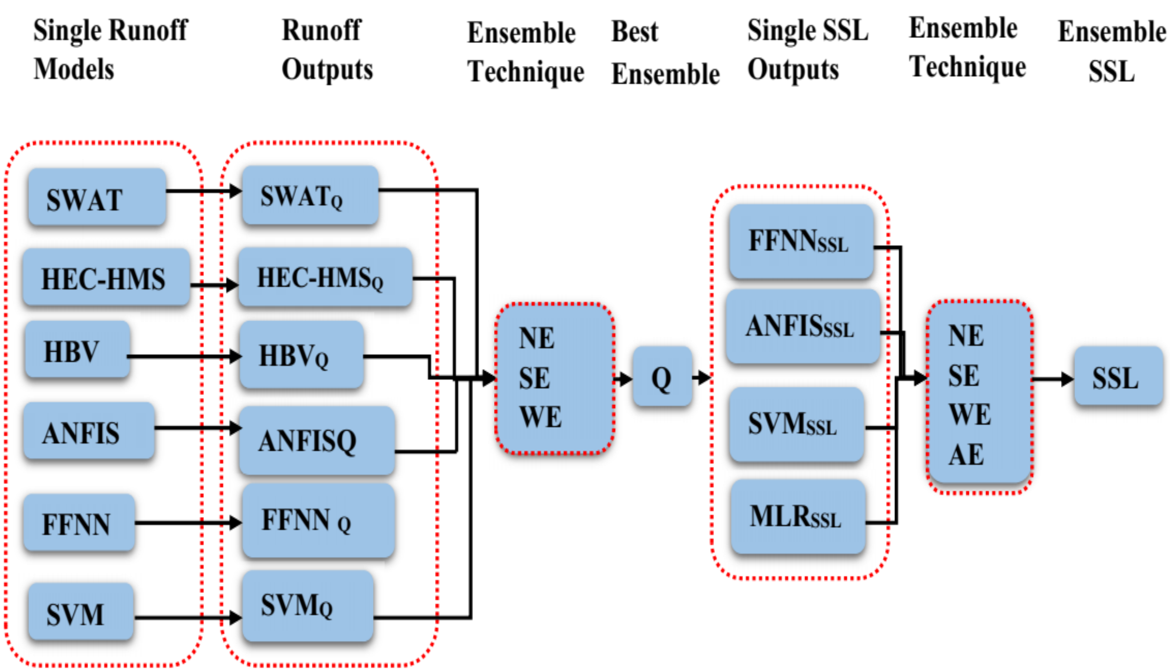
The value of NSE ranges between -∞ and 1 and it is a performance measure that shows how well the predicted value of SSL and runoff fits the measured value. A NSE value of 1 indicates that the model is perfect and the accuracy of the model decreases as the NSE value deviates far from 1(Nourani et al., 2020). According to Moriasi et al. (2007), the performance of a model can be interpreted considering its NSE value as unsatisfactory when the NSE value is below 0.5, satisfactory when the NSE value is between 0.5 and 0.65, good when the NSE value is between 0.65 and 0.75 and very good if the NSE value is above 0.75. RMSE, the other best model accuracy measurement method was used in this study. Its value is between 0 to +∞ and the perfect model is the one which have a value of 0. Similar to RMSE, the MAE construct the goodness-of-fit of the model irrespective of the error between the measured and predicted runoff or SSL value. RMSE is appropriate for a set of predictive errors with normal distribution and this may not be fulfilled by all the used models (Bonakdari et al., 2019). Therefore, in this study, MAE was used to evaluate the deviation of the simulated runoff and SSL from the observed values in equivalent way regardless of the sign.

Ensemble techniques

Ensemble technique is machine learning method where the results of various models are combined so as to increase the overall model accuracy (Sharghi et al., 2018). Combining the output of different model produces results which are more accurate than a single model (Nourani et al., 2018). For a particular dataset, one of the techniques used may give more accurate result than the others and entirely opposite result may be obtained when the data set is changed. Therefore, an ensemble technique is used to benefit from the strengths of all individual models and without losing generality (Kiran and Ravi, 2008). Ensemble technique have been used in different prediction studies such as regression, time series and classification (Kazienko et al., 2013), modeling dissolved oxygen concentration (Abba et al., 2020), modeling groundwater level (Sharafati et al., 2020), quality of river water (Asadollah et al., 2020) and modeling of wastewater quality (Sharafati et al., 2020). However, as far as we know, there was no study conducted on the applicability of ensemble techniques in hybrid rainfall-runoff and SSL modeling. Hence, this study used two linear and two nonlinear ensemble techniques to boost the accuracy of the individual models applied for rainfall-runoff and SSL modeling. Shamseldin et al. (1997) were probably the first to investigate the applicability of model combination for modelling rainfall-runoff processes. According Kiran and Ravi (2008), to ensemble technique are categorized as: (1) linear ensemble (e.g., simple, weighted and median averaging) and (2) nonlinear ensemble technique such as FFNN trained using the results of individual model as input to genrate improved result. Due to the simplicity of the methods, two linear (SE and WE) and two non-linear ensemble techniques (NE and AE) were developed to improve the accuracy of the single models. In the rainfall-runoff modeling, the ensemble technique was performed in three scenarios. In the first scenario, an ensemble was performed by amalgamation of the runoff results of the three physically-based models. In the second scenario, only the runoff output FFNN, SVR and FFNN were used as input for each ensemble techniques. In the third scenario, the runoff values of all the six models (SWAT, HVB, HEC-HMS, FFNN, SVR and ANFIS) were used as input for the three ensemble techniques. The runoff value obtained from the best ensemble technique in each scenario was used as input (separately) for the SSL modeling using ANFIS, FFNN and SVM and MLR models. The general ensemble procedure of the methodology is shown in Figure 14.

Figure 14

Schematic of Hybrid Rainfall-runoff-sediment Ensemble Process



Linear ensemble technique

Simple average ensemble (SE): In this technique, the outputs (SSL and runoff) of single models were arithmetically averaged and compared with the observed values as:

$$O = \frac{1}{N}\sum_{i=1}^{N} O_i \qquad (27)$$

Where O , Oi, N are SE result (runoff or SSL), result of single ith model and the number of single models (for rainfall-runoff modeling, N= 6 whereas N=4 for SSL modeling), respectively.

Weighted average ensemble (WE): This technique calculates a weighted average of the runoff and SSL by assigning different weights to the results of each model based on their relative significance (NSE value). WE is done as via:

$$O = \sum_{i=1}^{N} w_i O_i \quad (28)$$

Where is the assigned weight for the ith model's output and calculated as:

$$w_i = \frac{NSE_i}{\sum_{i=1}^{N} NSE_i} \quad (29)$$

Where: NSE_i represents the performance of the ith individual model.

Nonlinear ensemble technique

In this type of ensemble technique, nonlinear averaging is done by using the outputs of single models as input to train the AI-based models.

Neural network ensemble (NE): It this non-linear ensemble technique, non-linear averaging is performed by training another neural network. In this technique the runoff and the SSL values obtained from the considered individual models were used to train FFNN and to get ensemble output. Similar to the single FFNN, trial and error approach was used to define the maximum number of epoch and hidden layer neurons.

ANFIS ensemble (AE): In AE, the SSL values obtained from the individual MLR, ANFIS, FFNN and SVM models were used to train the ANFIS model using different membership functions and epoch numbers.

CHAPTER IV

Findings and Discussion

This study was conducted in five steps. In the first step of this study, a sensitivity analysis was performed to identify the most sensitive and important inputs. In the second step, rainfall- runoff and SSL were modeled using single models. In this regard, three physically- based (SWAT, HBV and HEC-HMS) and three AI models (ANFIS, FFNN and SVM) were used to model the rainfall-runoff. In addition, three AI models (FFNN, ANFIS, and SVM) and linear regression (MLR) were used for SSL estimation. In the third step, the rainfall-runoff and SSL values obtained by each model in the second step were combined by four ensemble techniques, namely NE, SAE, WE, and AE (for SSL modeling only). In the fourth step of the study, the runoff results of the best ensemble technique from the second step were used as input for SSL modeling using ANFIS, FFNN, SVM and MLR. Finally, the SSL values obtained in the fourth step were combined using NE, SE, AE and WE. The results of the individual models and ensemble technique for rainfall-runoff and SSL modeling are presented and discussed in the following sub-sections.

Sensitivity analysis result

In this section the result of the sensitivity analysis for single AI-based and physically-based models are presented in subsections.

Dominant input selection for single AI-based rainfall-runoff and SSL modeling

Selection of relevant and dominant inputs is a very important step in AI-based modeling of hydrological processes to achieve accurate prediction. This is because the inclusion of insufficient inputs can lead to inaccurate results, while too many inputs can lead to overfitting and unrealistic results, making the modeling process complex. There are different methods used for sensitivity analysis in order to identify dominant inputs. Among them, Pearson correlation (linear sensitivity method) has been previously applied to select sensitive input parameters in rainfall-runoff modeling (e.g., Kisi et al., 2013) and SSL modeling (e.g., Sharafati et al., 2020). However, the applicability of the Pearson correlation method to identify the most sensitive inputs has been criticized in previous studies because in nonlinear complex rainfall-runoff and SSL processes, there may be a stronger nonlinear relationship between output and input variables than their linear relationship (Nourani et al., 2020). For this reason, in this study, the identification of most dominant inputs for rainfall-runoff and SSL modeling was performed considering single-input single-output using FFNN model. This method is a single-input-single-output technique in which one input variable at a time was fed into the FFNN model to simulate runoff and SSL (individually). In this way, the relationship between the input variable and the output was determined without considering the other input variable's influence.

The current value of hydrologic parameters (e.g., runoff and SSL) correlates strongly with their past values. Factors such as rainfall, watershed characteristics and runoff (for SSL) are involved in the modeling of rainfall-runoff and SSL. According to Nourani et al. (2019), the effect of the above factors on SSL and runoff can be indirectly considered by including the antecedent values as inputs. In this study, for modeling the current day runoff (Qt), various lagged (up to 6 days in the past) of discharge, temperature and rainfall data were evaluated as inputs to AI-based models and ranked based on their NSE value in the validation phase, as shown in Table 2.

Table 2

Sensitivity Analysis Result for AI-based Rainfall-Runoff Modeling

Inputs	NSE	Rank
Q_{t-1}	0.875	1
Q_{t-2}	0.827	2
Q_{t-3}	0.777	3
P_t	0.544	4
P_{t-1}	0.539	5
Q_{t-4}	0.519	6
Q_{t-5}	0.4603	7
P_{t-2}	0.4266	8
P_{t-3}	0.2594	9
T_{t-1}	0.2027	10
T_{t-2}	0.1834	11
T_{t-3}	0.1134	12

From the sensitivity result in Table 2, the most sensitive input has a high NSE value. Therefore, Q_{t-1}, Q_{t-2} and Qt_{-3} were identified as the most relevant inputs and temperature was considered as the least relevant input. The result is supported by of Nourani et al. (2021). After ranking the inputs based on their NSE value, less relevant inputs were removed. It was found that P_{t-2}, P_{t-3}, Q_{t-5}, T_t, T_{t-1}, T_{t-2}, and T_{t-3} were identified as less relevant and were not included in the different input combinations. After removing the less important variables, different input combinations with significant inputs, i.e., Q_{t-1} ,Q_{t-2}, Q_{t-3}, P_t, P_{t-1}, and Q_{t-4} were used to model the rainfall-runoff process with the proposed AI-based models, and only the combination that led to the best result is discussed.

Similarly, discharge (Q_t, Q_{t-1},…Q_6) and antecedent SSL (SSl_{t-1}, SSL_{t-2},…and SSL_{t-6}) were used as input to estimate the current day SSL_t and ranked based on their validation phase NSE value as in Table 3.

Table 3

Sensitivity Analysis Result for AI-based SSL Modeling

Input variable	NSE	Rank
Q_t	0.8208	1
SS_{t-1}	0.7964	2
Q_{t-1}	0.7605	3
SS_{t-2}	0.6338	4
Qt-2	0.60438	5
Qt-3	0.5188	6
SSt-3	0.4966	7
Qt-4	0.3594	8
SSt-4	0.3027	9
Qt-5	0.2934	10
SSt-5	0.2134	11
St-7	0.383	12
Qt-5	0.362	13
Qt-6	0.293	14
Qt-7	0.271	15

In Table 3, the most dominant and relevant input had the highest NSE. Thus, Q_t, SS_{t-1} and Q_{t-1} are the most dominant inputs and ranked first, second and third, respectively. After ranking the input variables based on their NSE value, a Student t-test was performed to select the dominant input and remove inputs that are less important to the modeling result. Based on the student t-test, the inputs such as Q_{t-4}, SS_{t-4}, SS_{t-5} Q_{t-5}, SS_{t-6}, Q_{t-6}, SS_{t-7} and Q_{t-7} were identified as less relevant and removed from the input combination set. Afterwards, the current day SSL (SS_t) was modeled using different combinations of the dominant inputs such as $Q_{t,}$ SS_{t-1}, Q_{t-1}, SS_{t-2}, Q_{t-2}, SS_{t-3}, Q_{t-2} and Q_{t-3} by the proposed AI-base and MLR model.

Similarly, sensitivity analysis was performed to identify the most sensitive parameters for the conceptual (HBV) and physically-based models (SWAT and HEC-HMS). After watershed delineation, HRU analysis and weather definition, the SWAT model simulation was made and saved. Then, the SWAT model's simulated result was imported in to SWAT-CUP software to conduct sensitivity analysis, calibration and validation. In hydrological modeling using SWAT model, calibration is an important step for reducing uncertainties during simulation and to achieve better parameterization for a given condition. Therefore, global sensitivity analysis was conducted using SUFI-2 algorithm in the SWAT-CUP software to where selection of the most sensitive parameters was carried out based on the absolute p-value and the maximum t-stat. For sensitivity analysis many parameters were tried and only nine parameters were found to be more sensitive. The maximum and minimum values of the parameters selected for model calibration was collected from the literature and SWAT-CUP manual while their fitted value was obtained after several iterations during calibration process. Then, the parameters were ranked based on their t-stat value obtained after the global sensitivity analysis (see Table 5). After model calibration was completed, model validation was performed without changing the model input parameters.

Table 4

Most Sensitive Parameters Optimized Value and Rank for SWAT Model

Parameter	Description	Min Value	Max value	Fitted value	Rank
CN2.mgt	SCS runoff curve number	35	98	61.14	1
ALPHA_BF.gw	Base flow alpha factor	0	1	0.875	2
GW_DELY.gw	Groundwater delay	0	500	262	3
SOL_K.sol	Saturated hydraulic conductivity	0	2000	41	4
GW_REVAP.gw	Groundwater "revap" coefficient	0.02	0.2	0.18	5
GWQMN.gw	A threshold minimum depth of water in the shallow aquifer for base flow to occur	0	5000	267.5	6
SOL_AWC.sol	Available water capacity of the soil layer	0	1	0.55	7
HRU_SLP.hru	Average slope steepness	0	1	0.59	8
SURLAG.bsn	Surface runoff lag time	0.05	24	0.845	9

In sensitivity analysis result shown in Table 4, CN2, (ALPHA _BF) and GW_DELY were found the first, second and third sensitive parameter, respectively.The second physically-based model employed in this study was HEC-HMS. According to Shekar and Vinay (2021), runoff in this model is simulated by analyzing hydro-meteorological data through open-channel routing. Like other hydrological models, identification of most sensitive parameters for rainfall-runoff modeling using sensitivity analysis technique is an important step HEC-HMS model. In this regard, a one-at-a-time method was used in this study to identify the most sensitive parameters that have significant effect on the model output. In this method, the value of one parameter was changed (by decrease and increasing by 25%) while the value of others kept constant and sensitive parameters are selected based on their effect on the RMSE value between the actual and computed runoff value at outlet. This sensitivity analysis method was chosen due to simplicity and its successfully applicability by previous studies (e.g., Fanta and Sime, 2022; Tassew et al., 2019; Zelelew and Melesse, 2018). In this model, the most sensitive parameters identified during model optimization were ranked as shown in Table 5.

Table 5

Parameter Sensitivity Rank for HEC-HMS Model

Parameter	Description	Value range	Optimum value	Rank
CN	SCS_Curve Number	35-99	*	1
T_{lag}	Lag time	0.1-30000	*	2
I_a	SCS-CN initial abstraction	0.001-500	*	3
K (hr)	Flood wave travelling time	0.005-150	*	4
x	Weighted coefficient of discharge	0.005-0.5	*	5

Table 5 shows that curve number (CN), lag time (T_{lag}) and initial abstraction (I_a) were identified as the first, second, and third most sensitive parameters, respectively. Significant deviation of computed runoff from its previous value was observed when the value of these parameters was varied (specially CN) during sensitivity analysis. According to Fanta and Sime (2022), this could be due to the fact that runoff-forming factors such as topography, LULC and soil are combined into a single CN value. Similar result was obtaind in sensitivity analysis by Fanta and Sime (2022) and Zelelew and Melesse (2018) where CN is identified as the most sensitive parameter and T_{lag} is ranked second.

The third semi-distributed model used for this study was HBV, which requires only temperature, evapotranspiration, runoff, rainfall, information on LULC and elevation. The runoff and weather data (evapotranspiration, rainfall and temperature) were prepared in text file format as required by the HBV model. The HBV model can accept up to twenty elevation zones and three vegetation zones. Thus, the LULC map of Katar catchment prepared and used for the SWAT model was combined into three class considering vegetation similarity classification (as forest land, agricultural land and water body). In addition, the study area was divided into five elevation zones. In this study, the HBV model was configured with different model parameters, three vegetation zones, and five elevation zones. After adjusting the catchment and model settings, the Monte Carlo optimization method was used for sensitivity analysis and model calibration. In this method, the optimal values of the parameters (within their range of values) were automatically generated by setting the objective function. The result of the sensitivity analysis showed that the field capacity (FC) was the most sensitive input parameter and also the parameter controlling the contribution of precipitation to runoff (β) and the storage coefficient 1 (K1) were identified as the second and third sensitive parameters.

Rainfall-runoff modeling result using single models

As mentioned earlier, in the second step of this study, three physically-based (HEC-HMS, SWAT, and HBV) and three black-box AI-based (SVM, ANFIS and FFNN) models were used to model the rainfall-runoff of Katar catchment. The modeling accuracy of each model during the calibration and validation phases are shown in Table 5. Different input combinations using the identified dominant inputs were used for calibration (training) and validation through the AI-based models, and only the best results of the models are presented in Table 5. Different input combinations were tried and the best results were obtained by Q_{t-1}, Q_{t-2}, Q_{t-3} and P_t.

FFNN model, in this study was trained with the LM algorithm was developed with four inputs and one hidden layer for rainfall-runoff modeling. When modeling with the FFNN, determination of the optimal number of hidden neurons is an important task to achieve better results. The reason is that too many neurons can lead to overfitting, while too few neurons can give an unacceptable result. To determine the best structure of FFNN, a trial- and- error method was used by varying the number of hidden neurons until the desired accuracy was achieved. In this study, an FFNN with 7 neurons in the hidden layer using the identified input combination trained by 21 epochs provides the best result. In Table 5, d-e-f is to represents the number of inputs, hidden neurons and the output in the best structure of the FFNN model.

SVM, the second nonlinear AI-based model used in this study, was built using radial basis function (RBF) kernel. The reason for choosing the RBF kernel for the SVM model is that it requires fewer tuning parameters than polynomial kernels and sigmoid. Moreover, more modeling accuracy is achieved by this kernel compared to the others (Sharghi et al., 2018).

The third AI-based model, the ANFIS model, known to be a robust method in nonlinear relationship modeling, was used to model rainfall-runoff in this study. The ANFIS model is a hybrid of ANN and FIS which gives it a strong capability in handling complex nonlinear hydrologic problems such as rainfall-runoff and the SSL process. In this study, the ANFIS model's membership functions (MFs) parameters calibration was performed using the Sugeno Fuzzy Inference System through the hybrid algorithm. In order to obtain the best result, the method of trial-and-error was applied by changing the type of MF and the number of epochs. The study investigated different MF such as Trapezoidal, Triangular and Gaussian because they are suitable for modeling complex hydrologic processes (Nourani et al., 2020). The best ANFIS model result was obtained with Triangular MF trained with 60 epochs.

In addition to the AI-based models described above, three semi-distributed models such as HBV, HEC-HMS and SWAT models were applied to simulate rainfall-runoff. For the SWAT model, a DEM with a resolution of 30 x 30m was used to configure the model and delineate the watershed using SWAT interfaces in ArcGIS. In SWAT model, to account for the watershed heterogeneity, the catchment is subdivided into sub-catchments which are in turn subdivided into small units (HRUs) with unique soil, slopes and LULC characteristics. Then, HRU analysis was performed by overlaying the slope map, LULC map and soil map. In this study, the study area Katar catchment was sub-divided into 17 catchments and 156 HRUs. After watershed delineation, HRUs analysis and introducing the weather data (weather definition), the model was run and saved. Then, the simulated result was imported into the SWAT-CUP software and the SUFI-2 algorithm was used to perform sensitivity analysis, calibration and validation. Using sensitivity analysis, the modelers can able to compute the change in model output in relation to the change in model parameters and thus identifying the most influential parameters controlling rainfall-runoff process (Jimeno-Sáez et al., 2018). Model calibration is important for better parameterization for a given local condition and to reduce modeling uncertainty. First, the minimum and maximum values of the considered parameters were collected from the literature and the SWAT-CUP manual and several iterations were performed until the best agreement between the observed and computed discharge was obtained. The performance of the models was measured using RMSE, NSE and MAE as shown in Table 6.

HEC-HMS was the second physically-based semi-distributed model used for rainfall-runoff modeling in this study. This model was calibrated and validated using 10 years of (2008 to 2017) runoff data. Based on the performance measures, HEC-HMS model provided acceptable results, but not as good as the other physically-based and AI models.

The HBV model is the other semi-distributed conceptual model used in this study. Rainfall-runoff modeling with the HBV model requires spatial information (e.g., LULC), runoff and climatic data on evapotranspiration and temperature. Average temperature, rainfall, runoff and evapotranspiration data for the study area were prepared in text file format as required by the HBV model. The LULC map prepared for the SWAT model was merged in three LULC types in the view of the similarity of vegetation characteristics, as the model only accepts a maximum of three vegetation zones. Model calibration was performed using Monte Carlo optimization method by setting the objective function (NSE). The predictive performances of the single AI-based and physically-based models are shown in Table 6.

Table 6

The Results of Single Models for Rainfall-Runoff Modeling

Model	Model Structure	Calibration			Validation		
		RMSE	MAE	NSE	RMSE	MAE	NSE
SWAT	-	7.44	3.628	0.847	8.811	6.464	0.809
HEC-HMS	-	8.771	5.35	0.788	10.002	6.914	0.757
HBV	-	8.287	5.313	0.811	9.238	6.556	0.786
SVM	RBF	6.336	2.946	0.889	7.229	3.541	0.878
ANFIS	Triangular	5.229	2.432	0.925	6.018	2.847	0.913
FFNN	4-7-1	5.859	3.547	0.905	7.291	4.317	0.873

*RMSE and MAE are in m^3/s

Table 6 shows the performances of the AI-based models and the physically-based model employed for rainfall-runoff modeling. As shown in the table, the AI-based models outperformed all the physically-based models by providing the lowest RMSE and MAE, and the highest NSE value. Moreover, compared to the other AI-based models, ANFIS achieved the best result in modeling rainfall-runoff with RMSE = 7.018 m^3/s, NSE=0.913 and MAE= 2.847 m^3/s, followed by SVM and FFNN, respectively. The goodness- of- fit (NSE, RMSE and MAE) of the best model (ANFIS) clearly shows the ability of this model to handle the nonlinearity and complexity of the rainfall-runoff process. Among the semi-distributed models, the SWAT model provided the best result with RMSE = 8.811m^3/s, NSE=0.809 and MAE= 6.464m^3/s in the validation phase. The HEC-HMS model gave the worst prediction with RMSE = 10.002m^3/s, NSE=0.757and MAE= 6.914m^3/s in the validation phase. Although they gave lower prediction accuracy compared to the AI-based models, the physically-based (SWAT and HEC-HMS) and conceptual (HBV) models performed very well in simulating rainfall-runoff. According to Table 5, the application of ANFIS (the best models) could improve the performance of HEC-HMS, HBV and SWAT by up to 20.6%, 16.16% and 12.86%, respectively, based on the NSE value in the verification phase. Based on Moriasi et al. (2007) model performance classification guideline, the performance of a model is very good if its NSE value is above 0.75. In this regard, all the models used showed very good performance in modeling rainfall-runoff. In addition to the statistical model performance indices, boxplots, scatter plots and Taylor plot were also used in this study to provide a better overview of the modeling efficiency of the models used. Figure 13 shows the scatter plot of the results of each AI-based and physically-based model compared to the actual runoff value in the verification phase.

The scatter plot of actual runoff versus the computed runoff for each of the physically-based and AI-based models in the validation phase is shown in Figure 15. As it can be seen in Figure 13, the points are less scattered for AI models especially in ANFIS model compared to the other competing models. This could be due to the strong ability of the ANFIS model to deal with the nonlinearity and uncertainty of the rainfall-runoff process.

Figure 15

Scatter plot of Observed versus Predicted Runoff, at Verification Phase by a) HEC-HMS, b) SVM, c) HBV, d) FFNN, e) SWAT and f) ANFIS

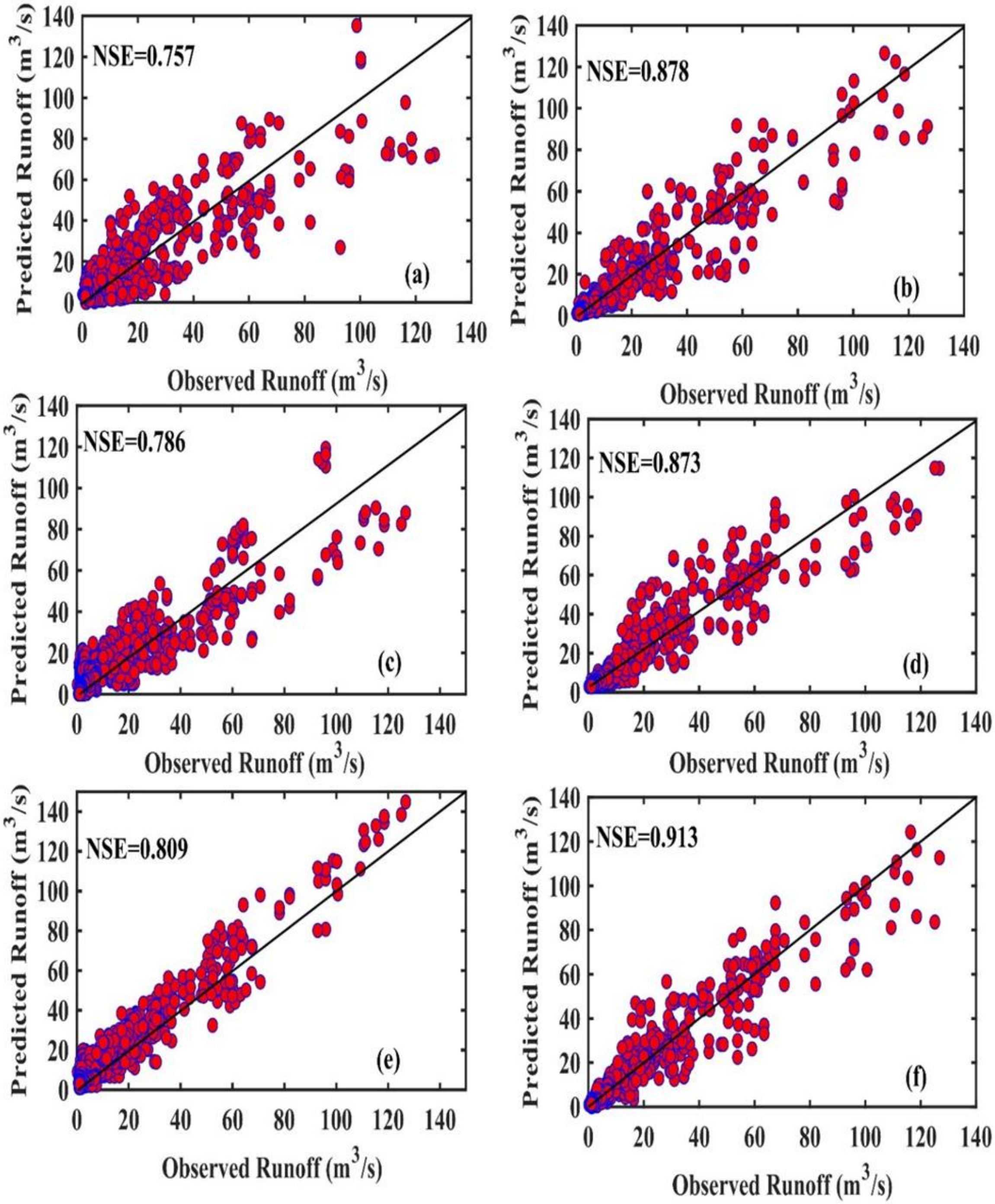


Figure 16

Radar Plot Comparison of Physical and AI Based Models

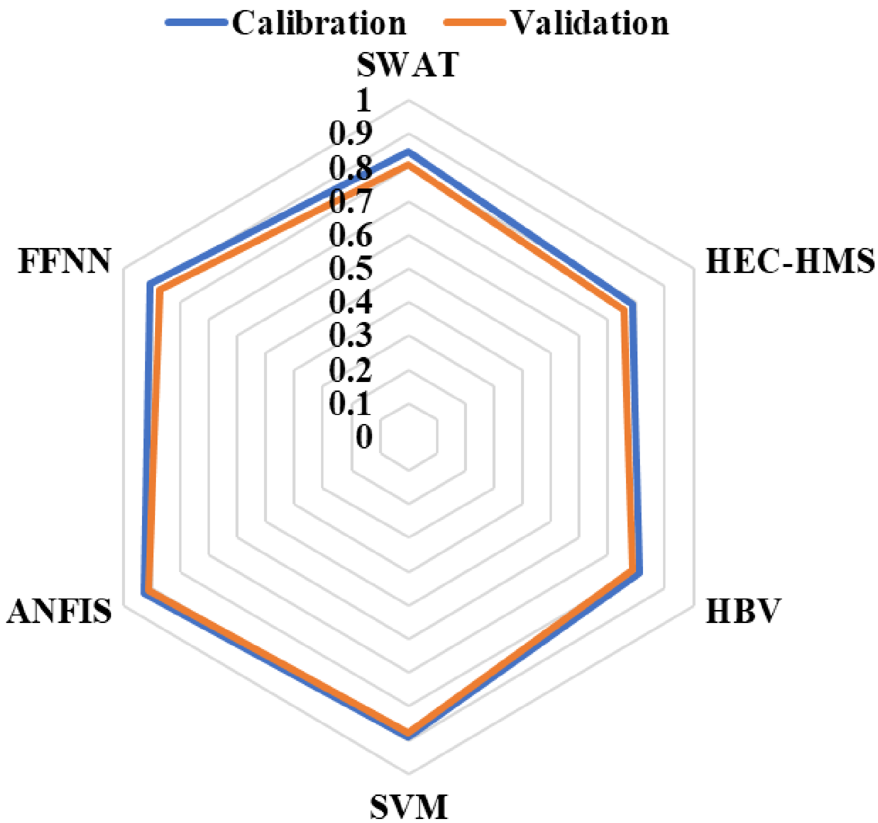
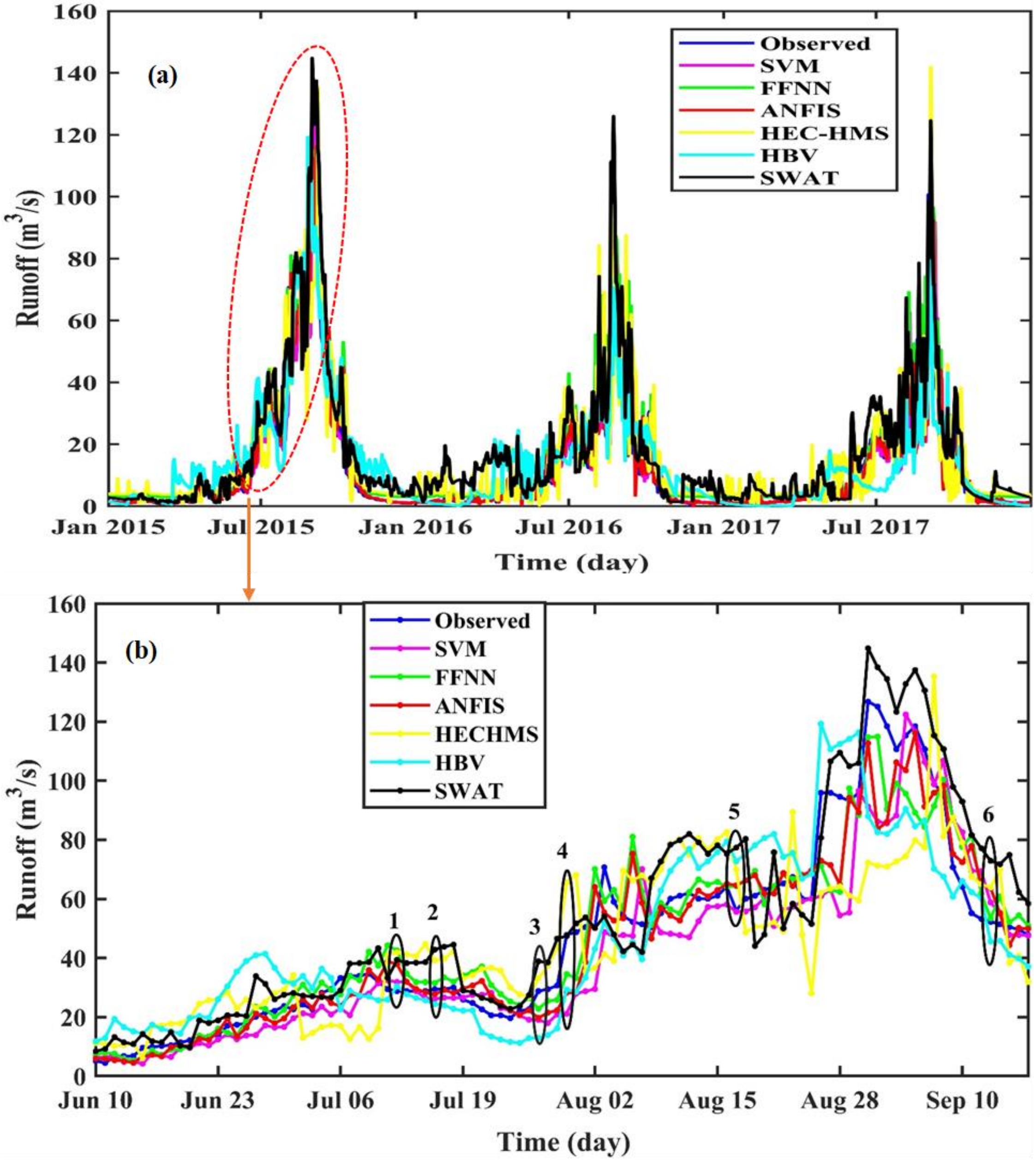


Figure 17a shows the time series of each of the physically-based and AI models used in this study for modeling rainfall-runoff during the validation phase. As can be seen in Figure 17a, the hydrograph of the AI-based models was more similar to the observed runoff hydrograph than that of the physically-based models. In addition, not all models were able to perform equally well at all points in the time series. Figure 17b shows a section of the time series (June 10 to September 17, 2015) from the validation phase to better illustrate the predicted runoff by both the AI and physically-based models. To further investigate the prediction accuracy of the models, six different points were randomly selected and designated as points 1,2,3,4,5 and 6 in the time series. The predicted runoff value obtained from each model was then compared to the actual runoff values at each of the selected points. For point 1, observed= 28.832 m^3/s, FFNN= 34.687m^3/s, ANFIS= 31.931 m^3/s, SVM= 32.052 m^3/s, HBV= 27.72 m^3/s, HEC-HMS =

41.217 m^3/s and SWAT = 38.3 m^3/s. This shows that the runoff value obtained by HBV model is closer to the observed value than the other models. At point 2, observed= 29.445m^3/s, FFNN= 33.456m^3/s, ANFIS= 29.187m^3/s, SVM= 26.636m^3/s, HBV= 23.96 m^3/s, HEC-HMS = 39.77 m^3/s, and SWAT = 43.85 m^3/s. This shows that the best agreement was observed between the observed runoff value and the ANFIS model. At point 3, observed runoff = 28.832m^3/s, ANFIS= 19.734m^3/s, FFNN= 22.81 m^3/s, SVM= 19.06^{3}m3/s, HBV= 12.9m^3/s, HEC-HMS = 33.101m^3/s and SWAT = 38.89m^3/s. This shows that the runoff value obtained with the HEC-HMS model is closer to the observed value than the other models. For point 4, observed= 47.867m^3/s, ANFIS= 28.266 m^3/s, FFNN= 34.58m^3/s, SVM= 21.2m^3/s, HBV= 29.309 m^3/s, HEC-HMS = 65.57m^3/s and SWAT = 47.45m^3/s, this means that the difference between the observed runoff value and the value obtained by SWAT model was less than the other models. At point 5, observed runoff = 56.086 m^3/s, ANFIS= 64.589 m^3/s, FFNN= 64.306m^3/s, SVM= 55.65m^3/s, HBV= 72.819 m^3/s, HEC-HMS = 69.926 m^3/s and SWAT = 77.4 m^3/s. This shows that SVM deviates less from the observed discharge than the other models. For point 6, observed= 52.322m^3/s, SVM= 58.754m^3/s, FFNN= 53.394 m^3/s, ANFIS= 63.7m^3/s, HEC-HMS = 63.873m^3/s, HBV= 45.637m^3/s and SWAT = 72.9m^3/s, this shows that the FFNN model gives a more accurate result than the other models.

Figure 17

Times series of Observed Versus Predicted Runoff Value in the Validation Phase, (a) from January 1, 2015-December 31, 2017 and (b) from June10,2015 to Sep. 17, 2015



From the selected points it is clear that different models could gave different predictive performance at different time points. Although, the AI models led to a bit better result but they ignore physics of the problem. Therefore, a reliable ensemble technique that combines the results of individual AI-based and physically-based models could be used to boost the overall modeling performance and led to more accurate result. To this end, in this study developed two linear (WA and SA) and one nonlinear (NE) ensemble technique were proposed to improve rainfall-runoff modeling in three scenarios.

Results of ensemble techniques for rainfall-runoff modeling

As mentioned earlier, in the third step of the study, the runoff values obtained from the individual AI-based and physically-based models were combined into three scenarios using three ensemble techniques, namely NE, SA, and WAE, to increase the overall efficiency of rainfall-runoff modeling. Ensemble modeling was conducted in three scenarios as described in chapter three. In the NE technique, the runoff values of each model (in different scenarios) were fed into the input layer and the model was trained using the LM algorithm. Through trial and error, the best result was obtained with a neuron number of 7, 5 and 9 for scenarios 1, 2 and 3, respectively. Thus, a-b-c in the NE mode structure shown in Table 7 represents the number of inputs, hidden neurons and outputs, respectively. In this study, two nonlinear ensemble techniques (WE and SE) were also developed to compare the performance of NE and the results are presented in Table 5. For the current study, FFNN was chosen as the nonlinear ensemble technique due to its popularity, compatibility and accuracy in model combination studies in different fields (Elkiran et al., 2018; Nourani et al., 2018; Nourani et al., 2020). In Table 6, d, e, f, g (e.g., in scenario 3) in the WE technique stands for the weights of ANFIS, SVM, FFNN, SWAT, HBV and HEC-HMS, respectively. Similarly, x-y in the SA model structure stands for the number of inputs and output, respectively.

Table 7

Results of Ensemble Rainfall-Runoff Techniques

Scenarios	Ensemble method	Model structure	Calibration			Validation		
			NSE	MAE	RMSE	NSE	MAE	RMSE
Scenario 1	SE	3-1	0.833	5.613	7.779	0.80	7.73	8.948
	WE	0.322, 0.334, 0.344	0.85	6.28	7.382	0.823	7.485	8.356
	NE	3-7-1	0.885	4.675	6.465	0.862	5.77	7.6
Scenario 2	SE	3-1	0.923	2.755	5.299	0.906	6.27	6.199
	WE	0.33, 0.328, 0.343	0.923	2.753	5.294	0.916	3.19	5.921
	NE	3-5-1	0.954	2.173	4.09	0.95	2.42	4.26
Scenario 3	SE	6-1	0.929	2.929	5.067	0.912	4.282	5.955
	WE	0.18,0.175,0.174, 0.16, 0.157,0.15	0.93	2.89	5.044	0.929	3.482	5.132
	NE	6-9-1	**0.971**	**1.672**	**3.215**	**0.966**	**2.375**	**3.79**

*RMSE and MAE in m^3/s

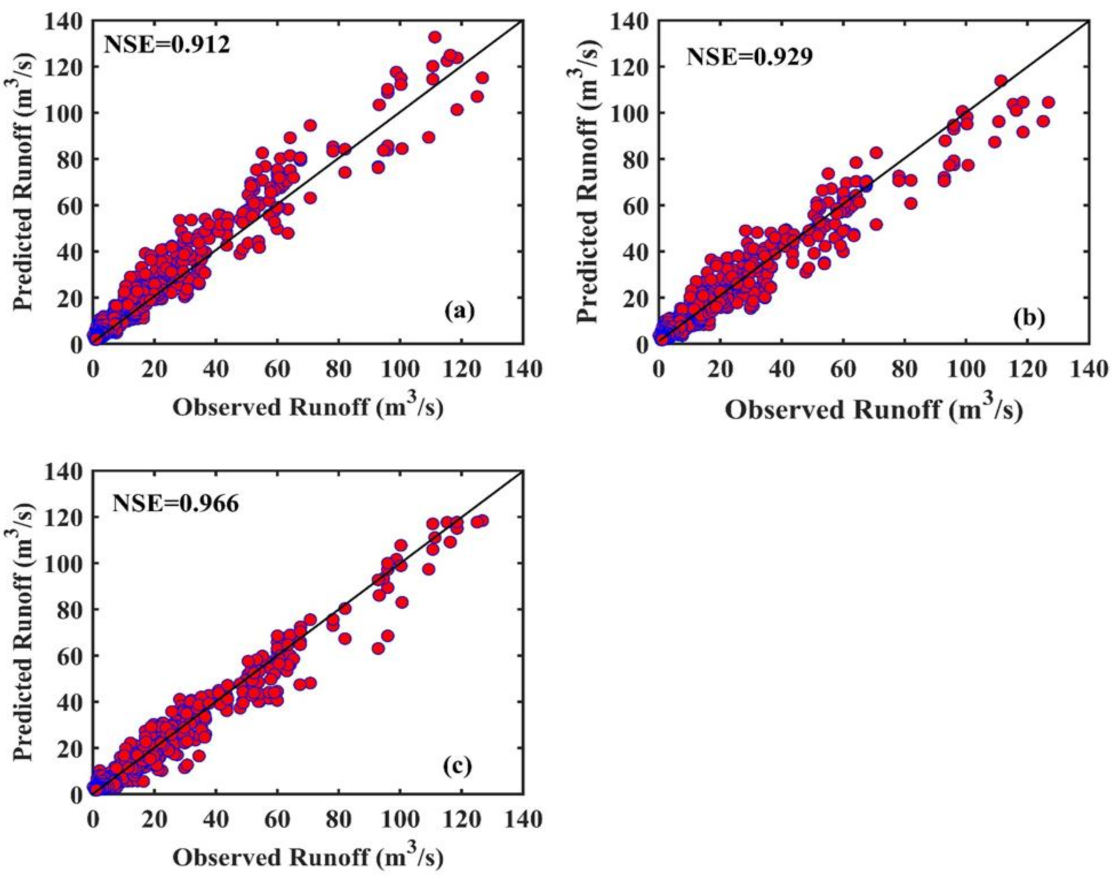
It can be infered from Table 7 that best result was obtained using scenario 3 and in the all senarios, NE performs better than the SE and WE techniques. In scenario three, the NE technique gave NSE, RMSE and MAE values of 0.966, 3.79 m^3/s and 2.375 m^3/s, respectively in verification phase. WE is the second best ensemble technique follwing NE technique with NSE, RMSE and MAE values of, 0.929, 5.132 m^3/s and 3.482 m^3/s, respectively in the verification verification phase. SAE ensemble gave the least acurate result compared to the others. SAE gave the lowest value of NSE than the ANFIS model (the best single model). This could be due to the fact that in the arithmetic averaging, the result is greater than the lowest number and less than the highest value in the data set. The RMSE and MAE value of the NE technique is lower than the single models and the linear ensemble techniques (SA and WE) in both the calibration and validation phases, showing an error reduction in the nonlinear ensemble technique.

As shown in the table, in scenario 1, NE improved the performance of HEC-HMS, HBV , and SWAT by 13.87%, 9.67%, and 6.55%, respectively, based on the verification phase of NSE values. In scenario 2, the NE technique improved the performance of FFNN, SVR, and ANFIS by 8.2%, 8.8%, and 4%, respectively. In scenario 3, the NE ensemble technique improved the accuracy of ANFIS, SVR, FFNN, SWAT, HBV, and HEC-HBV by 5.8%, 10.02%, 10.65, 16.4%, 22.9%, and 27.61%, respectively. The result and discussion in this section focus on scenario 3 (the best scenario).

The scatter plot, a visual investigation, of the three ensemble techniques (for scenario 3) is shown in Figure 18. The best ensemble technique was found to be NE, where the points are less scattered and close to the bisector line. For the linear ensemble techniques, especially SE, the values are comparatively dispersed, as can be seen in Figure 18.

Figure 18

Scatter plot of Ensemble Technique Runoff and Observed runoff by a) SE, b) WE and c)NE in the Verification phase



In addition, the time series plot was used to compare the similarity between the observed and predicted hydrographs, as shown in Figure 19. From the figure, it can be seen that NE achieves better agreement between the predicted values and the observed discharge values in both calibration and validation phase, while WE and SE rank second and third, respectively. In addition, the SE method overestimates the peak discharge.

Figure 19

Timeseries of Observed Runoff and Computed Runoff by Ensemble Technique a) Calibration and b) Validation phase

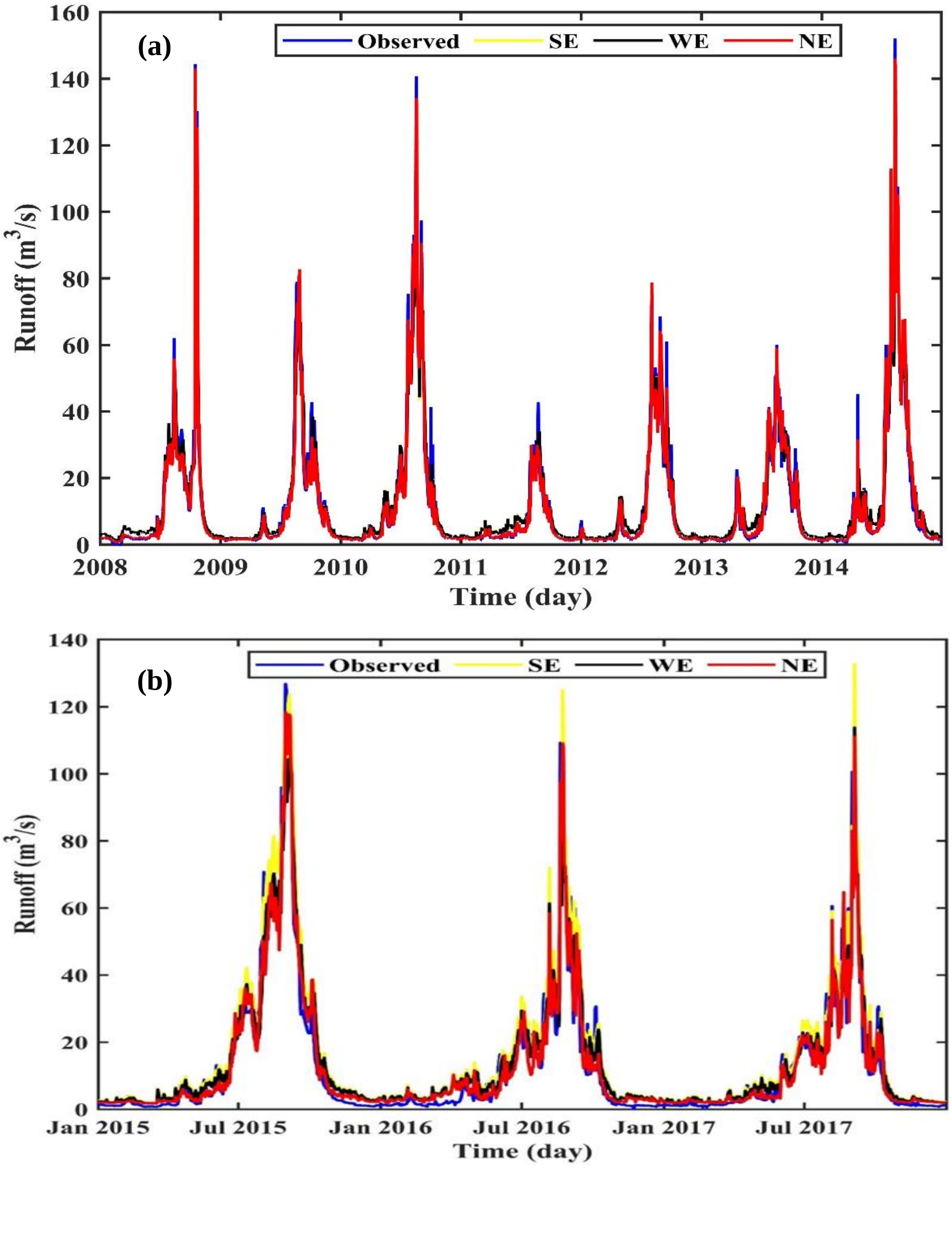
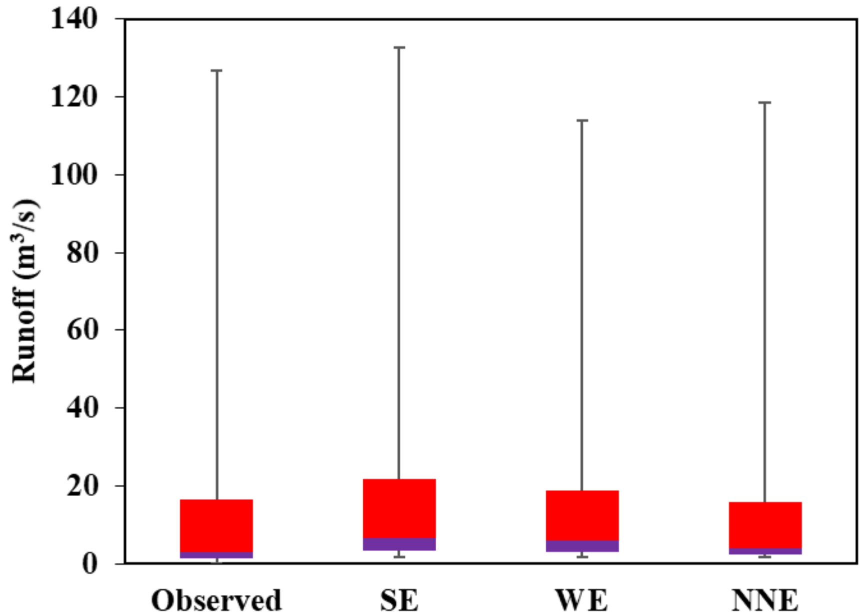


Figure 19 shows the boxplot of observed runoff and predicted runoff using the three ensemble techniques. As can be seen from the figure, the performance of the nonlinear ensemble (NE) technique is better in modeling rainfall-runoff. In this study, the variation between the observed runoff and predicted runoff value obtained by the three ensemble techniques was compared using different quartiles as shown in the boxplot (Figure 20). For example, the median value of runoff for observed=3.22 m^3/s , SAE=6.8161 m^3/s, NE=4.168 m^3/s and WE = 6.031 m^3/s. This shows that the value of NE was closer to the observed value than the other methods.

Figure 20

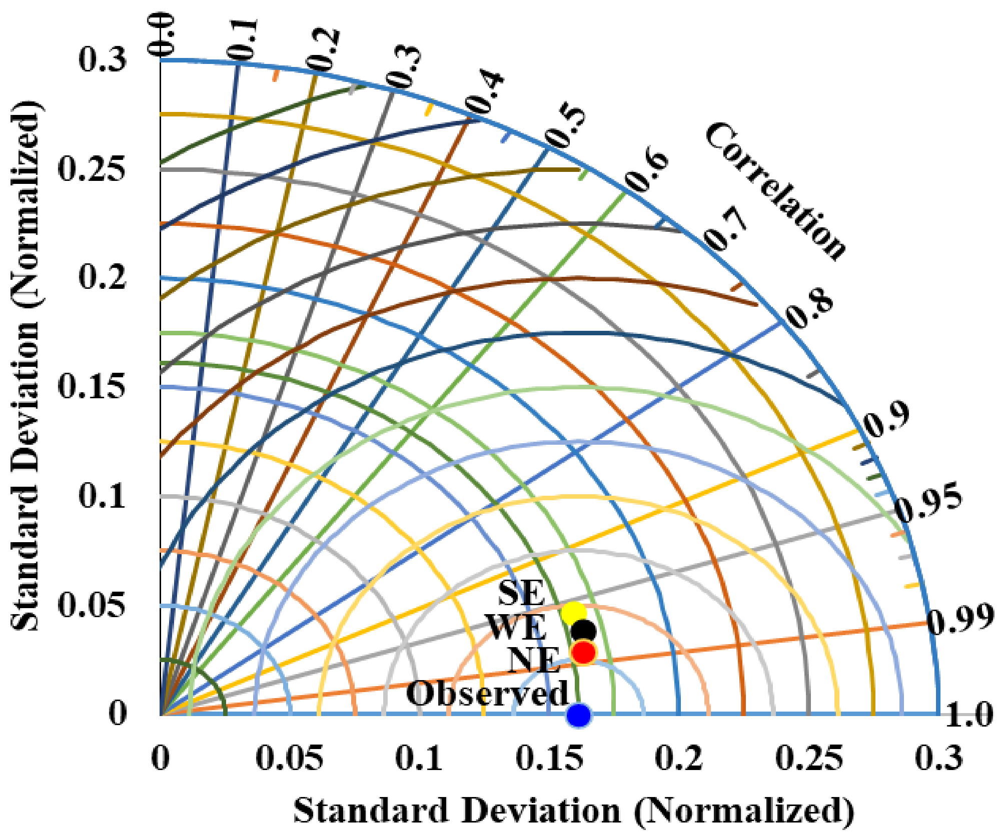
Boxplot of Observed Runoff and Ensemble Technique



The performances of WE, SE and NE were also demonstrated by two-dimensional Taylor diagram (see Figure 1), which shows the observed runoff and the computed runoff by each ensemble technique for better comparison. In this diagram, standard deviation (SD) and correlation coefficient (r) were combined to form multiple performance indices in a single diagram to analyze how close the computed value is to the observed value.

Figure 21

Taylor Diagram Showing the Performance of Ensemble Technique



The Taylor diagram of SE, NE and WE technique is indicated in Figure 21. In this chart, the model is best when its value is closer to the observed value. In this regard, as depicted in the figure, the NE technique is the closest to the observed runoff than the WE and SE, and hence more accurate than the other ensemble techniques.

Results of SSL modeling using single AI-based and MLR models

In the first strategy of SSL modeling, the current day SSL was estimated using different combination of lagged discharge and SSL value as input. For each of the input combination, the MLR, FFNN, SVM and ANFIS models were calibrated and verified and only the best result of each of the models was presented in Table 8. The best input combination that gave the best result was Qt, Q_{t-1}, Q_{t-2}, SS_{t-1} and SS_{t-2}. Determining the best model structure (e.g., hidden neuron's number) is the crucial step in modeling with the FFNN model to obtain an accurate result. The reason is that if too small neurons are used, incorrect information may be captured and an overfitting problem may occur if many neurons are included. Therefore, the best FFNN structure was determined by a trial-and-error method. The FFNN model with 8 hidden neurons and five inputs trained with the LM algorithm gave the best result in SSL modeling. The SVM, the second AI-based model, was build using RBF kernel to model SSL. Compared to the other kernels used in the SVM model, the RBF provided the better result (Sharghi et al., 2018).

The other Black-box AI-based model was the ANFIS model, which has strong ability to process the nonstationary and uncertain data using the fuzzy concept. For this study, the MFs of the ANFIS model were calibrated using hybrid algorithm. The type and number of MFs and the epoch number were iteratively changed until the best agreement between observed and predicted SSL was achieved. Among the analyzed MFs in the ANFIS model, the best result was obtained with Gaussian MFs calibrated with 55 epochs. Lastly, the MLR model which shows the linear relationship between dependent and independent parameters was applied for modeling the SSL and compared with the other AI-based models using the performance measures as shown in Table 8. In the structure of FFNN (Table 8), the number 5-3-1 represents the number of inputs, hidden neurons and output. In the same way, in MLR, the number 4-1 represents the number of input and output variables.

Table 8

Single AI-based and MLR Mode's Result for SSL Modeling (in strategy 1)

Model	Best structure	Calibration			Validation		
		NSE	MAE	RMSE	NSE	MAE	RMSE
SVM	RBF	0.867	630.69	1857.67	0.815	1376.05	2517.03
FFNN	5-8-1	0.876	597.114	1799.25	0.834	1032.04	2382.29
ANFIS	Gaussian	0.918	563.56	1462.06	0.884	897.37	1943.67
MLR	5-1	0.755	688.026	2528.5	0.708	2121.41	3170.65

*RMSE and MAE are in ton/day

The results of each model in SSL modeling are shown in Table 8. As, indicated in the table, the ANFIS model gave the best result with NSE=0.884, RMSE=1943.67 t/day and MAE= 897.37 t/day and FFNN and SVM being the second and third respectively, in the validation phase. The MLR model gave the least accurate result compared to the other AI based black-box models with NSE=0.708, RMSE= 3170.65 t/day and MAE= 2121.41 t/day. This could be due to the fact that for complex, nonlinear and dynamic problem like SSL, nonlinear models' (e.g., ANFIS) estimates more accurately than the linear models. From the result shown in the table, the best AI-based model (ANFIS) increased the performance of SVM, FFNN and MLR by up to 8.47%, 6% and 24.86%, respectively based on validation phase NSE value. Moreover, various graphical performance indicators such as boxplots, scatter plots and Taylor diagrams were applied to provide a better view each model's predictive performance. Figure 22 shows the scatter plots of the MLR and AI-based model compared to the actual SSL value.

Figure 22

The Scatter Plots of the Measured and Computed SSL, a) MLR, b) SVM, c) FFNN and d) ANFIS, in Validation phase

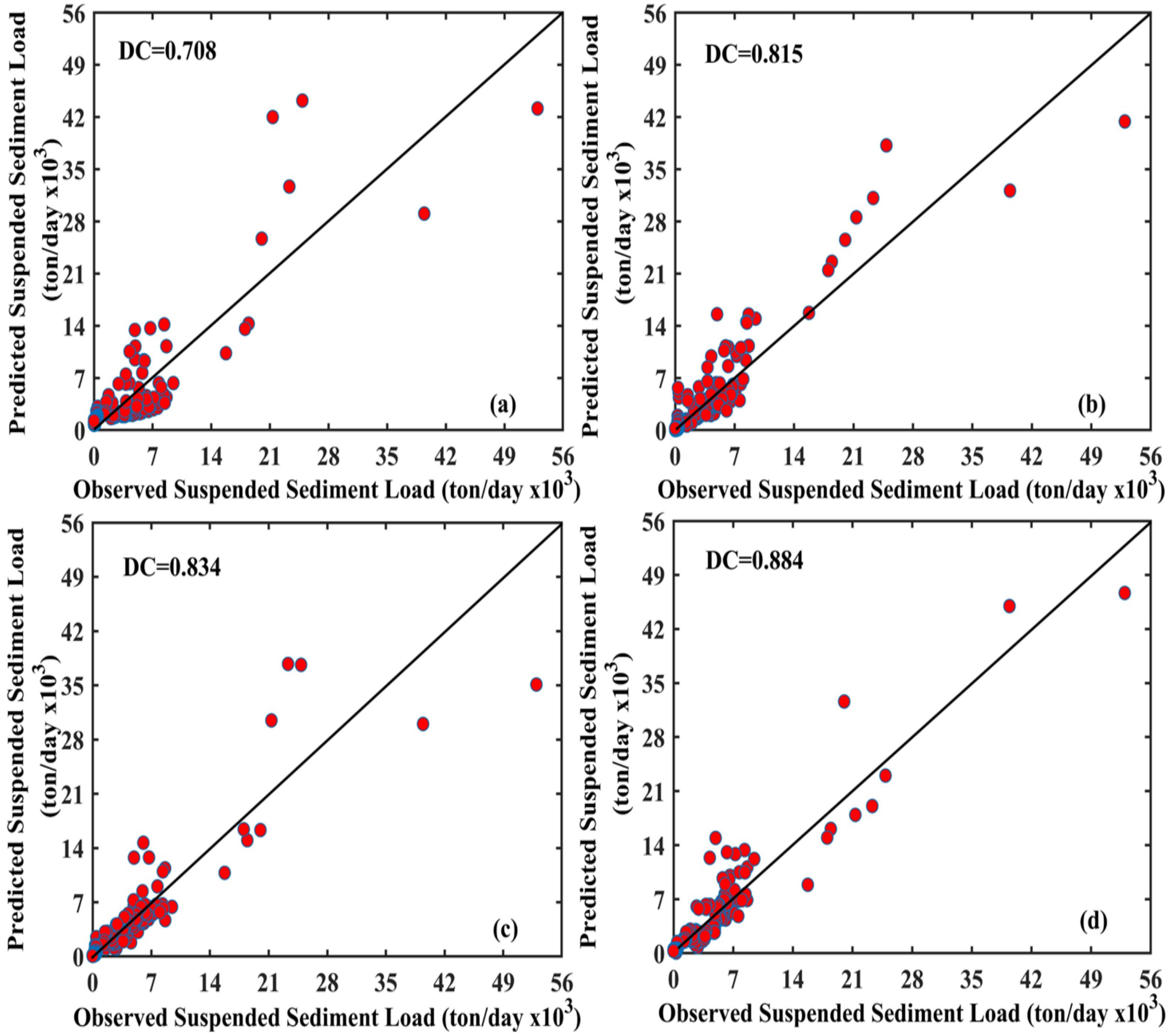
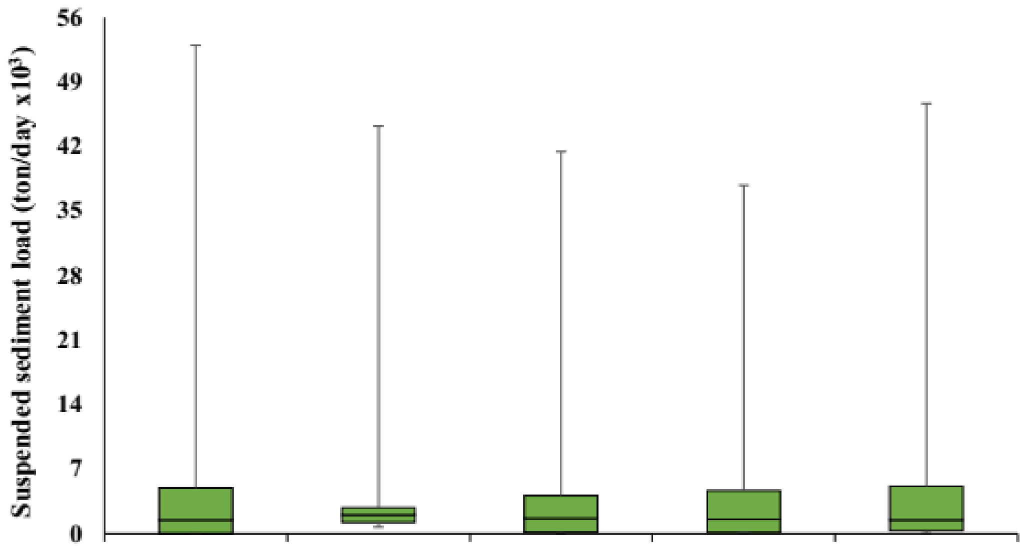


Figure 22 shows the scatter plot to compare the predictive accuracy of ANFIS, MLR, FFNN and SVM models in modeling SSL. The Figure shows that the data points of ANFIS model and observed SSL are close to each other and to the diagonal line. Whereas, more spread datapoints was observed in the MLR model.

Figure 23

Boxplot of Observed vs Estimated SSL in Validation Phase

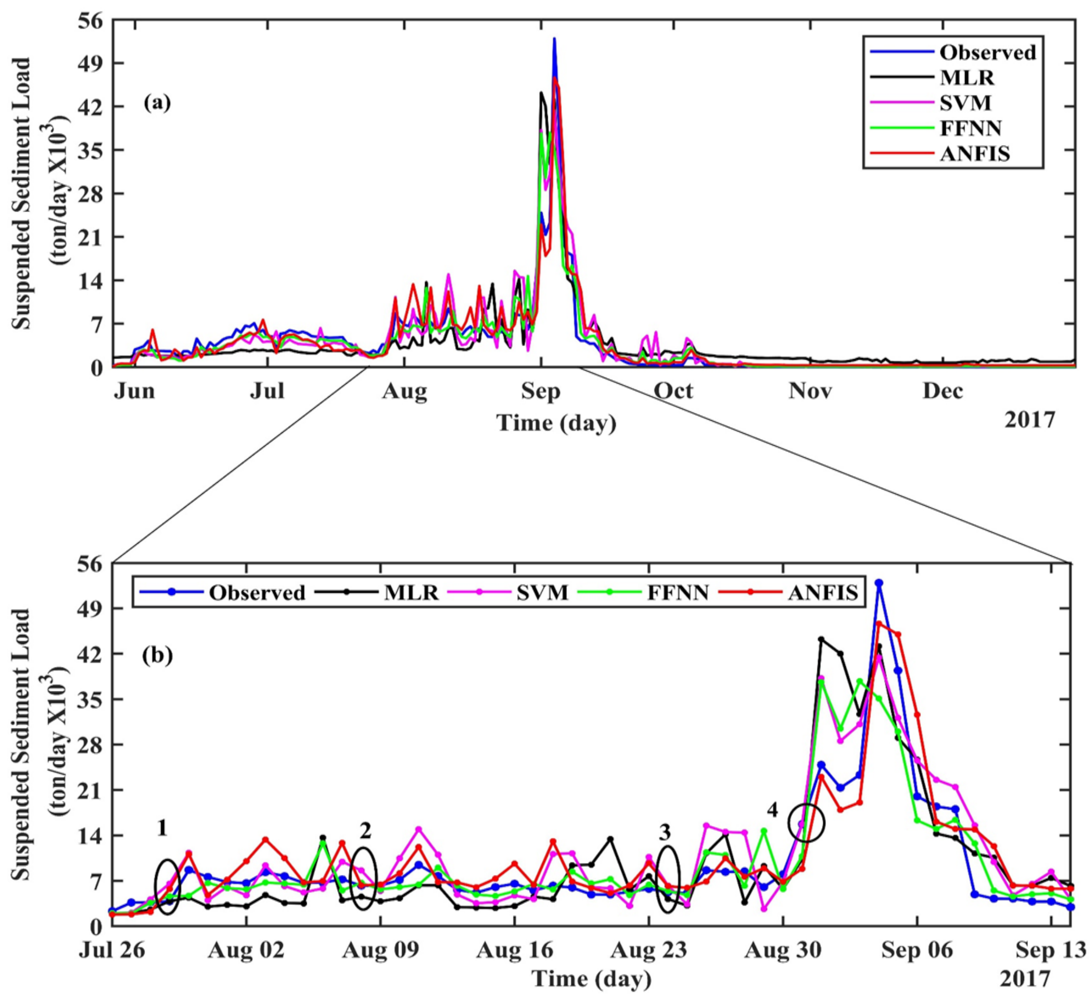


	Observed	MLR	SVM	FFNN	ANFIS
Min (ton/day x10^3)	0	0.708	0.0099	0.0720	0.0807
$Q_{25\%}$ (ton/day x10^3)	0.0234	1.2568	0.1344	0.1078	0.3175
$Q_{50\%}$ (ton/day x10^3)	1.4820	2.0144	1.6727	1.5628	1.4973
$Q_{75\%}$ (ton/day x10^3)	4.9532	2.8013	4.141	4.6364	5.1381
Max (ton/day x10^3)	52.9474	44.2235	41.4157	37.7572	46.6722

The performance of the models was also analyzed using box-plot (see Figure 23). As shown in the figure the median value ($Q_{50\%}$) for the MLR = 2014.4 t/day, the ANFIS model = 1,497.3 t/day, the FFNN = 1,562.8 t/day, the SVM = 1,672.7 tons/day and the actual runoff = 1,482 t/day. This indicates that the best predictive performance was obtained with the ANFIS model and FFNN was the second most accurate model, while the worst estimation result was obtained with MLR. Kumar et al. (2019) applied ANN and ANFIS to estimate the current-day runoff and SSL of the Godavari basin by using different combinations of previous day SSL and discharge data as input. In this study, it was found that better estimation performance was obtained using ANFIS model than ANN. Nourani and Andalib (2015) applied ANN and LSSVR to predict the SSL in daily and monthly time steps and found that LSSVR perform better than ANN. Buyukyildiz and Kumcu (2017) applied ANFIS and SVM, and ANN for SSL estimation using different combinations of lagged Q and SSL as inputs. The result of this model showed that better accuracy was obtained using ANN than the others. From these model comparison studies, it is clear that each AI-based model performs differently when applied to different catchments. As stated by Salih et al., (2020) this could be due to the stochasticity of the SSL data of the catchment and also the AI-based model's ability to deal with the non-linearity and non-stationarity in the data set. The time series of the observed SSL and the individual models were used to compare the performances of the applied AI-based and MLR models in different time spans (see Figure 24)

Figure 24

Observed and Predicted Value of SSL in the Validation Phase; (a) January, 2016-December, 2017 and b) July 26 to September 14, 2017



As can be seen in Fig.24b, four points (1, 2, 3, and 4) were randomly selected on July 29, August 08, August 24, and August 31, respectively. For point 1; MLR= 3857.018 t/day, ANFIS= 5752.136 ton/day, SVM=6573.967 ton/day, FFNN=4620.326 ton/day and observed =3831.348 ton/day. This shows that the MLR model gave more a closer value to the observed SSL value indicating that even the worst model can provide more accurate prediction at some point in the data span. Regarding point 2, MLR=4563.506 t/day, ANFIS=6313.366ton/day, FFNN=6695.642 ton/day SVM=8595.878 ton/day and observed =6245.252 ton/day. At this point, the ANFIS model provide the best result. For point 3, MLR= 4190.825 ton/day, ANFIS= 6181.81ton/day, FFNN= 5424.629 ton/day, SVM= 6270.75 ton/day and observed = 5249.579 ton/day. This shows that the deviation of the predicted SSL from the observed value is smaller for the FFNN model. Also, SVM model perform better than the other models at point 4. From thee points selected, it can be inferred that different models may lead to different accuracy at different times in the data span. Therefore, the goal of better accuracy in modeling SSL could be achieved by ensemble techniques. In this context, four ensemble techniques such as AE, SE, NE and WE were applied to enhance the overall SSL modeling.

SSL modeling results using ensemble techniques

In order to increase the accuracy of the SSL modeling, the outputs of the individual MLR and AI models were combined using four different ensemble techniques and the result is shown in Table. The prediction performances of the ensemble techniques (SE, AE, WE and NE) for modeling SSL is shown in Table 9. From the table, it can be seen that the ANFIS ensemble (AE) led to the most accurate result among the other model combination methods due to the robustness it has in its framework by combining ANN and FIS.

The SE improved the performance of FFNN, MLR and SVM, but it provided less accurate results than the best model (ANFIS). According to Nourani et al. (2020), arithmetical averaging produces a result that is between the minimum and maximum values in the data set. WE gave better performance than SE due to the weights assigned to each model in the ensemble unit based on its NSE value.

Table 9

Results of the Proposed Ensemble Methods for SSL Modeling (strategy 1)

Ensemble technique	Best structure	Calibration			validation		
		MAE	RMSE	NSE	MAE	NSE	RMSE
SE	4-1	498.56	1391.2	0.922	1191.4	0.879	2089.46
AE	Gausian	241.8	713.93	0.98	496.78	0.97	1009.29
WE	0.26, 0.27,0.25, 0.22	498.56	1391.2	0.926	1092.57	0.888	1873.87
NE	4-7-1	485.55	1105.9	0.953	741.92	0.924	1610.1

*RMSE and MAE are in ton/day

The performance of each ensemble technique in SSL modeling are shown in Table 9. As shown in the table, the AE technique provided the best result with NSE=0.97, RMSE=1009.29 ton/day and MAE= 496.78 ton/day while the NE is the second best accurate ensemble technique, in the validation phase. The SE technique gave the least accurate result compared to the other ensemble techniques with NSE=0.879, RMSE= 2089.46 ton/day and MAE= 1191.4 ton/day. The higher performance of AE could be due to its ability to deal with the complex, nonlinear and dynamic problem like SSL.

As it is shown in the Table 9, the nonlinear ensemble techniques i.e., AE and NE greatly improved the performances of the single models. The comparison of the modeling performance improvement of the nonlinear ensemble technique with the performances of each MLR and AI models considering their NSE value in the calibration and validation phase is presented in the table.

Table 10

Performance Comparison Between Nonlinear Ensemble and Individual Models

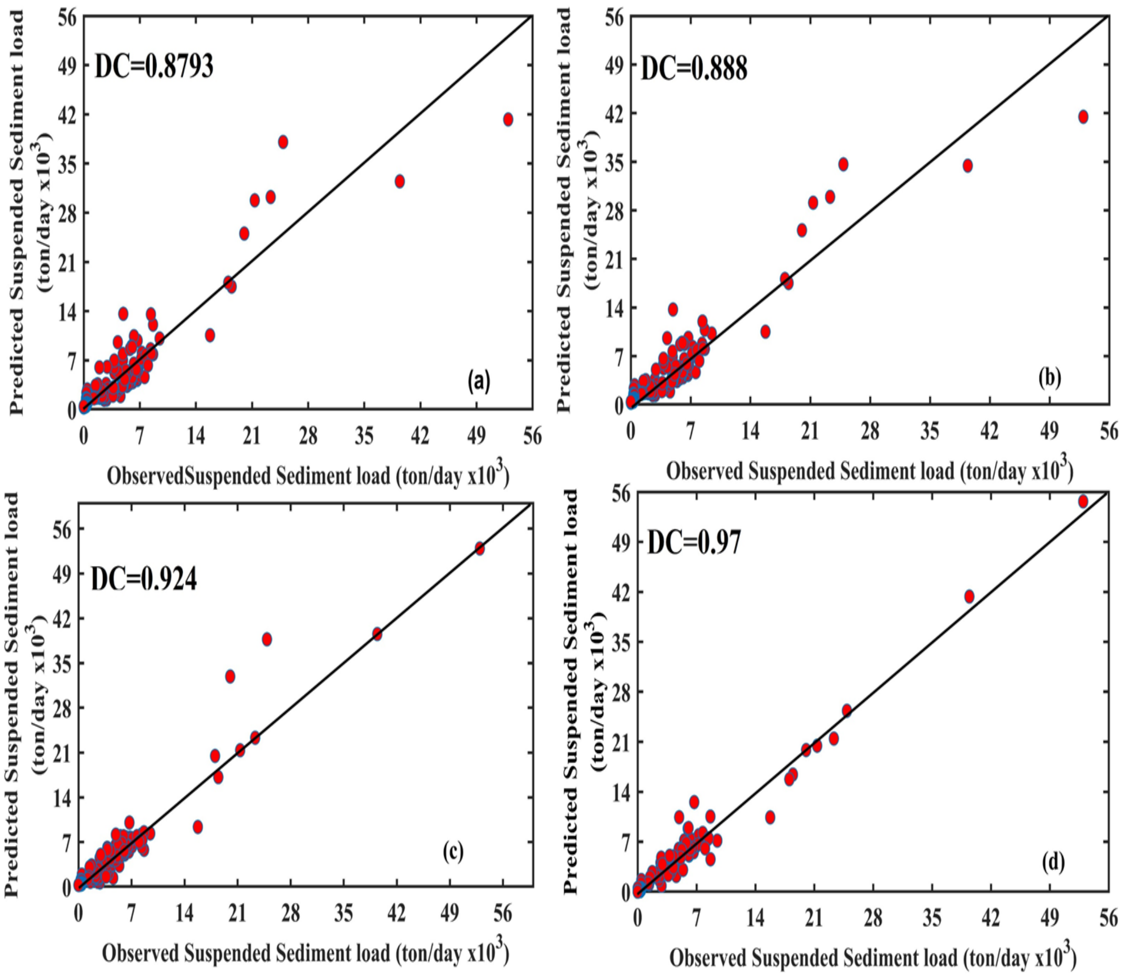
Model	Calibration	validation
AE vs MLR	29.85%	37%
AE vs SVM	13.08%	19.02%
AE vs FFNN	11.9%	16.3%
AE vs ANFIS	6.8%	9.73%
NE vs ANFIS	3.8%	4.5%
NE vs MLR	26.22%	30.5%
NE vs FFNN	8.8%	10.79%
NE vs SVM	9.92%	13.37%

The comparison result in Table 10 shows the ability of the nonlinear ensemble technique to increase the prediction accuracy of each model considering the NSE values of the calibration and validation phase. As can be seen from the result of this study, both the linear and nonlinear ensemble techniques can be used as a model combination method to boost the individual model's performance in SSL modeling. However, AE and NE technique were superior to the linear ensemble techniques (SE and WE). This could be because the SE and WE methods, unlike the nonlinear ensemble techniques (NE and AE), are not able to go through another black-box learning process. The NE improved the accuracy of the FFNN, SVM, MLR and ANFIS models by up to 10.79%, 13.37%, 30.5% and 4.5%, respectively in the validation phase (based on NSE value). Similarly, by using AE, the accuracy of FFNN, SVM, MLR and ANFIS models could be improved by 16.3%, 19%, 37 and 9.73%, respectively, in the validation phase.

The SSL estimation result of each ensemble techniques and the observed values in the validation phase was also presented in scatter plot. Figure 25 compares the scatter plots of the four-ensemble technique versus the observed SSL in validation phase. As can be seen in the figure, AE shows a less scattered estimate and points are closer to the 1:1 bisector line, while more scatter points are seen in the WE and SE technique.

Figure 25

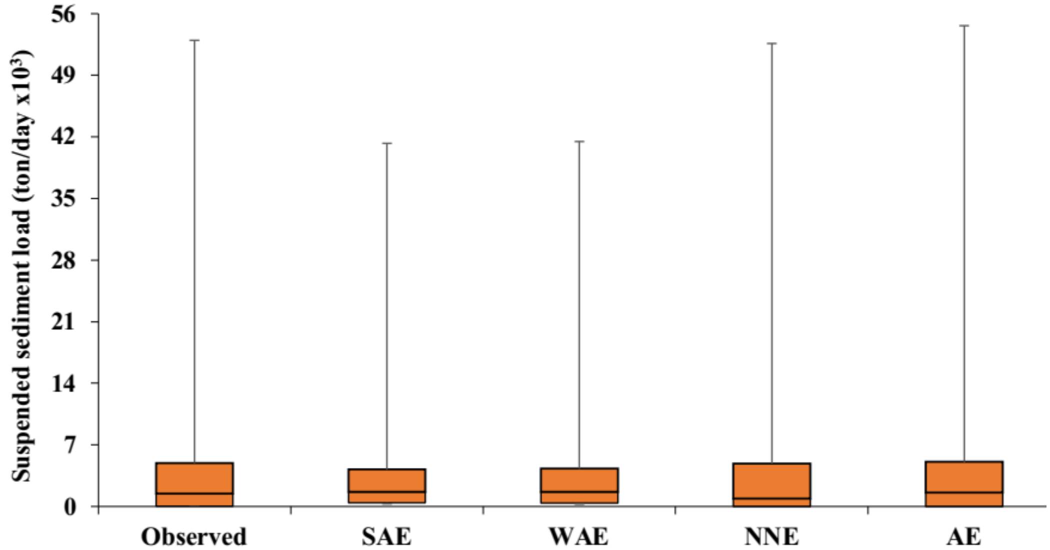
Scatter Plots of Observed SSL Versus a) SAE, b) WE, c) NE and d) AE, in the Validation Phase



Comparison of the performance of the ensemble technique developed against the observed SSL was made using the boxplot (see Figure 26) considering different quartiles and higher accuracy was achieved using AE technique.

Figure 26

Boxplot of Predicted SSL by Ensemble Technique and Observed Value

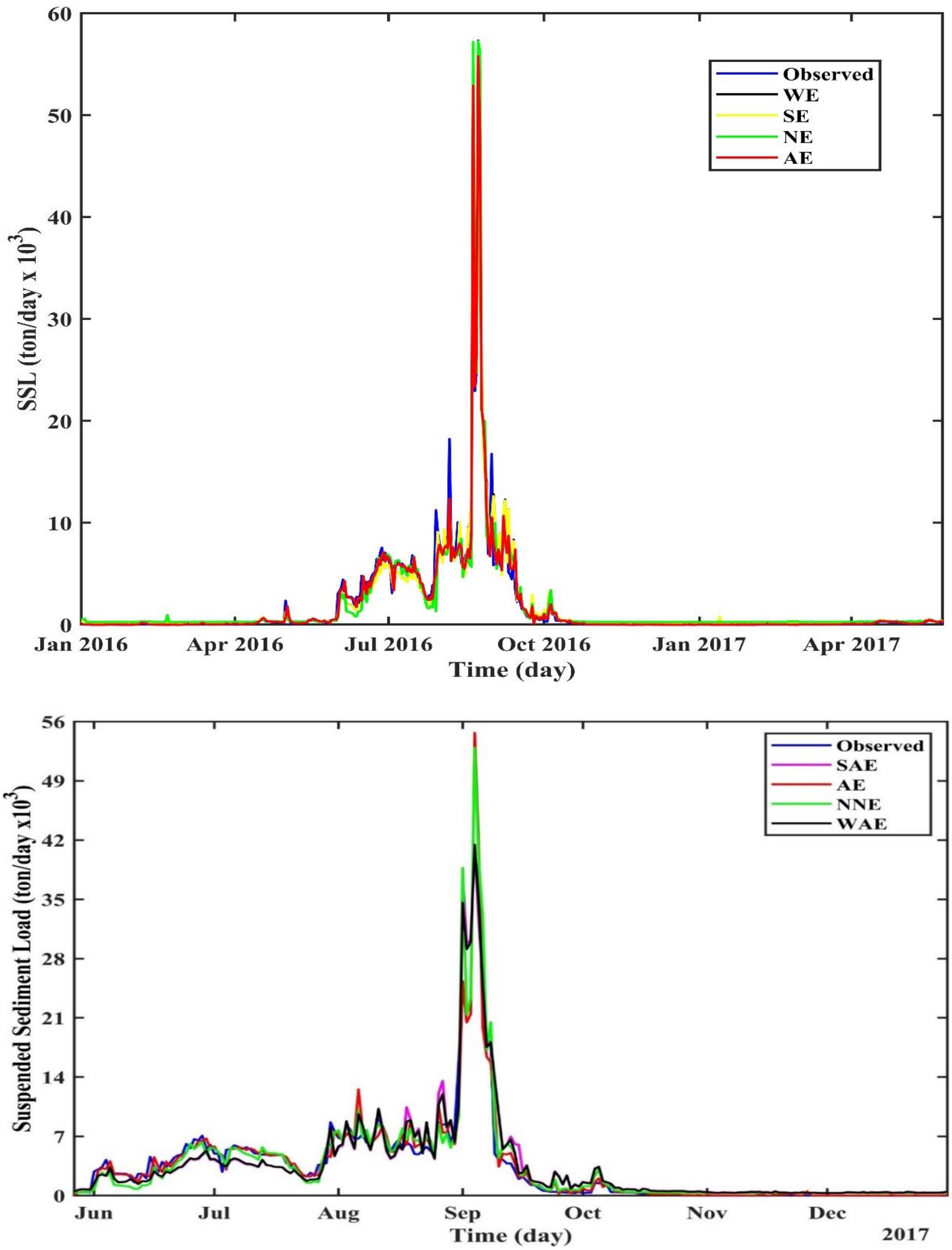


	Observed	SAE	WAE	NNE	AE
Min (ton/day x10^3)	0	0.3069	0.2931	0.30300	0.00042
$Q_{25\%}$ (ton/day x10^3)	0.0234	0.4372	0.4071	0.31176	0.0513
$Q_{50\%}$ (ton/day x10^3)	1.482	1.6811	1.678	1.21242	1.6364
$Q_{75\%}$ (ton/day x10^3)	4.9532	4.2354	4.293	5.1948	5.0196
IQR(ton/day x10^3)	4.9298	3.7982	3.8858	4.883	4.9683
Max (ton/day x10^3)	52.9474	41.2708	41.4685	52.90406	54.6722

The time series of predicted SSL by each ensemble technique (AE, NE, WE and SE) and the observed SSL in validation phase is shown in the Figure. As it can be depicted from the Figure 27, AE and SE gave less accurate result as wide fluctuation is seen between them and the observed times series in both dry and wet season. In nonlinear ensemble technique (AE and NE) in the other hand, the predicted SSL agreed better with the actual value.

Figure 27

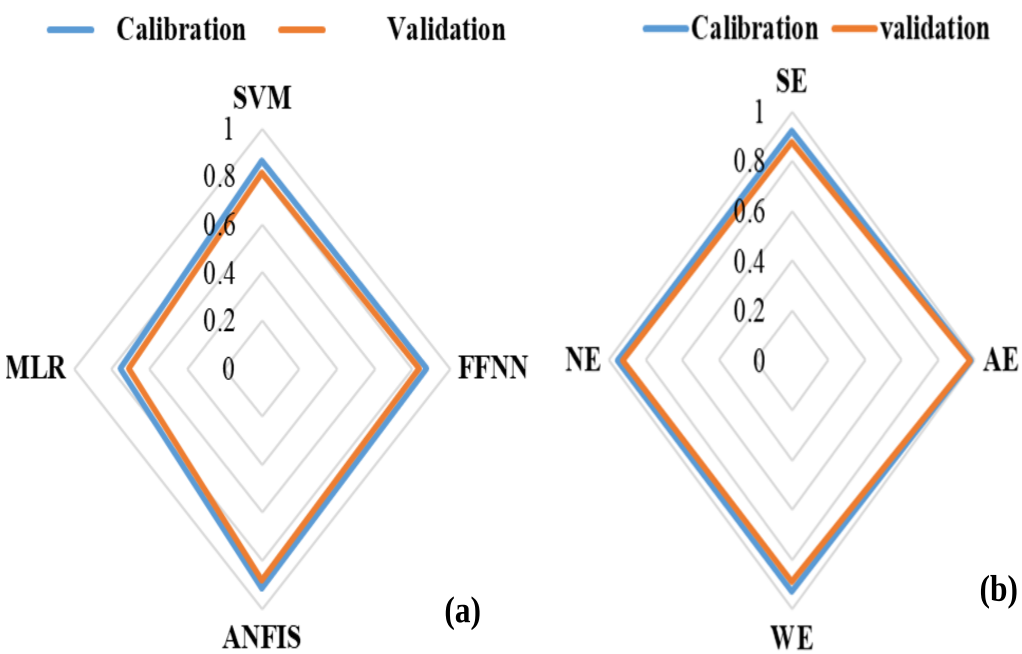
Time Series of Ensemble Technique and Observed SSL in a) Calibration Phase and b) Validation Phase



The performance of single and ensemble models used in the first strategy of SSL modeling was also compared using the Radar plot based on the NSE value shown in Figure 28.

Figure 28

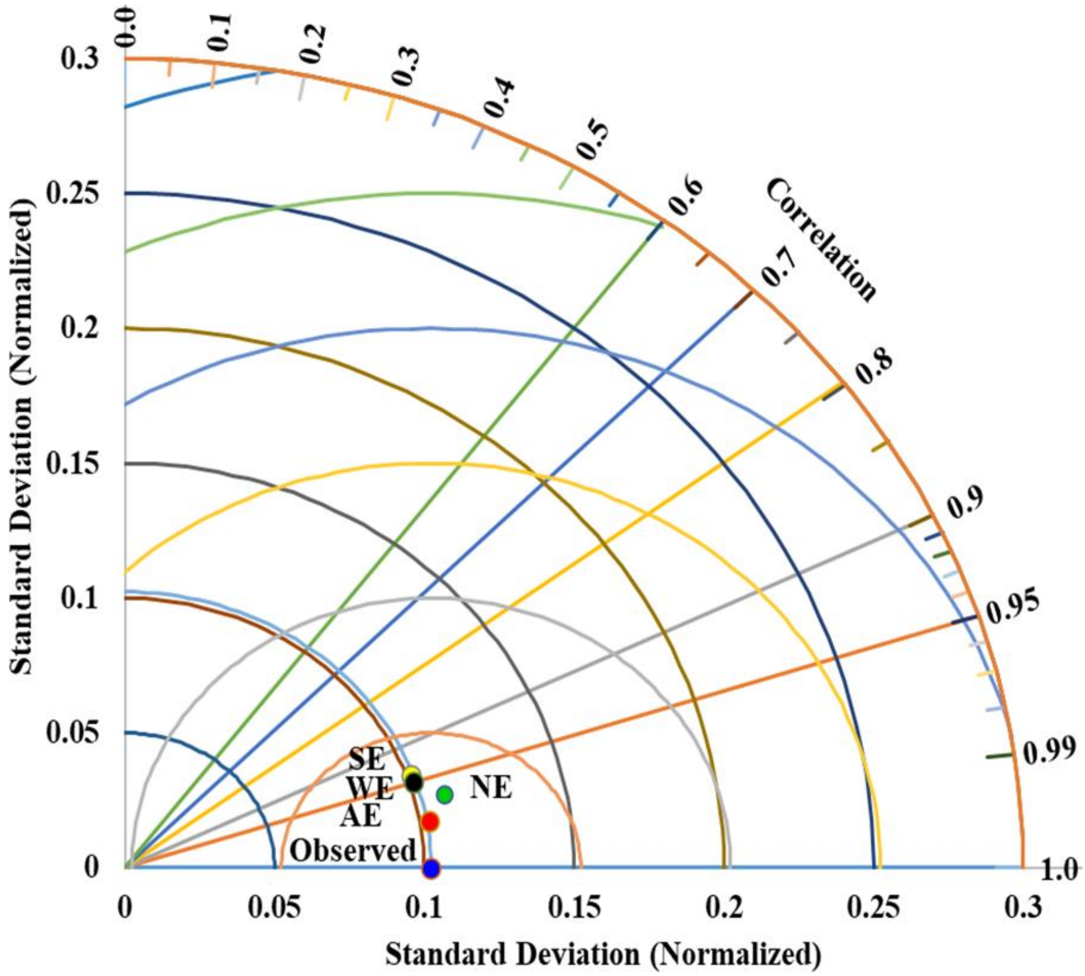
Radar Plot Comparison of a) single, b) Ensemble Technique for SSL Modeling



Taylor diagram was also used to evaluate the performance of each ensemble techniques. In this graphical comparison technique, a model is best when its result is closer to the observed SSL value. In this context, from the Figure 29 it can be inferred that ANFIS model showed better performance with r=0.985 while SE gave least accurate result with r =0.927.

Figure 29

Tayler diagram Comparing Ensemble Techniques in SSL Modeling



Hybrid runoff-SSL modeling

In step four of this study (i.e., in the strategy 2 of SSL modeling), due to SSL data scarcity, only two years of (2016-2017) runoff result of the best ensemble technique (NE in the three scenarios separately) with lagged runoff and SSL were used as input for SSL modeling using ANFIS, FFNN, SVM, and MLR. In this SSL modeling process, the input layer of ANFIS, SVM, FFNN and MLR was fed by the runoff outputs of ensemble techniques (NE) in three scenarios, which was considered as input variable. Similar to rainfall-runoff modeling, LM algorithm was used to train FFNN for SSL modeling using the runoff value resulted from the best ensemble technique in three scenarios separately in step three of this study. As too many neurons or too small neurons may cause unrealistic result, selecting optimum neuron number is important in FFNN modeling. Thus, in all scenarios, trial and error method, by varying neuron numbers was used until the best agreement between observed and predicted SSL value is reached. FFNN with 6, 7and 7 hidden neurons was found to give the best result in scenario 1, 2 and 3, respectively. The other AI based model used in the SSL modeling was the ANFIS model in which hybrid training algorithm was used for MF function calibration. To get best result, different types of MF was trained with different epoch number by trial-and-error method. ANFIS model with gaussian MF trained by 50 epochs gave the best result. SVM is the third AI model applied for SSL modeling in the current study using radial basis function (RBF) kernel. The fourth model used for SSL modeling in this study was MLR. This model was used to see the linear relationship between the inputs and the outputs. The performance of ANFIS, SVM FFNN and MLR models were evaluated using NSE, MAE and RMSE and presented in Table 11.

Table 11

Performances of AI-based and MLR Models for Hybrid SSL Modeling (strategy 2)

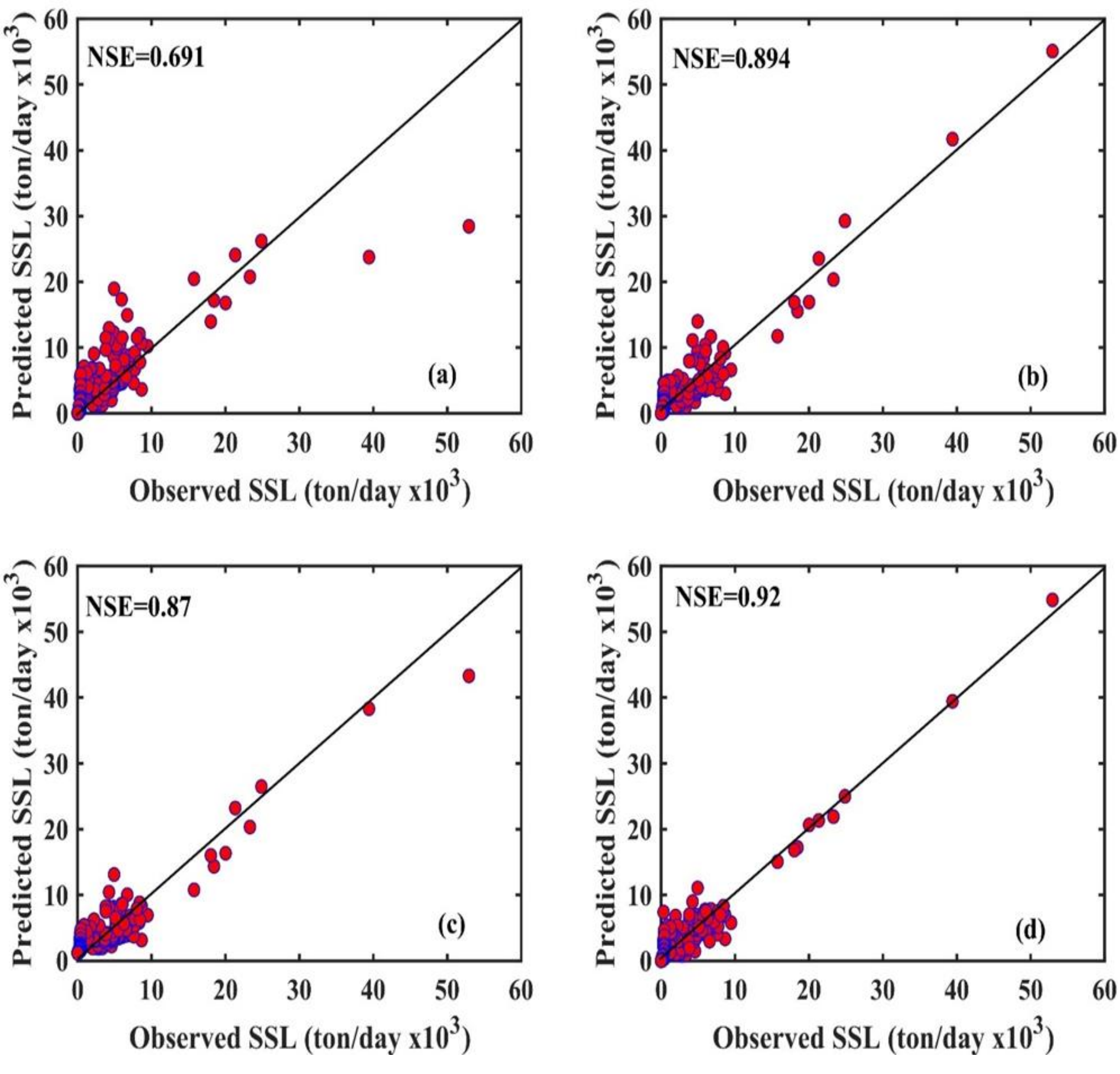
Scenario		Calibration			Validation		
	Ensemble Method	NSE	MAE (ton/day)	RMSE (ton/day)	NSE	MAE (ton/day)	RMSE (ton/day)
Scenario 1	MLR	0.702	905.72	2786.27	0.649	1801.3	3464.93
	FFNN	0.854	1460.02	1952.55	0.816	1871.59	2506.25
	SVM	0.861	728.27	1902.45	0.803	1454.87	2597.55
	ANFIS	0.887	665.7	1717.37	0.85	1282.31	2273.41
Scenario 2	MLR	0.741	1488.7	2587.19	0.681	1702.72	3305.25
	FFNN	0.883	932.03	1821.41	0.858	1748.29	2208
	SVM	0.902	673.34	1516.36	0.868	1344.55	2124.44
	ANFIS	0.914	583.81	1496.07	0.898	1137.96	1865.19
Scenario 3	MLR	0.756	1389.2	2519.54	0.691	1698.47	3250.6
	FFNN	0.892	863.91	1674.88	0.87	1694.16	2110.88
	SVM	0.924	635.41	1402.29	0.894	1239.39	1905.54
	ANFIS	0.948	522.99	1125.83	0.92	1018.31	1628.26

The efficiency of the applied models was evaluated using NSE, RMSE and MAE (see Table 11). In this regard, ANFIS is the best model in SSL modeling with NSE=0.85, 0.898 and 0.92, RMSE=2273,41t/day,1865.19 t/day and 1881628.259 t/day and MAE=1282.31 t/day, 1137.96 t/day and 1018.312 t/day in scenario 1, scenario 2 and scenario 3, respectively. Similar to the rainfall-runoff modeling, the ANFIS model showed its superiority over the applied models in the hybrid rainfall-runoff-sediment modeling. Moreover, in all models, best result was obtained from scenario 3 and therefore, the discussion in this section focuses on this scenario.

Scatter plot, another model performance evaluation tool was used to compare the predicted and observed SSL values as shown in Figure 30. According to Jimeno-Sáez et al. (2021), the least accurate models give more scattered data points. The model with higher NSE value gives the better data fit to the 1:1 line. In this regard, ANFIS model provided the best fit between computed and observed SSL. In scatter plot shown in Figure 30, the ANFIS model with NSE value of 0.92 shows that the data points are very close to each other and the diagonal line.

Figure 30

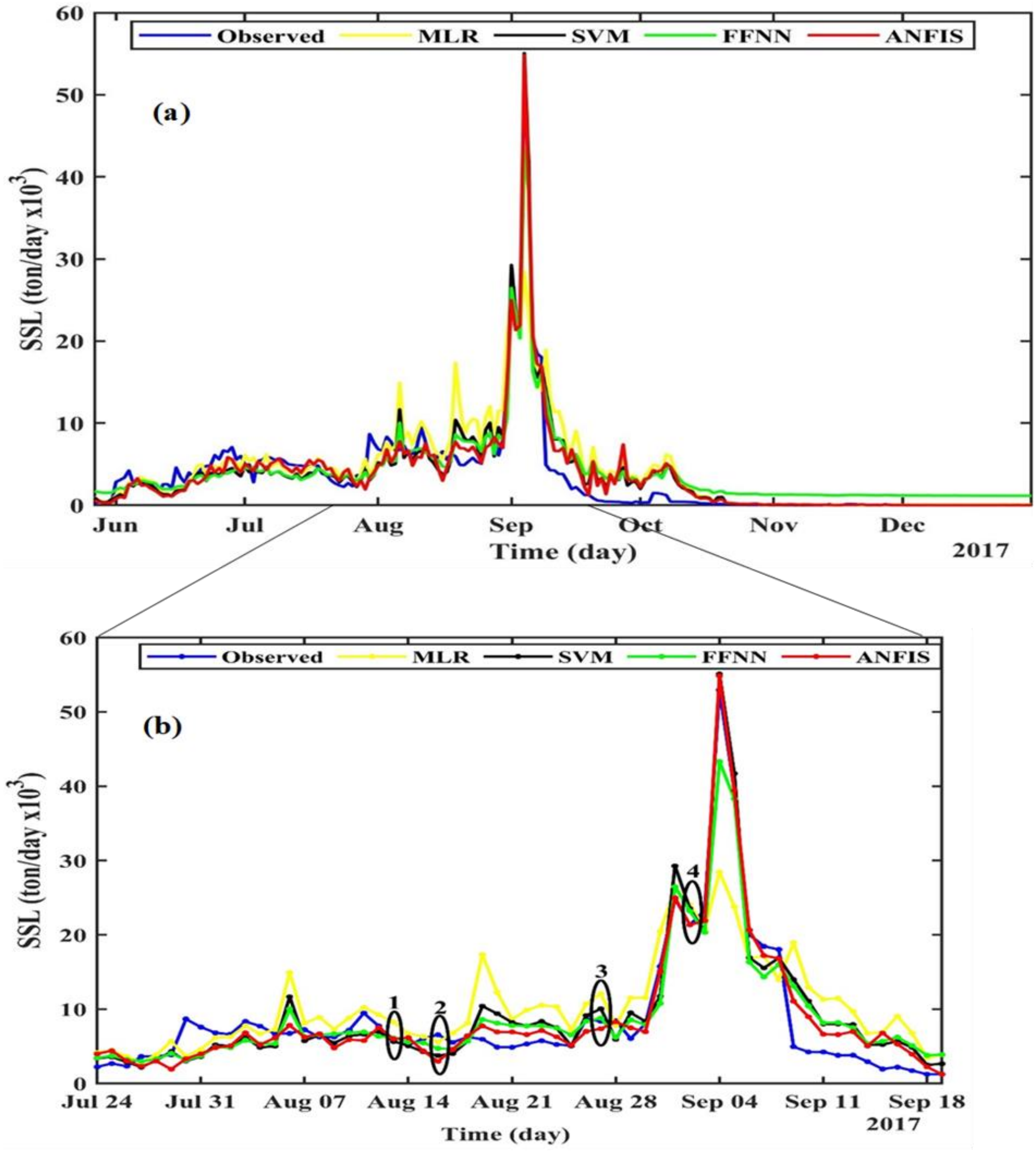
The Scatter of Observed SSL and Individual Models in the Verification Phase



Time series plot of the observed SSL versus predicted SSL values in the validation phase are shown in Figure 31a. In the figure, high agreement between predicted and observed values is seen in the ANFIS model. A section of the time series plot of observed SSL value versus computed SSL values by MLR, ANFIS, SVM and FFNN is shown in Figure 29b. To have better visibility of the SSL values, only 58 days (from July 24, 2017 to September 19, 2017) were included in Figure 31b.

Figure 31

Time series of Observed and Predicted SSL in Validation Phase a) June 27,2017 and b) from July 24, 2002 to September 19, 2017



As shown in Figure 31b, four points on August 13, August 16, August, 27 and September 27 were randomly chosen and named as points 1, 2, 3 and 4, respectively. For point 1, SVM= 5,685.497 t/day, FFNN= 6,141.208 t/day, ANFIS = 6,000.747 t/day, MLR= 8,269.8095 t/day and observed SSL value = 5,626.669 t/day. It shows that the SSL value predicted by SVM is closer to the observed SSL value than the other models. For point 2, MLR= 5,586.05 ton/day, SVM= 3,769.007 ton/day, ANFIS= 2,979.931 ton/day, FFNN= 4,721.752 ton/day and observed SSL value = 6,555.725 ton/day. This shows that the SSL value of MLR is close to the observed value than the values of the other models. It is also clear from point 2 that even the least accurate model can give the best result at a particular point in the time series. Regarding point 3, FFNN= 8,803.296 ton/day, MLR= 12,063.97 ton/day, SVM= 10,049.6439 ton/day, ANFIS= 7,365.95and observed SSL value = 8,382.12t/day. For point 4, ANFIS= 21,327.973ton/day, SVM= 23,537,739ton/day, MLR= 24, 093.617 ton/day, FFNN= 23,211,713 ton/day and observed SSL value = 21,333.43ton/day. This indicates that ANFIS gave better result than the other models. It could be seen from the randomly selected points that different models might gave different prediction accuracy at different points of the time series. Hence, more accurate prediction of SSL could be achieved by using different ensemble technique. In this regard, this study developed three ensemble technique for SSL modeling to enhance the overall accuracy and the result is discussed in the next sub-sections.

Results of runoff-SSL by model combination technique

In the last step of the current study, to improve the overall modeling accuracy of the hybrid runoff-SSL modeling, the SSL value resulted from each single models such as ANFIS, MLR, SVM and FFNN were combined and used as input for the four ensemble techniques (NE, AE, WE and SE). The procedure is the same as the ensemble process followed in the rainfall-runoff and SSL (strategy 1) modeling. The SSL values of ANFIS, SVM, FFNN and MLR obtained in step four was fed to NE, SA, AE and WE technique as input. Table 12 shows the performance measure of results of ensemble techniques in hybrid SSL model.

Table 12

Results of Ensemble Technique for SSL Modeling

Ensemble Method	Best structure	Calibration			Validation		
		NSE	MAE	RMSE	NSE	MAE	RMSE
SE	4-1	0.923	795.67	1414.95	0.887	1332.16	1970.82
WE	0.205, 0.258, 0.265, 0.273	0.927	790.15	1378.8	0.893	1312.94	1915.74
AE	gbell	0.984	649.32	300.111	0.981	383.63	685.497
NE	4-7-1	0.964	496.03	963.78	0.953	830.44	1221.08

*MAE and RMSE in ton/day

Table 12 shows the ability of ensemble techniques especially the AE and NE, to improve the performance of all individual models in both calibration and validation phase. The best ensemble technique, the AE improved the efficiency of ANFIS, FFNN, SVM and MLR up to 6.22%, 12.76%, 9.73% and 41.8%, respectively. The other ensemble technique, the NE improved the efficiency of ANFIS, FNN, SVM and MLR by up to 3.59%, 9.54%, 6.6% and 37.9%, respectively in the validation phase based on NSE value. This indicated the nonlinear ensemble technique are more efficient in increasing the accuracy of nonlinear black-box models. The high performance of ANFIS model over the other AI-based models employed in SSL estimation was confirmed by the AE technique.

Figure 32 compares the scatter plots of the four ensemble techniques used for hybrid SSL modeling in the validation phase. As can be seen in the figure, the AE and NE technique has points close to each other (more dense data point) and closer to the 1:1 bisector line, while the SE and WE produced the most widely scattered estimates.

Figure 32

Scatter plot of Observed Versus Predicted SSL, at Verification Phase by a) SE b) WE and c) NE and d) AE

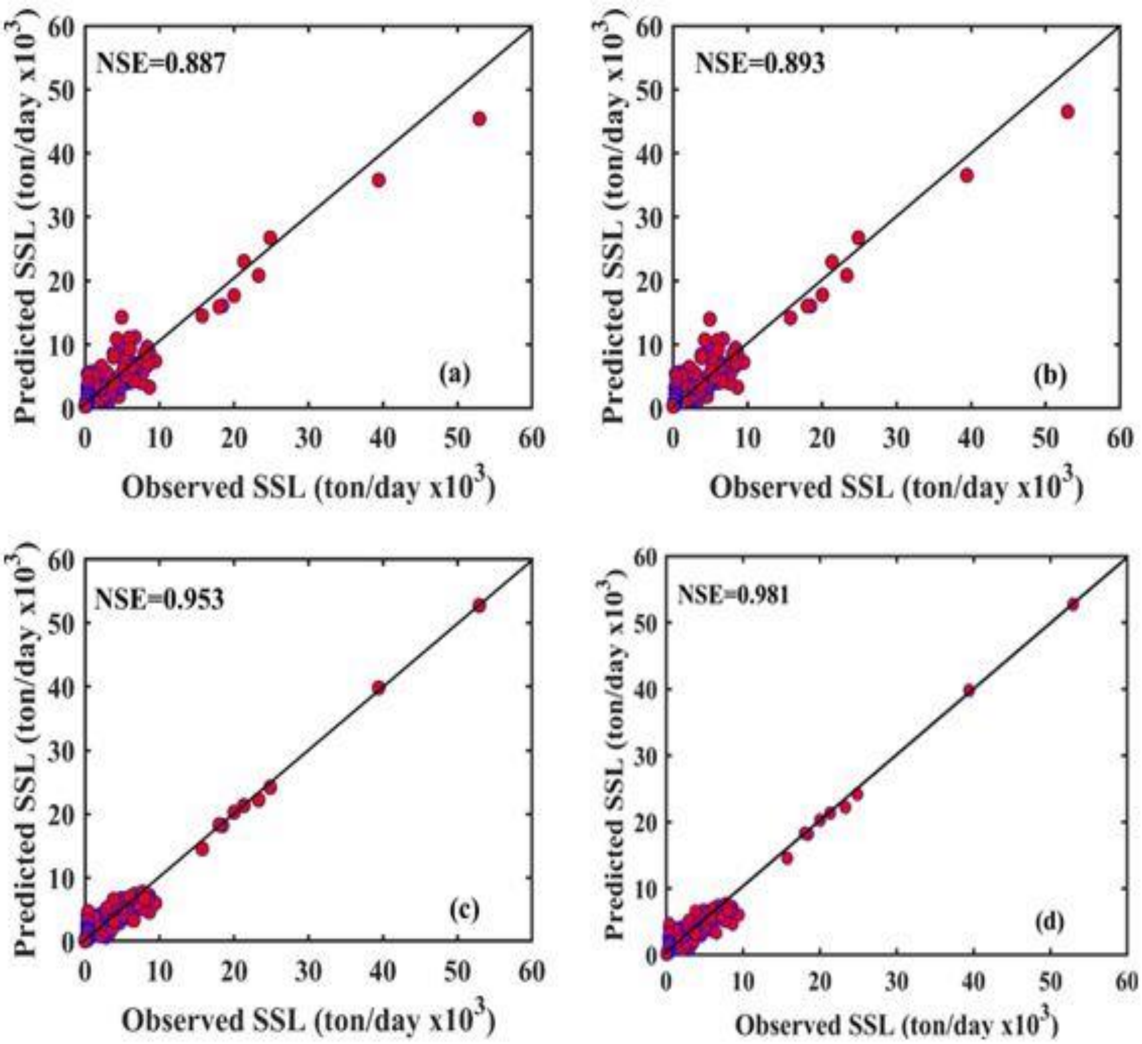
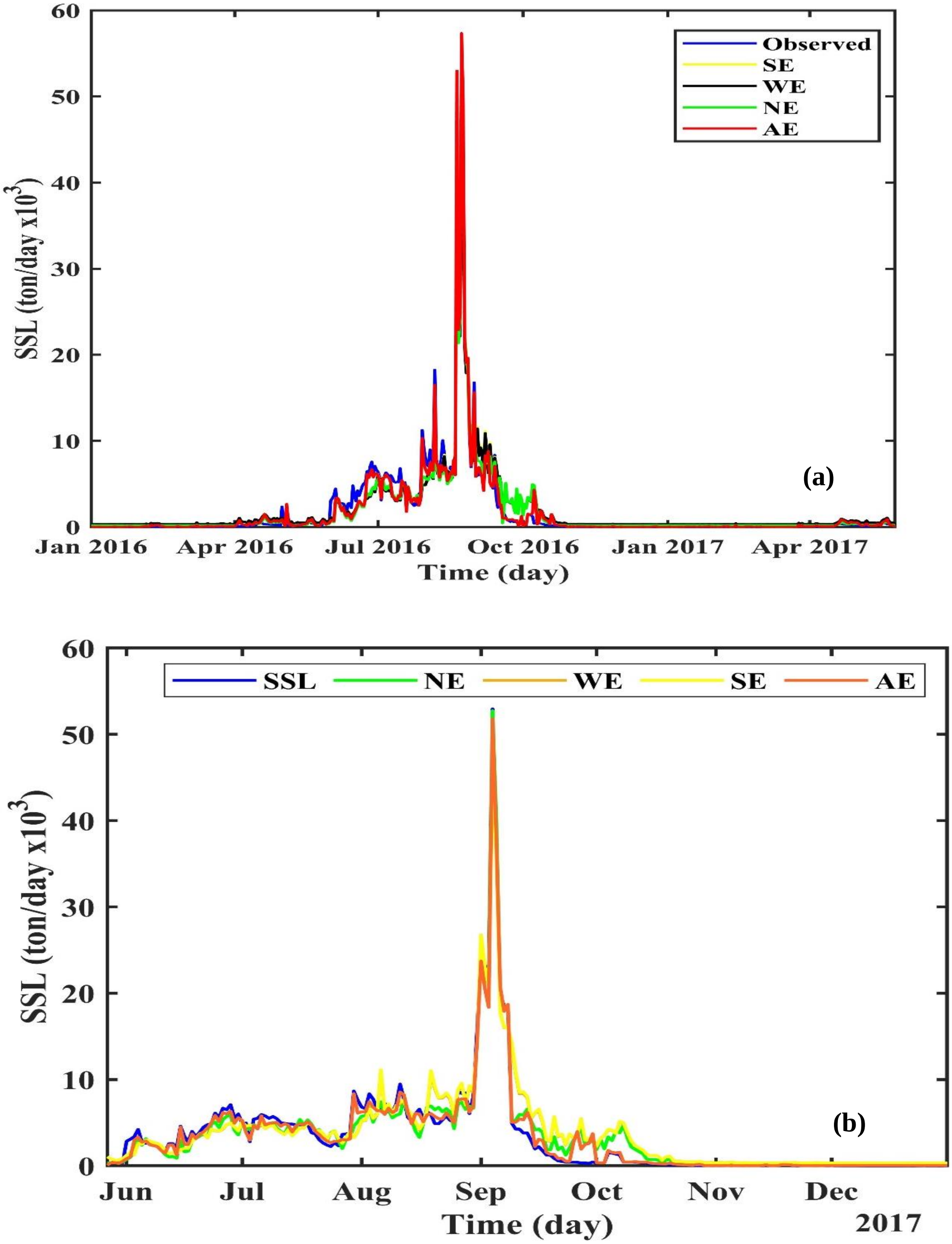


Figure 33 depicts the time series of observed versus predicted SSL values of the applied ensemble technique (WE, SE, AE and NE) in the validation phase. From Figure 33 it can be seen that the linear ensemble techniques (SE and WE) led to a less accurate result than nonlinear ensemble techniques. The SSL value of nonlinear ensemble techniques (especially AE) agreed better with the observed value, while larger variation is observed between the observed value and the predicted SSL values of SE and WE technique.

Figure 33

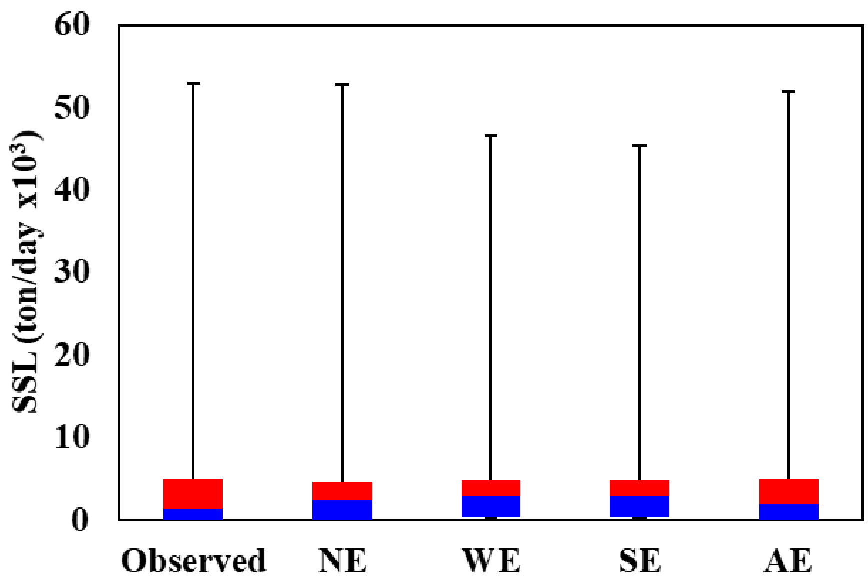
Time series of Observed Versus Predicted SSL Value by Ensemble Techniques in the a) Calibration Phase and b) Verification phase



Another graph, boxplot, is often used to compare the actual value and the predicted value resulted from different models (Sharafati et al., 2020). Boxplot was also used in this study to compare the performances of ensemble techniques for rainfall-runoff and SSL modeling as shown in Figure 34.

Figure 34

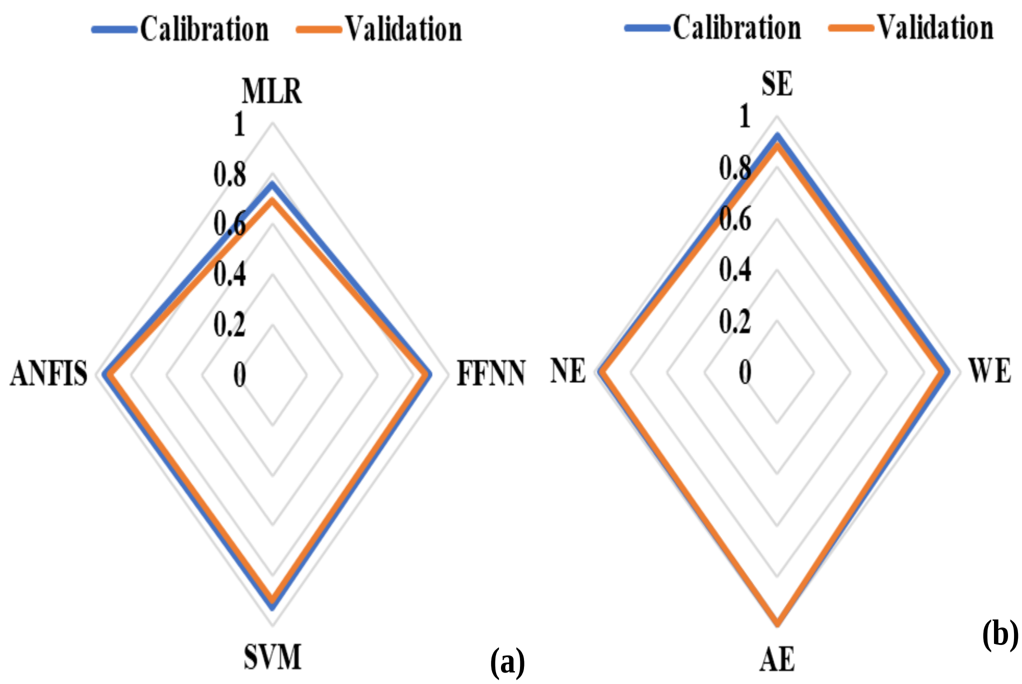
Boxplot of Observed and Predicted SSL Value by Ensemble Techniques in the Verification Phase



In Figure 34 it is revealed that the better performance of nonlinear ensemble technique for SSL modeling. In this study, the variation between the observed SSL and predicted SSL value obtained by the four ensemble techniques was compared using different quartiles as shown in the boxplot (Figure 33). Fore example, Figure 33, the median (Q50%) value of SSL for observed= 1,481.9544 t/day, NE=2,395.85 t/day, SE 2,960.337 t/day, WE=2,953.691t/day and AE=1,933.067 ton/day. This shown that the nonlinear especially AE technique performs better than the linear ensemble technique as there is a closest match between the nonlinear ensemble technique result and observed value in SSL modeling. For a clearer comparison of NSE values the single models and ensemble techniques, a radar plot was used as shown in Figure 35.

Figure 35

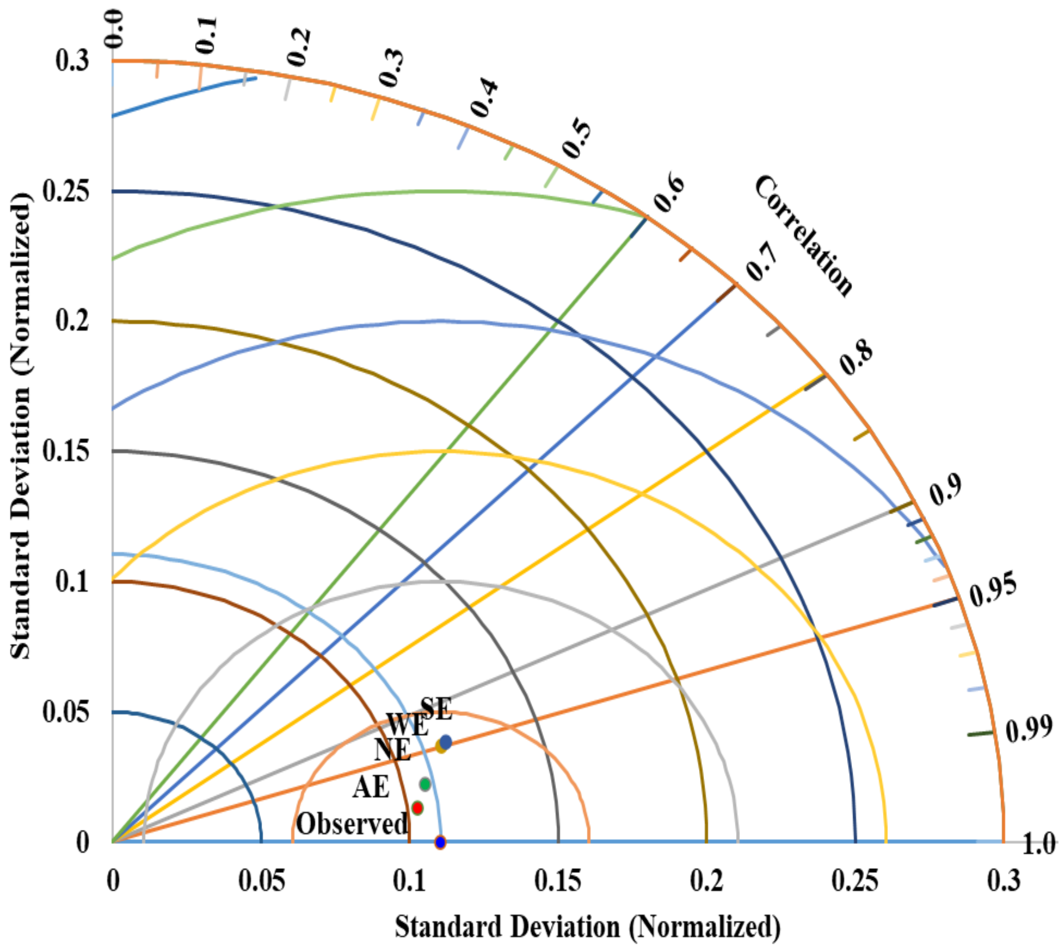
Radar Plot Comparison of a) Single, b) Ensemble technique for Hybrid SSL Modeling (strategy 2)



For a more comprehensive comparison of the models used, another graphical comparison method, the Taylor diagram, was used in this study. This graph shows how close the predicted value is to the actual value by considering the standard deviation (SD) and the NSE (Taylor, 2001). This diagram combines different performance indicators of the models (e.g., NSE and SD) into a single diagram and statistically quantify the similarity between the observed and predicted values of SSL the different models, as shown in Figure 36. In this Figure it can be inferred that AE provides the best prediction accuracy with r= 0.988 in the verification phase. Among, linear ensemble technique, WE provided slightly higher performance than the SE technique with r= 0.948 and SD=0.11675 ton/day in the verification phase. A perfect model is one that yields an r-value of 1 (Yaseen et al., 2018).

Figure 36

Taylor diagram of Ensemble Techniques for Hybrid SSL Modeling in Verification Phase



CHAPTER V

Discussions

In rainfall-runoff and SSL modeling, the incorporating of all inputs in the simulation may not be necessary in the same time. Some inputs may be more important than the others. Therefore, selection of optimum and most influential inputs is very important to get acceptable result as incorporating too many parameters may cause overfitting and too small parameter may not represent the reality of the process. For rainfall-runoff modeling via physical models, different physical components can be considered in modeling that could affect the output. As it is very difficult to include all the possible physical components, sensitivity analysis was conducted to identify the most sensitive parameters during calibration of the physical models. There are different methods that can be used for sensitivity analysis. For this particular study, only some parameters and commonly used approach is applied for sensitivity analysis.

The current value of runoff and SSL correlates strongly with their past values. Runoff and SSL forming factors such as precipitation, watershed characteristics, and runoff (for SSL) are involved in modeling precipitation-runoff and SSL. According to Nourani et al. (2019), the effect of these factors on the current day SSL and runoff value can be considered indirectly by including the antecedent values as inputs. In this study, for modeling current daily runoff (Qt) by AI-based models, various lags (up to 6 days in the past) of runoff, temperature, and precipitation data were evaluated as inputs to AI-based models and ranked based on their NSE value in the validation phase. Similarly, for SSL modeling different lags (up to 6days in the past) of runoff and SSL were considered as input, and evaluated and ranked using FFNN model.

In this study, three physically-based and three AI-based models were used for rainfall-Ruoff models. Also, three AI-based and one linear model (AI) were used for SSL modeling. In HEC-HMS model, selection of sensitive parameter was conducted using one-at-a- time approach in which the assigned value of each parameter is changed sequentially (±25%) and the modeling result was compared. The result of sensitivity analysis for HEC-HMS model showed that curve number (CN), lag time (T_{lag}), initial abstraction (Ia) and Muskingum k were ranked first, second, third and fourth, respectively. During the sensitivity analysis, varying the value of CN led a significant change in the value of runoff from its previous value. According to Fanta and Sime (2022), it could be due to the fact that most runoff forming factors such as soil, LULC and topography are lumped in a single CN value.

The second semi-distributed model used for rainfall-runoff modeling was the SWAT model in which sensitivity analysis, calibration and validation was performed using SWAT-CUP software. This software used different approach for sensitivity analysis and model calibration. This includes Generalized Likelihood Uncertainty Estimation (GLUE), Particle Swarm Optimization (POS), Parameter Solution (ParaSol), Markov Chain Monte Carol (MCMC) and SUFI -2 algorithm. In the current study sensitivity analysis for SWAT model was performed using SUFI -2 algorithm. The main reason for choosing this algorithm was its efficiency, better performance for selecting parameter and fast learning speed (Zakizadeh et al., 2020). Various parameters were selected for sensitivity analysis and ranked after global sensitivity based on their significance and contribution for generating runoff (see Table 5). The result of the global sensitivity analysis showed that CN, ALPHA _BF, and GW_DELY were identified as the first, second, and third most sensitive parameters, respectively. Similar to the HEC-HMS model, soil curve number was identified as the most sensitive parameter because it is a function of runoff generating factors such as land use, hydrological soil group and soil type. Nearly similar result was obtained by previous studies (e.g., Aliye et al., 2020; Fanta and Sime, 2022). The Katar watershed is predominantly composed of agricultural land, which increases runoff. This could be the main reason why the curve number is the most sensitive parameter.

The other semi-distributed model used in this study was HBV in which sensitivity analysis was performed using automated Monte Carlo method. The sensitivity analysis result revealed that field capacity (FC) was the most sensitive parameter. Similar study was found in different studies that used HBV for rainfall-runoff simulation(Bizuneh et al., 2021; Ouatiki. et al., 2020).The maximum soil water holding capacity (FC) is one of the parameters in the soil routine which greatly influences the initiation of runoff. Under wet soil condition the contribution of FC to runoff could be high and its contribution could be low under dry soil condition.

In this study, three physically-based (SWAT, HEC-HMS and HBV) and AI models (SVM, FFNN and ANFIS) were used for rainfall-runoff modeling. Afterwards, the result of these single models was combined using three ensemble techniques. Comparison was made between performance of physically-based and AI models. According to Moriasi et al. (2007) guideline, a model performance is acceptable when the NSE value is above 0.5 and very good when its NSE >0,75. Based on this criteria all the applied models provide very good result though they didn't gave the same performance. In general, the AI-based models outperformed the physically-based models in both calibration and validation phase. The finding is supported by other studies that have compared the performance of AI-based and physically-based models for predicting rainfall-runoff process (Senent-Aparicio et al., 2019; Young et al., 2017). From the proposed physically based models, the SWAT model led better simulation performance than the HBV and HEC-HMS models in both the calibration and validation phase. This could be due to the ability of the SWAT model to better discretize the study watershed into more detailed sub-watershed that have similar hydrological and spatial characteristics. The HEC-HMS model showed the least modeling performance with fluctuation in both low and high flow periods.

The study used three AI model ANFIS, SVM and FFNN for rainfall-runoff modeling. All the applied AI-based model gave excellent result in rainfall-runoff models. From the applied AI models, the ANFIS (with the NSE=0.913) model gave better prediction accuracy than the SVM and FFNN model rainfall-runoff modeling in both calibration and validation phase. The better accuracy obtained from the ANFIS model could be due to its structure as it is a hybrid of ANN and FIS. It benefits from the advantage of learning ability of ANN and reasoning ability of fuzzy system. Also, to further improve the modeling accuracy, three ensemble techniques were applied in rainfall-runoff modeling. The main idea behind ensemble modeling is to combine the results of two or more simple and complex rainfall-runoff models with different information to increase the overall accuracy of the simulation and obtain unique information. According to

Tegegne et al. (2017), the main advantage of ensemble modeling is that the random and systematic errors in the results of the individual models tend to canceled out in the aggregate since different information is obtained from each model. Therefore, in this study, three ensemble techniques (NE, WE and SE) were developed in three scenarios. In the first scenario, only the results of the three physically-based models were considered in the ensemble unit. In scenario 2, only the results of the three AI-based models (FFNN, ANFIS, and SVM) were considered for ensemble modeling, while in scenario 3, all results of each model were combined. Based on the performance indicators, the best result was obtained in scenario 3, while scenario 1 provided the least accurate result (see Table 7).

The result in Table 6 showed that the physically based models gave less accurate than the AI-based models. However, when the physically-based models were used together with AI-based models in the multi-model combination system, they made a significant contribution to the generation of the improved ensemble outputs (scenario 3) (see Table 7). This is a strong justification for the argument that the worst performance of the complex model, which contains many parameters based on complex laws of physical elements, can improve the performance of the ensemble technique. According to Young et al. (2017), the physically-based and AI-based models when combined in the ensemble unit, which follow different philosophies, complement each other in terms of their inherent drawbacks and strengths. The weak simulation accuracy of the physically-based models can be mitigated by powerful AI-based models, especially for poorly gauged watersheds. Similarly, the important hydrologic process in the physically-based models can make up the back-box function of the AI-based models. This could be the reason for best performance of ensemble technique in the scenario 3 which combines both the AI and physically-based models. In all scenarios, the NE technique surpassed the linear ensemble techniques (WE and SE). The high performance of the NE technique may be due to the fact that when the FFNN model is used as an ensemble technique, the nonlinear behavior of the rainfall-runoff process is simulated more accurately with the nonlinear kernel than with the linear ensemble technique. The NE technique showed its superiority over the linear ensemble techniques in previous studies (e.g., Nourani et al., 2021; Sharghi et al., 2018). Also, in the best scenario (scenario 3), it was found the nonlinear ensemble (NE) technique improved the accuracy of ANFIS, SVM, FFNN, SWAT, HBV and HEC-HMS by 5.8%, 10%, 10.65%, 19.4%, 22.9% and 27.6% (based on NSE value), respectively in validation phase. Similarly, the NE technique improved the performance of the ANFIS, SVM, FFNN, SWAT, HBV and HEC-HMS models by 4.9%, 9.2%, 7.29%, 14.64%, 19.73% and 23.2%, respectively in the calibration phase.

Four black box models were used in the SSL modeling, namely FFNN, ANFIS, SVM, and MLR. Two strategies were followed for SSL modeling by each AI-based and MLR models. In the first strategy, SSL was estimated by ANFIS, SVM, FFNN and MLR model using different lagged value of discharge and suspended sediment load as input. Due to large data requirement of physically-based models and data scarcity, the SSL was estimated using only the AI-based (FFNN, SVM and ANFIS) and MLR models. For this study only two years of SSL and discharge data were used as input for estimating the suspended sediment load of Katar catchment. The second strategy used in this study for modeling SSL was to use the runoff result of the best ensemble technique (from each scenario separately) and lagged discharge and SSL as input for estimating SSL using FFNN, MLR, SVM and ANFIS model. There are only two years (2016-2017) of SSL data were available and therefore not enough to use for physically-based models. To benefit from the contribution of physically-based models, this study used the ensemble runoff from physical and AI-based models as input for SSL modeling. In this modeling process, the runoff values from NE (the best ensemble) together with the lagged runoff and SSL were fed into the input layer of the SVM, MLR, FFNN, and ANFIS models (in three scenario). It can be seen that using the best ensemble runoff (from step 3) result as input for SSL modeling significantly improved the performance of the SSL modeling compared to the first stage modeling. In both strategies of SSL modeling the ANFIS model led to best result than the other black-box models. The result showed that the ANFIS model outperformed all other individual models with NSE=0.884 and RMSE=1943.67t/day and NSE=0.92 and RMSE=1628.259 t/day in strategy 1 and 2, respectively in the verification phase. From this result, it is clear that the hybrid modeling (strategy 2) improved the accuracy of the best model in strategy 1 by 4.1 % (based on NSE value) and reduces the error by 16.23% (based on the validation phase RMSE value). The ANFIS model when developed using the best ensemble runoff as input (in the second strategy) increased the performance of MLR, FFNN, SVM and ANFIS (in the first strategy of SSL modeling) model by 29.9%, 10.3%, 12.9% and 4% , respectively in the verification phase.

In this study, the nonlinear (AE and NE) and linear ensemble (WE and SE) techniques were applied in both strategies of SSL modeling to further improve the modeling capacity. It was believed that the ensemble technique could be used to improve SSL modeling by combining the strengths of each model into a single unit. It was found that the nonlinear ensemble technique (AE and NE) resulted in more accurate SSL predictions than the linear ensemble techniques (SE and WE). This could be due to the ability of the nonlinear models to better understand the complex and nonlinear relationship between runoff and SSL. WE and SE, on the other hand, perform well when there is a direct linear relationship between the input and output variables of the model. Also, linear averaging gave a result smaller than the best model and larger than the worst individual model. In this regard, the SA technique provided the lowest performance than the best single model (ANFIS) in both strategies of SSL modeling. The AE improved the performance of the least performing model (MLR) by 37% and 42% in the first strategy and hybrid SSL modeling (strategy 2), respectively in the verification phase.

CHAPTER VI

Conclusions and Recommendations

Conclusions

The current study evaluates the predictive performances of SWAT, HEC-HMS, HBV, ANFIS, FFNN, SVM and MLR (for SSL only) for rainfall-runoff-sediment modeling. For this purpose, Katar catchment, Ethiopia was chosen as a case study and twelve years of hydrological and climatic data (2006-2017) was considered. In addition, LULC map, soil data and DEM were also used for physically based models. For AI-based modes, relevant inputs were selected by using nonlinear sensitivity analysis. Less relevant inputs were removed after conducting a t-student test and different combinations of dominant inputs were applied for rainfall-runoff modeling. Similarly, sensitivity analysis was carried out to identify the most sensitive parameters for physically-based models. In this regard, global sensitivity was conducted using the SUFI-2 algorithm to identify the most sensitive parameters for the SWAT model. The result showed that CN was the most sensitive parameter, ALPHA_BF and GW_DELEY being the second and the third sensitive parameters, respectively. For the HEC-HMS model, based on a one-a-time approach, CN was the most sensitive parameter, whereas T_{lag} (lag time) and initial abstraction (Ia) were the second and third sensitivity parameter, respectively. For the HBV model, FC, LP, BETA and K1 were identified as the most sensitive parameters.

A comparison of the results obtained with each model showed that the AI-based models especially the ANFIS model were able to achieve the highest predictive performance over SVM, FFNN, SWAT, HEC-HMS and HBV in rainfall-runoff modeling. This could be due to the strength of the ANFIS model in processing the complex, dynamic and nonlinear rainfall-runoff processes using the fuzzy concept. Following the development of individual physically-based and AI models, three ensemble techniques (SE, NE, and WE) were developed using the results of the individual models as input to improve the overall accuracy of rainfall-runoff modeling. The ensemble technique improved the accuracy of the individual models in rainfall-runoff modeling. The NE technique resulted in the highest prediction accuracy with an NSE value of 0.966 and an RMSE of 3.79 m3/s in the validation phase due to its strong ability to handle the uncertainties of the non-stationary and complex nature of the rainfall-runoff process. It increases the performance of SWAT, HBV and HEC-HMS by up to 19.4%, 22.9% and 27.6% (based on NSE value), respectively in the validation phase.

SSL was also modeled using SVM, ANFIS, MLR and FFNN in strategy 2. Due to limited data availability, only two years of data were used. In strategy 2 of SSL modeling, different combinations of the previous and current day discharge and the previous day's SSL were used as input. In strategy 2, two years (2016-2017) of runoff results from the best ensemble technique (NE) were used as input for SSL modeling using SVM, ANFIS, MLR and FFNN. For both strategies, the ANFIS model provided better accuracy. The MLR model, on the other hand, provided the worst modeling performance than the AI-based mode in SSL modeling. This could be due to the fact that linear models (e.g., MLR) are not able to capture a highly nonlinear and complex process such as SSL. To further increase the SSL modeling accuracy in both strategies, the NE, AE, WE and SE techniques were developed using the single models' SSL result as input. In ensemble modeling the nonlinear ensemble techniques outperformed the linear techniques. AE increased the performances of ANFIS, FFNN, SVM and MLR (based on the validation phase NSE value) by 3.59%, 9.54%, 6.6% and 37.9%, respectively in the validation phase. For both runoff and SSL modeling, the SA technique resulted in lower NSE values than the ANFIS model (best single model). This could be due to the fact that the result of linear averaging is always higher than the lowest number, but lower than the highest number.

In general, the results of the current study show a promising effect of ensemble techniques in rainfall-runoff-sediment modeling. The ensemble technique in general, especially the nonlinear ensemble method, showed that better accuracy can be achieved by combining the results of the individual models than by using individual models in rainfall-runoff and SSL modeling. This study used two linear ensemble (SE and WE) and one nonlinear ensemble (NE) technique for both rainfall-runoff and SSL modeling.

Recommendation

Based on the result of this study the following recommendation are suggested for future study:

- ✓ The result of this study would be used as pioneering steps towards using model combination technique in rainfall-runoff-suspended sediment modeling in data scarce catchment.
- ✓ This study used only two linear ensemble (SE and WE) and two nonlinear ensembles namely NE and AE (for SSL only) technique for both rainfall-runoff and SSL modeling. Therefore, future studies should test the use of other nonlinear kernel such as SVM as ensemble technique.
- ✓ Also, the applied models should be tested to analyze the impact of climate change on the hydrological process (e.g., runoff and SSL).
- ✓ For this study only two years (2016-2017) of data were used for SSL modeling. Therefore, more input data should be used for future studies.

References

Abba, S. I., Linh, N. T.T., Abdullahi, J., Ali, S. I. A., Pham, Q. B., Abdulkadir, R .A., Costache, R., Nam, V.T., Anh, D. T. (2020). Hybrid machine learning ensemble techniques for modeling dissolved oxygen concentration. *IEEE Access*, *8*(September), 157218–157237. https://doi.org/10.1109/ACCESS.2020.3017743

Abba, S. I., & Elkiran, G. (2017). Effluent prediction of chemicaloxygen demand from the astewater treatment plant using artificial neural network application. *Procedia Computer Science*, *120*, 156–163. https://doi.org/10.1016/j.procs.2017.11.223

Abrahart, R. J., & See, L. (2010). Multi-model data fusion for river flow forecasting: an evaluation of six alternative methods based on two contrasting catchments. *Hydrology and Earth System Sciences*, *6*(4), 655–670. https://doi.org/10.5194/hess-6-655-2002

Abushandi, E., & Merkel, B. (2013). Modelling Rainfall Runoff Relations Using HEC-HMS and IHACRES for a Single Rain Event in an Arid Region of Jordan. *Water Resources Management*, *27*(7), 2391–2409. https://doi.org/10.1007/s11269-013-0293-4

Adnan, R. M., Liang, Z., Trajkovic, S., Zounemat-Kermani, M., Li, B., & Kisi, O. (2019). Daily streamflow prediction using optimally pruned extreme learning machine. *Journal of Hydrology*, *577*(July), 123981. https://doi.org/10.1016/j.jhydrol.2019.123981

Afan, H.A., El-Shafie, A., Yaseen, Z. M., Hameed, M. M., Mohtar, W.H.M.W., Hussain, A. (2014). ANN Based Sediment Prediction Model Utilizing Different Input Scenarios. *Water Resources Management*, *29*(4), 1231–1245. https://doi.org/10.1007/s11269-014-0870-1

Aga, A.O., Melesse, A.M., Chane, B. (2018). Estimating the sediment flux and budget for a data limited Rift Valley Lake in Ethiopia. *Hydrology*, *6*(1), 1. https://doi.org/10.3390/hydrology6010001

Ahmadi, M., Moeini, A., Ahmadi, H., Motamedvaziri, B., & Zehtabiyan, G. R. (2019). Comparison of the performance of SWAT, IHACRES and artificial neural networks models in rainfall-runoff simulation (case study: Kan watershed, Iran). *Physics and Chemistry of the Earth*, *111*, 65–77.

https://doi.org/10.1016/j.pce.2019.05.002

Al-Mukhtar, M. (2019). Random forest, support vector machine, and neural networks to modelling suspended sediment in Tigris River-Baghdad. *Environmental Monitoring and Assessment*, *191*(11). https://doi.org/10.1007/s10661-019-7821-5

Aliye, M. A., Aga, A. O., Tadesse, T., & Yohannes, P. (2020). Evaluating the Performance of HEC-HMS and SWAT Hydrological Models in Simulating the Rainfall-Runoff Process for Data Scarce Region of Ethiopian Rift Valley Lake Basin. *Open Journal of Modern Hydrology*, *10*(04), 105–122. https://doi.org/10.4236/ojmh.2020.104007

Alp, M., & Cigizoglu, H. K. (2007). Suspended sediment load simulation by two artificial neural network methods using hydrometeorological data. *Environmental Modelling and Software*, *22*(1), 2–13. https://doi.org/10.1016/j.envsoft.2005.09.009

Anderson, M. L., Chen, Z. Q., Kavvas, M. L., & Feldman, A. (2002). Coupling HEC-HMS with atmospheric models for prediction of watershed runoff. *Journal of Hydrologic Engineering*, *7*(4), 312–318. https://doi.org/10.1061/(ASCE)1084-0699(2002)7:4(312)

Armstrong, J. S. (2001). Combining forecasts Principles of Forecasting. *A Handbook for Researchers and Practitioners*, *1878*.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J. R. (1998). Large area hydrologic modeling and assessment—Part 1: Model development. *Journal of the American Water Resources Association*, *34*(1), 73–89.

Asadi, S., Shahrabi, J., Abbaszadeh, P., & Tabanmehr, S. (2013). Neurocomputing A new hybrid arti fi cial neural networks for rainfall – runoff process modeling. *Neurocomputing*, *121*, 470–480. https://doi.org/10.1016/j.neucom.2013.05.023

Asadollah, S. B. H.S., Sharafati, A., Motta, D.., Yaseen, Z. M. (2020). River water quality index prediction and uncertainty analysis: A comparative study of machine learning models. *Journal of Environmental Chemical Engineering*, *xxxx*, 104599. https://doi.org/10.1016/j.jece.2020.104599

Aytek, A., Asce, M., & Alp, M. (2008). An application of artificial intelligence for rainfall-runoff modeling. *Journal of Earth System Science*, *117*(2), 145–155. https://doi.org/10.1007/s12040-008-0005-2

Babanezhad, M., Behroyan, I., Marjani, A., & Shirazian, S. (2021). Artificial intelligence simulation of suspended sediment load with different membership functions of ANFIS. *Neural Computing and Applications*, *33*(12), 6819–6833. https://doi.org/10.1007/s00521-020-05458-6

Badrzadeh, H., Sarukkalige, R., & Jayawardena, A. W. (2015). Hourly runoff forecasting for flood risk management: Application of various computational intelligence models. *Journal of Hydrology*, *529*, 1633–1643. https://doi.org/10.1016/j.jhydrol.2015.07.057

Bartoletti, N., Casagli, F., Marsili-Libelli, S., Nardi, A., & Palandri, L. (2018). Data-driven rainfall/runoff modelling based on a neuro-fuzzy inference system. *Environmental Modelling and Software*, *106*, 35–47. https://doi.org/10.1016/j.envsoft.2017.11.026

Bates, J. M., Granger, C. W. J. (1969). The combination of forecasts. *Journal of the Operational Research Society*, *20*, 451–468.

Bates B, Kundzewicz Z, Wu S, P. J. (2008). *Climate Change and Water. Technical Paper of the Intergovernmental Panel on Climate Change* (Issue June 2008). https://doi.org/10.1007/978-94-007-5796-7

Behzad, M., Asghari, K., Eazi, M., & Palhang, M. (2009). Generalization performance of support vector machines and neural networks in runoff modeling. *Expert Systems with Applications*, *36*(4), 7624–7629. https://doi.org/10.1016/j.eswa.2008.09.053

Biru, Z., & Kumar, D. (2018). Calibration and validation of SWAT model using stream flow and sediment load for Mojo watershed, Ethiopia. *Sustainable Water Resources Management*, *4*(4), 937–949. https://doi.org/10.1007/s40899-017-0189-1

Bizuneh, B. B., Moges, M. A., Sinshaw, B. G., & Kerebih, M. S. (2021). SWAT and HBV models' response to streamflow estimation in the upper Blue Nile Basin, Ethiopia. *Water-Energy Nexus*, *4*, 41–53. https://doi.org/10.1016/j.wen.2021.03.001

Bonakdari, H., Ebtehaj, I., Samui, P., & Gharabaghi, B. (2019). *Lake Water-Level fluctuations forecasting using Minimax Probability Machine Regression , Relevance Vector Machine , Gaussian Process Regression , and Extreme Learning Machine*. 3965–3984.

Bourdin, D. R., Fleming, S. W., & Stull, R. B. (2012). Streamflow modelling: A primer on applications, approaches and challenges. *Atmosphere - Ocean*, *50*(4), 507–536. https://doi.org/10.1080/07055900.2012.734276

Brighenti, T. M., Bonumá, N. B., Grison, F., Mota, A. de A., Kobiyama, M., & Chaffe, P. L. B. (2019). Two calibration methods for modeling streamflow and suspended sediment with the swat model. *Ecological Engineering*, *127*(November 2018), 103–113. https://doi.org/10.1016/j.ecoleng.2018.11.007

Buyukyildiz, M., Kumcu, S. Y. (2017). An Estimation of the Suspended Sediment Load Using Adaptive Network Based Fuzzy Inference System, Support Vector Machine and Artificial Neural Network Models. *Water Resources Management, 31*(4), 1343–1359. https://doi.org/10.1007/s11269-017-1581-1

Cavadias, G., Morin, G. (1986). The Combination of Simulated Discharges of Hydrological Models. *Nordic Hydrology*, *17*, 21–32.

Chandwani, V., Vyas, S. K., Agrawal, V., & Sharma, G. (2015). Soft Computing Approach for Rainfall-runoff Modelling : A Review Soft computing approach for rainfall-runoff modelling : A review. *Aquatic Procedia*, *4*(April), 1054–1061. https://doi.org/10.1016/j.aqpro.2015.02.133

Chen, C. N., Tsai, C. H., & Tsai, C. T. (2011). Simulation of Runoff and Suspended Sediment Transport Rate in a Basin with Multiple Watersheds. *Water Resources Management*, *25*(3), 793–816. https://doi.org/10.1007/s11269-010-9727-4

Cobaner, M., Unal, B., & Kisi, O. (2009). Suspended sediment concentration estimation by an adaptive neuro-fuzzy and neural network approaches using hydro-meteorological data. *Journal of Hydrology*, *367*(1–2), 52–61. https://doi.org/10.1016/j.jhydrol.2008.12.024

Demirel, M. C., Venancio, A., & Kahya, E. (2014). Flow forecast by SWAT model and ANN in Pracana basin, Portugal. *Advances in Engineering Software*, *40*(7), 467–473. https://doi.org/10.1016/j.advengsoft.2008.08.002

Desta, H., & Fetene, A. (2020). Land-use and land-cover change in Lake Ziway watershed of the Ethiopian Central Rift Valley Region and its environmental impacts. *Land Use Policy*, *96*, 104682. https://doi.org/10.1016/j.landusepol.2020.104682

Deutsch, M., Granger, C. W. J., & Teräsvirta, T. (1994). The combination of forecasts using changing weights. *International Journal of Forecasting*, *10*(1), 47–57. https://doi.org/10.1016/0169-2070(94)90049-3

Dogan, E., Ates, A., Yilmaz, E. C., & Eren, B. (2008). Application of Artificial Neural Networks to Estimate Wastewater Treatment Plant Inlet Biochemical Oxygen Demand. *Wiley InterScience*, *DOI 10.100*, 319–323. https://doi.org/10.1002/ep

Dounia, M., Sabri, D., & Yassine, D. (2014). Rainfall- Rain off Modeling Using Artificial Neural Network. *Procedia - Social and Behavioral Sciences*, *10*, 251–256. https://doi.org/10.1016/j.apcbee.2014.10.048

Eckhardt, K., Fohrer, N., & Frede, H. G. (2005). Automatic model calibration. *Hydrological Processes*, *19*(3), 651–658. https://doi.org/10.1002/hyp.5613

Elkiran, G., Nourani, V., Abba. S. I., Abdullahi, J. (2018). Artificial intelligence-based approaches for multi-station modelling of dissolve oxygen in river. *Global Journal of Environmental Science and Management*, *4*(4), 439–450. https://doi.org/10.22034/gjesm.2018.04.005

Esmaeili-gisavandani, H., Morteza, L., Sofla, M. S. D., & Ashrafzadeh, A. (2021). Improving the performance of rainfall-runoff models using the gene expression programming approach. *Journal of Water and Climate Change*, *12*(7), 3308–3329. https://doi.org/10.2166/wcc.2021.064

Exbrayat, J. F., Viney, N. R., Seibert, J., Frede, H. G., & Breuer, L. (2011). Multi-model data fusion as a tool for PUB: Example in a Swedish mesoscale catchment. *Advances in Geosciences*, *29*, 43–50. https://doi.org/10.5194/adgeo-29-43-2011

Fanta, S. S., & Sime, C. H. (2022). Performance assessment of SWAT and HEC-HMS model for runoff simulation of Toba watershed, Ethiopia. *Sustainable Water Resources Management*, *8*(8). https://doi.org/10.1007/s40899-021-00596-8

Feldman, A. D. (2000). *Hydrologic Modeling System HEC-HMS, Technical Reference Manual. U.S. Army Corps of Engineers, Hydrologic Engineering Center, HEC, Davis, CA, USA.*

Fenicia, F., Solomatine, D. P., Savenije, H. H. G., & Matgen, P. (2007). Soft combination of local models in a multi-objective framework. *Hydrology and Earth System Sciences*, *11*(6), 1797–1809. https://doi.org/10.5194/hess-11-1797-2007

Fernando, A. K., Shamseldin, A. Y., & Abrahart, R. J. (2012). Use of Gene Expression

Programming for Multimodel Combination of Rainfall-Runoff Models. *Journal of Hydrologic Engineering*, *17*(9), 975–985. https://doi.org/10.1061/(asce)he.1943-5584.0000533

Folorunsho, J. O., Iguisi, E. O., Mu'azu, M. B., & Garba, S. (2012). Application of adaptive neuro fuzzy inference system (Anfis) in River Kaduna discharge forecasting. *Research Journal of Applied Sciences, Engineering and Technology*, *4*(21), 4275–4283.

Gautam, D. K., & Holz, K. P. (2018). Rainfall-runoff modelling using adaptive neuro-fuzzy systems. *Journal of Hydroinformatics*, *3*(1), 3–10. https://doi.org/10.2166/hydro.2001.0002

Gebre, S. L. (2015). Application of the HEC-HMS Model for Runoff Simulation of Upper Blue Nile River Basin. *Journal of Waste Water Treatment & Analysis*, *06*(02). https://doi.org/10.4172/2157-7587.1000199

Ghaffari, A., Abdollahi, H., Khoshayand, M. R., Bozchalooi, I. S., Dadgar, A., & Rafiee-Tehrani, M. (2006). Performance comparison of neural network training algorithms in modeling of bimodal drug delivery. *International Journal of Pharmaceutics*, *327*(1–2), 126–138. https://doi.org/10.1016/j.ijpharm.2006.07.056

Ghumman, A. R. (2011). Runoff forecasting by artificial neural network and conventional model. *Alexandria Engineering Journal*, *50*(4), 345–350. https://doi.org/10.1016/j.aej.2012.01.005

Govindaraju, R. S., & Rao, A. R. (2000). A RTIFICIAL N EURAL N ETWORKS IN H YDROLOGY. *Journal of Hydrologic Engineering*, *5*(2), 124–137.

Gumindoga, W., Rwasoka, D. T., Nhapi, I., & Dube, T. (2017). Ungauged runoff simulation in Upper Manyame Catchment, Zimbabwe: Application of the HEC-HMS model. *Physics and Chemistry of the Earth*, *100*, 371–382. https://doi.org/10.1016/j.pce.2016.05.002

Hadi, S. J., & Tombul, M. (2018). Forecasting Daily Streamflow for Basins with Different Physical Characteristics through Data-Driven Methods. *Water Resources Management*, *32*(10), 3405–3422. https://doi.org/10.1007/s11269-018-1998-1

Hallouz, F., Meddi, M., Mahé, G., Alirahmani, S., & Keddar, A. (2018). Modeling of discharge and sediment transport through the SWAT model in the basin of Harraza

(Northwest of Algeria). *Water Science*, *32*(1), 79–88. https://doi.org/10.1016/j.wsj.2017.12.004

Halwatura, D., & Najim, M. M. M. (2013). Application of the HEC-HMS model for runoff simulation in a tropical catchment. *Environmental Modelling and Software*, *46*(August 2016), 155–162. https://doi.org/10.1016/j.envsoft.2013.03.006

He, Z., Wen, X., Liu, H., & Du, J. (2014). A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region. *Journal of Hydrology*, *509*, 379–386. https://doi.org/10.1016/j.jhydrol.2013.11.054

Iskender, I., & Sajikumar, N. (2016). Evaluation of Surface Runoff Estimation in Ungauged Watersheds Using SWAT and GIUH. *Procedia Technology*, *24*, 109–115. https://doi.org/10.1016/j.protcy.2016.05.016

Jain, A., & Kumar, A. M. (2007). Hybrid neural network models for hydrologic time series forecasting. *Applied Soft Computing Journal*, *7*(2), 585–592. https://doi.org/10.1016/j.asoc.2006.03.002

Jang, J. S. R. (1993). ANFIS : Adap tive-Ne twork-Based Fuzzy Inference System. IEEE Transactions on Systems. *Man and Cybernetics*, *23*(3), 665–685. https://doi.org/10.1109/21.256541

Jang, J. S. R., Sun, C. T., & Mizutani, E. (1997). Neurofuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. *PrenticeHall, New Jersey*. https://doi.org/10.1080/00420980020014884

Jeong, J., Kannan, N., Arnold, J., Glick, R., Gosselink, L., & Srinivasan, R. (2010). Development and Integration of Sub-hourly Rainfall-Runoff Modeling Capability Within a Watershed Model. *Water Resources Management*, *24*(15), 4505–4527. https://doi.org/10.1007/s11269-010-9670-4

Jimeno-Sáez, P., Martínez-España, R., Casalí, J., Pérez-Sánchez, J., & Senent-Aparicio, J. (2021). A comparison of performance of SWAT and machine learning models for predicting sediment load in a forested Basin, Northern Spain. *Catena*, *xxxx*. https://doi.org/10.1016/j.catena.2021.105953

Jimeno-Sáez, P., Senent-Aparicio, J., Pérez-Sánchez, J., & Pulido-Velazquez, D. (2018). A comparison of SWAT and ANN models for daily runoff simulation in different climatic zones of peninsular Spain. *Water (Switzerland)*, *10*(2). https://doi.org/10.3390/w10020192

Kakaei, L. E., Moghaddam Nia, A., & Ahmadi, A. (2013). Daily suspended sediment load prediction using artificial neural networks and support vector machines. *Journal of Hydrology*, *478*, 50–62. https://doi.org/10.1016/j.jhydrol.2012.11.048

Kalteh, A. M. (2013). Monthly river flow forecasting using artificial neural network and support vector regression models coupled with wavelet transform. *Computers and Geosciences*, *54*, 1–8. https://doi.org/10.1016/j.cageo.2012.11.015

Kan, G., Yao, C., Li, Q., Li, Z., Yu, Z., Liu, Z., Ding, L., He, X., & Liang, K. (2015). Improving event-based rainfall-runoff simulation using an ensemble artificial neural network based hybrid data-driven model. *Stochastic Environmental Research and Risk Assessment*, *29*(5), 1345–1370. https://doi.org/10.1007/s00477-015-1040-6

Kasiviswanathan, K. S., Cibin, R., Sudheer, K. P., & Chaubey, I. (2013). Constructing prediction interval for artificial neural network rainfall runoff models based on ensemble simulations. *Journal of Hydrology*, *499*, 275–288. https://doi.org/10.1016/j.jhydrol.2013.06.043

Kaveh, K., Duc Bui, M., & Rutschmann, P. (2017). A comparative study of three different learning algorithms applied to ANFIS for predicting daily suspended sediment concentration. *International Journal of Sediment Research*, *32*(3), 340–350. https://doi.org/10.1016/j.ijsrc.2017.03.007

Kazemi, H., Sarukkalige, R., & Badrzadeh, H. (2019). Evaluation of streamflow changes due to climate variation and human activities using the Budyko approach. *Environmental Earth Sciences*, *78*(24), 1–17. https://doi.org/10.1007/s12665-019-8735-9

Kazienko, P., Lughofer, E., Trawiński, B. (2013). Hybrid and ensemble methods in machine learning J.UCS special issue. *Journal of Universal Computer Science*, *19*(4), 457–461.

Keskin, M. E., Taylan, D., & Terzi, Ö. (2010). Adaptive neural-based fuzzy inference system (ANFIS) approach for modelling hydrological time series Adaptive neural-based fuzzy inference system (ANFIS) approach for modelling hydrological time series. *Hydrological Sciences Journal*, *6667*, 2150–3435. https://doi.org/10.1623/hysj.51.4.588

Khan, M. Y. A., Tian, F., Hasan, F., & Chakrapani, G. J. (2018). Artificial neural network simulation for prediction of suspended sediment concentration in the River Ramganga, Ganges Basin, India. *International Journal of Sediment Research*, *2002*, 1–13. https://doi.org/10.1016/j.ijsrc.2018.09.001

Kim, Y.-O., Jeong, D., & Ko, I. H. (2006). Combining Rainfall-Runoff Model Outputs for Improving Ensemble Streamflow Prediction. *Journal of Hydrologic Engineering*, *11*(6), 578–588. https://doi.org/10.1061/(asce)1084-0699(2006)11:6(578)

Kiran, R.N., Ravi, V. (2008). Software reliability prediction by soft computing techniques. *Journal of Systems and Software*, *81*(4), 576–583. https://doi.org/10.1016/j.jss.2007.05.005

Kisi, O., Dailr, A. H., Cimen, M., Shiri, J. (2012). Suspended sediment modeling using genetic programming and soft computing techniques. *Journal of Hydrology*, *450–451*, 48–58. https://doi.org/10.1016/j.jhydrol.2012.05.031

Kisi, O., Shiri, J., Tombul, M. (2013). Modeling rainfall-runoff process using soft computing techniques. *Computers and Geosciences*, *51*, 108–117. https://doi.org/10.1016/j.cageo.2012.07.001

Kisi, O. (2012). Modeling discharge-suspended sediment relationship using least square support vector machine. *Journal of Hydrology*, *456–457*, 110–120. https://doi.org/10.1016/j.jhydrol.2012.06.019

Kişi, O., & Çimen, M. (2009). Evapotranspiration modelling using support vector machines. *Hydrological Sciences Journal*, *54*(5), 918–928. https://doi.org/10.1623/hysj.54.5.918

Kisi, O., Ozkan, C., & Akay, B. (2012). Modeling discharge-sediment relationship using neural networks with artificial bee colony algorithm. *Journal of Hydrology*, *428–429*, 94–103. https://doi.org/10.1016/j.jhydrol.2012.01.026

Kisi, Ozgur, Shiri, J., & Nikoofar, B. (2012). Forecasting daily lake levels using artificial intelligence approaches. *Computers and Geosciences*, *41*, 169–180. https://doi.org/10.1016/j.cageo.2011.08.027

Knebl, M. R., Yang, Z. L., Hutchison, K., & Maidment, D. R. (2005). Regional scale flood modeling using NEXRAD rainfall, GIS, and HEC-HMS/ RAS: A case study for the San Antonio River Basin Summer 2002 storm event. *Journal of Environmental Management*, *75*(4 SPEC. ISS.), 325–336. https://doi.org/10.1016/j.jenvman.2004.11.024

Kottuvayal, S., Kuni, T., & Mohandas, C. (2014). *Rainfall Runoff Modelling Using ANN and ANFIS*. *April*.

Kumar, A. R. S., Sudheer, K. P., Jain, S. K., & Agarwal, P. K. (2005). *Rainfall-runoff modelling using artificial neural networks : 1291*(December 2004), 1277–1291. https://doi.org/10.1002/hyp.5581

Kumar, Arun, Singh, R., Jena, P. P., Chatterjee, C., & Mishra, A. (2015). Identification of the best multi-model combination for simulating river discharge. *Journal of Hydrology*, *525*, 313–325. https://doi.org/10.1016/j.jhydrol.2015.03.060

Kumar, Ashish, Kumar, P., & Singh, V. K. (2019). Evaluating Different Machine Learning Models for Runoff and Suspended Sediment Simulation. *Water Resources Management*, *33*(3), 1217–1231. https://doi.org/10.1007/s11269-018-2178-z

Kumar Lohani, N.K.Goel, K. K. S. B. (2011). Comparative study of neural network , fuzzy logic and linear transfer function techniques in daily rainfall-runoff modelling under different input domains. *Hydrological Processes*, *25*, 175– 193. https://doi.org/10.1002/hyp.7831

Kumar, M., Kumar, P., Kumar, A., Elbeltagi, A., & Kuriqi, A. (2022). Modeling stage–discharge–sediment using support vector machine and artificial neural network coupled with wavelet transform. *Applied Water Science*, *12*(5), 1–21. https://doi.org/10.1007/s13201-022-01621-7

Kumar, P., Nigam, S. P., & Kumar, N. (2014). Vehicular traffic noise modeling using artificial neural network approach. *Transportation Research Part C: Emerging Technologies*, *40*, 111–122. https://doi.org/10.1016/j.trc.2014.01.006

Kwin, T., Talei, A., Quek, C., & Pauwels, V. R. N. (2018). Rainfall-runo ff modelling using a self-reliant fuzzy inference network with fl exible structure. *Journal of Hydrology*, *564*(July), 1179–1193. https://doi.org/10.1016/j.jhydrol.2018.07.074

Lateef Ahmad, D. (2017). Rainfall-Runoff Modeling using Multiple regression

Technique. *İnternational Journal for Research in Applied Science & Engineering Technology(IJRASET)*, *5*(VII). https://www.ijraset.com/fileserve.php?FID=8769

Liang, Z., Dai, R., Guo, Y., Wang, D., & Zhang, Y. (2011). Application of Bayesian Model Averaging Approach to Multimodel Ensemble Hydrologic Forecasting. *Journal of Hydrologic Engineering*, *18*(11), 1426–1436. https://doi.org/10.1061/(asce)he.1943-5584.0000493

Lin, G. F., Chen, G. R., Huang, P. Y., & Chou, Y. C. (2009). Support vector machine-based models for hourly reservoir inflow forecasting during typhoon-warning periods. *Journal of Hydrology*, *372*(1–4), 17–29. https://doi.org/10.1016/j.jhydrol.2009.03.032

Lindstrom, G., Johansson, B., Persson, M., Gardelin, M., & Bergstrom, S. (1997). Development and test of the distributed HBV-96 hydrological model. *Journal of Hydrolog*, *201*, 272–288. https://doi.org/10.2166/wst.2009.488

Liong, S. Y., & Sivapragasam, C. (2002). Flood stage forecasting with support vector machines. *Journal of the American Water Resources Association*, *38*(1), 173–186. https://doi.org/10.1111/j.1752-1688.2002.tb01544.x

M.P. Rajurkara, U.C. Kothyarib, U. C. C. (2005). Modeling of the rainfall-runoff relationship with artificial neural network. *Proceedings - HIS 2005: Fifth International Conference on Hybrid Intelligent Systems*, *2005*, 548–550. https://doi.org/10.1109/ICHIS.2005.73

Makridakis, S., & Winkler, R. L. (2008). Averages of Forecasts: Some Empirical Results. *Management Science*, *29*(9), 987–996. https://doi.org/10.1287/mnsc.29.9.987

Manish Kumar Goyala , Birendra Bharti, John Quilt, Jan Adamowski, A. P. (2014). Modeling of daily pan evaporation in sub tropical climates using ANN , LS-SVR , Fuzzy Logic , and ANFIS. *Expert Systems With Applications*, *41*(11), 5267–5276. https://doi.org/10.1016/j.eswa.2014.02.047

McIntyre, N., Lee, H., Wheater, H., Young, A., & Wagener, T. (2005). Ensemble predictions of runoff in ungauged catchments. *Water Resources Research*, *41*(12), 1–14. https://doi.org/10.1029/2005WR004289

Mehr, A. D., & Nourani, V. (2018). Season Algorithm-Multigene Genetic Programming:

A New Approach for Rainfall-Runoff Modelling. *Water Resources Management*, *32*(8), 2665–2679.

Melaku, N. D., & Wang, J. (2019). A modified SWAT module for estimating groundwater table at Lethbridge and Barons, Alberta, Canada. *Journal of Hydrology*, *575*(May), 420–431. https://doi.org/10.1016/j.jhydrol.2019.05.052

Melesse, A. M., Ahmad, S., McClain, M. E., Wang, X., & Lim, Y. H. (2011). Suspended sediment load prediction of river systems: An artificial neural network approach. *Agricultural Water Management*, *98*(5), 855–866. https://doi.org/10.1016/j.agwat.2010.12.012

Meshram, S. G., Singh, V. P., Kisi, O., Karimi, V., & Meshram, C. (2020). Application of Artificial Neural Networks, Support Vector Machine and Multiple Model-ANN to Sediment Yield Prediction. *Water Resources Management*, *34*(15), 4561–4575. https://doi.org/10.1007/s11269-020-02672-8

Mirabbasi, R., Kisi, O., Sanikhani, H., & Gajbhiye Meshram, S. (2018). Monthly long-term rainfall estimation in Central India using M5Tree, MARS, LSSVR, ANN and GEP models. *Neural Computing and Applications*, *9*, 1–20. https://doi.org/10.1007/s00521-018-3519-9

Misra, D., Oommen, T., Agarwal, A., Mishra, S. K., & Thompson, A. M. (2009). Application and analysis of support vector machine based simulation for runoff and sediment yield. *Biosystems Engineering*, *103*(4), 527–535. https://doi.org/10.1016/j.biosystemseng.2009.04.017

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. *Transactions of the ASABE*, *50*(3), 885–900. https://doi.org/10.13031/2013.23153

Mutlu, E., Chaubey, I., Hexmoor, H., & Bajwa, S. G. (2008). *Comparison of artificial neural network models for hydrologic predictions at multiple gauging stations in an agricultural watershed*. *5106*(September), 5097–5106. https://doi.org/10.1002/hyp

Nadeem Nawaza, Sobri Haruna, Rawshan Othmanb, A., & Heryansyaha. (2016). RAINFALL RUNOFF MODELING BY MULTILAYER PERCEPTRON NEURAL NETWORK FOR LUI RIVER CATCHMENT. *Jurnal Teknologi*, *12*, 37–42.

Nawaz, N., Harun, S., Talei, A., & Chang, T. K. (2016). Event-Based Rainfall-Runoff Modeling Using Adaptive Network-Based Fuzzy Inference System. *Jurnal Teknologi*, *78*(9–4). https://doi.org/10.11113/jt.v78.9693

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2011). Soil and Water Assessment Tool Theoretical Documentation Version 2009. Texas, USA.: *Texas Water Resources Institute Technical Report No.406.*

Noori, N., & Kalin, L. (2016). Coupling SWAT and ANN models for enhanced daily streamflow prediction. *Journal of Hydrology*, *533*, 141–151. https://doi.org/10.1016/j.jhydrol.2015.11.050

Nourani, V., Andalib, G. (2015). Daily and Monthly Suspended Sediment Load Predictions Using Wavelet Base Artificial Intelligence Approaches. *Journal of Mountain Science*, *12*(1), 85–100.

Nourani, V., Elkiran, G., Abba, S. I. (2018). Wastewater treatment plant performance analysis using artificial intelligence – an ensemble approach. *Water Science and Technology*, *November*. https://doi.org/10.2166/wst.2018.477

Nourani, V., Elkiran, G., Abdullahi, J., Tahsin, A. (2019). Multi-region Modeling of Daily Global Solar Radiation with Artificial Intelligence Ensemble. *Natural Resources Research*. https://doi.org/10.1007/s11053-018-09450-9

Nourani, V., Elkiran, G., Abdullahi, J. (2020). Multi-step ahead modeling of reference evapotranspiration using a multi-model approach. *Journal of Hydrology*, *581*(October 2019), 124434. https://doi.org/10.1016/j.jhydrol.2019.124434

Nourani, V., Gökçekuş, H., Umar, I.K. (2020). Artificial intelligence based ensemble model for prediction of vehicular traffic noise. *Environmental Research*, *180*(October 2019), 108852. https://doi.org/10.1016/j.envres.2019.108852

Nourani, V., Kalantari, O., Baghanam, A. H. (2012). Two semidistributed ANN-based models for estimation of suspended sediment load. *Journal of Hydrologic Engineering*, *17*(12), 1368–1380. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000587

Nourani, V., Khanghah, T. R., Baghanam, A. H. (2015). Application of entropy concept for input selection of wavelet-ANN based rainfall-runoff modeling. *Journal of*

Environmental Informatics, *26*(1), 52–70. https://doi.org/10.3808/jei.201500309

Nourani, V., Komasi, M. (2013). A geomorphology-based ANFIS model for multi-station modeling of rainfall-runoff process. *Journal of Hydrology*, *490*, 41–55. https://doi.org/10.1016/j.jhydrol.2013.03.024

Nourani, V., Molajou, A., Tajbakhsh, A. D., Najafi, H. (2019). A Wavelet Based Data Mining Technique for Suspended Sediment Load Modeling. *Water Resources Management*, *33*(5), 1769–1784. https://doi.org/10.1007/s11269-019-02216-9

Nourani, V., Mousavi, S., Dabrowska, D., Sadikoglu, F. (2017). Conjunction of radial basis function interpolator and artificial intelligence models for time-space modeling of contaminant transport in porous media. *Journal of Hydrology*, *548*, 569–587. https://doi.org/10.1016/j.jhydrol.2017.03.036

Nourani, V. (2017). An Emotional ANN (EANN) approach to modeling rainfall-runoff process. *Journal of Hydrology*, *544*, 267–277. https://doi.org/10.1016/j.jhydrol.2016.11.033

Nourani, Vahid, Gökçekuş, H., & Gichamo, T. (2021). Ensemble data-driven rainfall-runoff modeling using multi-source satellite and gauge rainfall data input fusion. *Earth Science Informatics*, *14*(4), 1787–1808. https://doi.org/10.1007/s12145-021-00615-4

Nourani, Vahid, Gökçekuş, H., & Umar, I. K. (2020). Artificial intelligence based ensemble model for prediction of vehicular traffic noise. *Environmental Research*, *180*(September 2019), 108852. https://doi.org/10.1016/j.envres.2019.108852

Nourani, Vahid, Kisi, Ö., & Komasi, M. (2011). Two hybrid Artificial Intelligence approaches for modeling rainfall – runoff process. *Journal of Hydrology*, *402*(1–2), 41–59. https://doi.org/10.1016/j.jhydrol.2011.03.002

Nourani, Vahid, Uzelaltinbulat, S., Sadikoglu, F., & Behfar, N. (2019). Artificial Intelligence Based Ensemble Modeling for Multi-Station Prediction of Precipitation. *Atmosphere*, *10*(2), 80. https://doi.org/10.3390/atmos10020080

Okkan, U., & Serbes, Z. A. (2012). Rainfall-runoff modeling using least squares support vector machines. *Environmetrics*, *23*(6), 549–564. https://doi.org/10.1002/env.2154

Ouatiki., H., Boudhar., A., Ouhinou, A., Beljadid., A., Leblanc., M., & Chehbouni, A. (2020). Sensitivity and Interdependency Analysis of the HBV Conceptual Model

Parameters in a Semi-Arid. *Water*, *12*(9), 2440. https://doi.org/https://dx.doi.org/10.3390/w12092440

Palm, F. ., & Zellner, A. (1992). To Combine or Not To Combine. *Journal of Forecasting*, *11*(5), 687–701. https://doi.org/10.23736/S1973-9087.17.04551-8

Panchal, R., Suryanarayana, T. M. V, & Parekh, F. P. (2016). *Adaptive Neuro-Fuzzy Inference System For Rainfall-Runoff Modeling*. *4*(6), 202–206.

Pervin, L., Gan, T. Y., Scheepers, H., & Islam, M. S. (2021). Application of the hbv model for the future projections of water levels using dynamically downscaled global climate model data. *Journal of Water and Climate Change*, *12*(6), 2364–2377. https://doi.org/10.2166/wcc.2021.302

Phukoetphim, P., Shamseldin, ; Asaad Y., & Adams, ; and Keith. (2016). Multimodel Approach Using Neural Networks and Symbolic Regression to Combine the Estimated Discharges of Rainfall-Runoff Models. *Journal of Hydrologic Engineering*, *21*(8), 1–18. https://doi.org/10.1061/(ASCE)HE.1943-5584

Rai, A. A., Pai, P. S., & Rao, B. R. S. (2015). Prediction models for performance and emissions of a dual fuel CI engine using ANFIS. *Sadhana - Academy Proceedings in Engineering Sciences*, *40*(2), 515–535. https://doi.org/10.1007/s12046-014-0320-z

Rajaee, T., Nourani, V., Zounemat-Kermani, M., Kisi, O. (2011). River Suspended Sediment Load Prediction: Application of ANN and Wavelet Conjunction Model. *Journal of Hydrologic Engineering*, *17*(5), 604–614. https://doi.org/10.1061/(ASCE)HE

Ren, W. W., Yang, T., Huang, C. S., Xu, C. Y., & Shao, Q. X. (2018). Improving monthly streamflow prediction in alpine regions: integrating HBV model with Bayesian neural network. *Stochastic Environmental Research and Risk Assessment*, *32*(12), 3381–3396. https://doi.org/10.1007/s00477-018-1553-x

Rezaeianzadeh, M., Stein, A., Tabari, H., Abghari, H., Jalalkamali, N., Hosseinipour, E. Z., & Singh, V. P. (2013). Assessment of a conceptual hydrological model and artificial neural networks for daily outflows forecasting. *International Journal of Environmental Science and Technology*, *10*(6), 1181–1192. https://doi.org/10.1007/s13762-013-0209-0

Sahoo, M., Das, T., Kumari, K., & Dhar, A. (2017). Space–time forecasting of groundwater level using a hybrid soft computing model. *Hydrological Sciences Journal*, *62*(4), 561–574. https://doi.org/10.1080/02626667.2016.1252986

Salih, S.Q., Sharafati, A., Khosravi, K., Faris, H., Kisi, O., Tao, H., Ali, M., Yaseen, Z. M. (2020). River suspended sediment load prediction based on river discharge information: application of newly developed data mining models. *Hydrological Sciences Journal*, *65*(4), 624–637. https://doi.org/10.1080/02626667.2019.1703186

Sedighi, F., Vafakhah, M., & Javadi, M. R. (2016). Rainfall–Runoff Modeling Using Support Vector Machine in Snow-Affected Watershed. *Arabian Journal for Science and Engineering*, *41*(10), 4065–4076. https://doi.org/10.1007/s13369-016-2095-5

See, L., & Abrahart, R. J. (2001). Multi-model data fusion for hydrological forecasting. *Computers and Geosciences*, *27*(8), 987–994. https://doi.org/10.1016/S0098-3004(00)00136-9

See, L., & Openshaw, S. (2000). A hybrid multi-model approach to river level forecasting. *Hydrological Sciences Journal*, *45*(4), 523–536. https://doi.org/10.1080/02626660009492354

Senent-Aparicio, J., Jimeno-Sáez, P., Bueno-Crespo, A., Pérez-Sánchez, J., & Pulido-Velázquez, D. (2019). Coupling machine-learning techniques with SWAT model for instantaneous peak flow prediction. *Biosystems Engineering*, *177*, 67–77. https://doi.org/10.1016/j.biosystemseng.2018.04.022

Shamseldin, A. Y., O'Connor, K. M., Liang, G. C. (1997). Methods for combining the outputs of different rainfall-runoff models. *Journal of Hydrology*, *197*(1–4), 203–229. https://doi.org/10.1016/S0022-1694(96)03259-3

Shamseldin, A. Y., O'Connor, K. M., Nasr, A. E. (2007). A comparative study of three neural network forecast combination methods for simulated river flows of different rainfall-runoff models. *Hydrological Sciences Journal*, *52*(5), 896–916. https://doi.org/10.1623/hysj.52.5.896

Shamseldin, A. Y., & O'connor, K. M. (1999). A real-time combination method for the outputs of different rainfall-runoff models. *Hydrological Sciences Journal*, *44*(6), 895–912. https://doi.org/10.1080/02626669909492288

Sharafati, A., Asadollah, S. B. H. S., Hosseinzadeh, M. (2020). The potential of new ensemble machine learning models for effluent quality parameters prediction and related uncertainty. *Process Safety and Environmental Protection*, *140*, 68–78. https://doi.org/10.1016/j.psep.2020.04.045

Sharafati, A., Asadollah, S. B.H. S., Neshat, A. (2020). A new artificial intelligence strategy for predicting the groundwater level over the Rafsanjan aquifer in Iran. *Journal of Hydrology*, *591*(May), 125468. https://doi.org/10.1016/j.jhydrol.2020.125468

Sharafati, A., Haji Seyed Asadollah, S. B., Motta, D.,Yaseen, Z. M. (2020). Application of newly developed ensemble machine learning models for daily suspended sediment load prediction and related uncertainty analysis. *Hydrological Sciences Journal*, *65*(12), 1–21. https://doi.org/10.1080/02626667.2020.1786571

Sharghi, E., Nourani, V., Behfar, N. (2018). Earthfill dam seepage analysis using ensemble artificial intelligence based modeling. *Journal of Hydroinformatics*, jh2018151. https://doi.org/10.2166/hydro.2018.151

Sharghi, E., Nourani, V., Najafi, H., Molajou, A. (2018). Emotional ANN (EANN) and Wavelet-ANN (WANN) Approaches for Markovian and Seasonal Based Modeling of Rainfall-Runoff Process. *Water Resources Management*, *32*(10), 3441–3456. https://doi.org/10.1007/s11269-018-2000-y

Sharma, N., Zakaullah, M., Tiwari, H., & Kumar, D. (2015). Runoff and sediment yield modeling using ANN and support vector machines: a case study from Nepal watershed. *Modeling Earth Systems and Environment*, *1*(3), 1–8. https://doi.org/10.1007/s40808-015-0027-0

Shekar, S. . N. C., & Vinay, D. C. (2021). Performance of HEC-HMS and SWAT to simulate streamflow in the sub-humid tropical Hemavathi catchment. *Journal of Water and Climate Change*, *12*(7), 3005–3017. https://doi.org/10.2166/wcc.2021.072

Shoaib, M., Shamseldin, A. Y., & Melville, B. W. (2014). Comparative study of different wavelet based neural network models for rainfall-runoff modeling. *Journal of Hydrology*, *515*(February 2016), 47–58. https://doi.org/10.1016/j.jhydrol.2014.04.055

Singh, A., Isaac, R. K., & Denis, D. M. (2013). *Comparison of Artificial Neural Network Models for Sediment Yield Prediction at Single Gauging Station of Watershed in Eastern India Comparison of Artificial Neural Network Models for Sediment Yield Prediction at Single Gauging Station of Watershed in Eas*. *September 2016*. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000601

Singh, V. P. (1989). Hydrologic Systems: Watershed Modeling Volume II. *Prentice-Hall,I Nc. Division OfSimon & Schuster Engle Wood Cliffs, New Jersey 07632*.

Solomatine, D. P., & Dulal, K. N. (2003). Model trees as an alternative to neural networks in rainfall-runoff modelling. *Hydrological Sciences Journal*, *48*(3), 399–412. https://doi.org/10.1623/hysj.48.3.399.45291

Srinivasan, R. ., Ramanarayanan, T. S., Arnold, J. G., & Bednarz, S. T. (1998). Large area hydrologic modeling and assessment part II: model application. *Journal of the American Water Resources Association*, *34*(1), 91–101. https://doi.org/10.1111/j.1752-1688.1998.tb05962.x

Srinivasulu, S., & Jain, A. (2006). A comparative analysis of training methods for artificial neural network rainfall-runoff models. *Applied Soft Computing Journal*, *6*(3), 295–306. https://doi.org/10.1016/j.asoc.2005.02.002

Sudheer, K. P., Gowda, P., Chaubey, I., & Howell, T. (2010). Artificial Neural Network approach for mapping contrasting tillage practices. *Remote Sensing*, *2*(2), 579–590. https://doi.org/10.3390/rs2020579

Tabari, H., Kisi, O., Ezani, A., & Hosseinzadeh Talaee, P. (2012). SVM, ANFIS, regression and climate based models for reference evapotranspiration modeling using limited climatic data in a semi-arid highland environment. *Journal of Hydrology*, *444–445*, 78–89. https://doi.org/10.1016/j.jhydrol.2012.04.007

Tabari, H., Marofi, S., & Sabziparvar, A. A. (2010). Estimation of daily pan evaporation using artificial neural network and multivariate non-linear regression. *Irrigation Science*, *28*(5), 399–406. https://doi.org/10.1007/s00271-009-0201-0

Tabari, H., Martinez, C., Ezani, A., & Hosseinzadeh Talaee, P. (2013). Applicability of support vector machines and adaptive neurofuzzy inference system for modeling potato crop evapotranspiration. *Irrigation Science*, *31*(4), 575–588. https://doi.org/10.1007/s00271-012-0332-6

Tabari, H., Sabziparvar, A. A., & Ahmadi, M. (2011). Comparison of artificial neural network and multivariate linear regression methods for estimation of daily soil temperature in an arid region. *Meteorology and Atmospheric Physics*, *110*(3), 135–142. https://doi.org/10.1007/s00703-010-0110-z

Tahmoures, M., Nia, A. R. M., & Naghiloo, M. (2015). Modeling of streamflow-suspended sediment load relationship by adaptive neuro-fuzzy and artificial neural network approaches (Case study : Dalaki River , Iran). *Desert*, *2*, 177–195.

Tanty, R.,Desmukh, T.S. (2015). Application of Artificial Neural Network in Hydrology- A Review. *International Journal of Engineering and Technical Research*, *4*(06), ISSN: 2278-0181. https://doi.org/10.17577/IJERTV4IS060247

Tassew, B. G., Belete, M. A., & Miegel, K. (2019). 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*(21), 1–17. https://doi.org/10.3390/hydrology6010021

Taylor, K. E. (2001). Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research*, *106*(D7), 7183–7192. https://doi.org/10.1029/2000JD900719

Tegegne, G., Park, D. K., & Kim, Y. O. (2017). Comparison of hydrological models for the assessment of water resources in a data-scarce region, the Upper Blue Nile River Basin. *Journal of Hydrology: Regional Studies*, *14*(October), 49–66. https://doi.org/10.1016/j.ejrh.2017.10.002

Tewolde, M. H., & Smithers, J. C. (2006). Flood routing in ungauged catchments using Muskingum methods. *Water SA*, *32*(3), 379–388. https://doi.org/10.4314/wsa.v32i3.5263

Timmermann, A. G. (2005). Forecast Combinations. *Centre for Economic Policy Research, 90–98 Goswell Rd, London EC1V 7RR, UK.*

Uhlenbrook, S., Mohamed, Y., & Gragne, A. S. (2010). Analyzing catchment behavior through catchment modeling in the Gilgel Abay, Upper Blue Nile River Basin, Ethiopia. *Hydrology and Earth System Sciences*, *14*(10), 2153–2165. https://doi.org/10.5194/hess-14-2153-2010

Umar, I. K., Nourani, V., & Gökçekuş, H. (2021). A novel multi-model data-driven ensemble approach for the prediction of particulate matter concentration. *Environmental Science and Pollution Research*, *28*(36), 49663–49677. https://doi.org/10.1007/s11356-021-14133-9

USACE. (2010). Hydrologic Modeling System HEC-HMS User ' s Manual Version 3.5. *US Army Corps of Engineers, Hydrologic Engineering Center, Davis, CA*, *August*, 318.

Vapnik, V. (2013). The Nature of Statistical Learning Theory. Springer Science & Business Media. *Springer*.

Vapnik, V. N. (1995). The Nature of Statistical Learning Theory. *Springer, New York*.

Verma, A. K., Jha, M. K., & Mahana, R. K. (2010). Evaluation of HEC-HMS and WEPP for simulating watershed runoff using remote sensing and geographical information system. *Paddy and Water Environment*, *8*(2), 131–144. https://doi.org/10.1007/s10333-009-0192-8

Vilaysane, B., Takara, K., Luo, P., Akkharath, I., & Duan, W. (2015). Hydrological Stream Flow Modelling for Calibration and Uncertainty Analysis Using SWAT Model in the Xedone River Basin, Lao PDR. *Procedia Environmental Sciences*, *28*(SustaiN 2014), 380–390. https://doi.org/10.1016/j.proenv.2015.07.047

Wang, W., Xu, D., Chau, K., & Chen, S. C. (2013). Improved annual rainfall-runoff forecasting using PSO-SVM model based on EEMD. *Journal of Hydroinformatics*, *15*(4), 1377–1390. https://doi.org/10.2166/hydro.2013.134

Wu, C. L., & Chau, K. W. (2011). Rainfall – runoff modeling using artificial neural network coupled with singular spectrum analysis. *Journal of Hydrology*, *399*, 394–409. https://doi.org/10.1016/j.jhydrol.2011.01.017

Xiong, L., Shamseldin, A. Y., & O'Connor, K. M. (2001). A non-linear combination of the forecasts of rainfall-runoff models by the first-order Takagi-Sugeno fuzzy system. *Journal of Hydrology*, *245*(1–4), 196–217. https://doi.org/10.1016/S0022-1694(01)00349-3

Yang, S., Yang, D., Chen, J., Santisirisomboon, J., Lu, W., & Zhao, B. (2020). A physical process and machine learning combined hydrological model for daily streamflow simulations of large watersheds with limited observation data. *Journal of Hydrology*, *590*, 125206. https://doi.org/10.1016/j.jhydrol.2020.125206

Yaseen, Z. M., Deo, R. C., Hilal, A., Abd, A. M., Bueno, L. C., Salcedo-Sanz, S., & Nehdi, M. L. (2018). Predicting compressive strength of lightweight foamed concrete using extreme learning machine model. *Advances in Engineering Software*, *115*(April 2017), 112–125. https://doi.org/10.1016/j.advengsoft.2017.09.004

Yaseen, Z. M., El-shafie, A., Jaafar, O., Afan, H. A., & Sayl, K. N. (2015). Artificial intelligence based models for stream-flow forecasting : 2000 – 2015. *Journal of Hydrology*, *530*, 829–844. https://doi.org/10.1016/j.jhydrol.2015.10.038

Young, C. C., Liu, W. C., & Wu, M. C. (2017). A physically based and machine learning hybrid approach for accurate rainfall-runoff modeling during extreme typhoon events. *Applied Soft Computing Journal*, *53*, 205–216. https://doi.org/10.1016/j.asoc.2016.12.052

Zakhrouf, M., Chettih, M., & Mesbah, M. (2014). Adaptive neural fuzzy inference systems for the daily flow forecast in Algerian coastal basins. *Desalination and Water Treatment*, *52*(10–12), 2131–2138. https://doi.org/10.1080/19443994.2013.873740

Zakizadeh, H., Ahmadi, H., Zehtabian, G., Moeini, A., & Moghaddamnia, A. (2020). A novel study of SWAT and ANN models for runoff simulation with application on dataset of metrological stations. *Physics and Chemistry of the Earth*, *120*(July), 102899. https://doi.org/10.1016/j.pce.2020.102899

Zelelew, D. G., & Melesse, A. M. (2018). Applicability of a spatially semi-distributed hydrological model for watershed scale runoff estimation in Northwest Ethiopia. *Water (Switzerland)*, *10*(7), 10–12. https://doi.org/10.3390/w10070923

Zhang, L., & Yang, X. (2018). Applying a multi-model ensemble method for long-term runoff prediction under climate change scenarios for the Yellow River Basin, China. *Water (Switzerland)*, *10*(3). https://doi.org/10.3390/w10030301

Zhang, X., Srinivasan, R., Debele, B., & Hao, F. (2008). Runoff simulation of the headwaters of the yellow river using the SWAT model with three snowmelt algorithms. *Journal of the American Water Resources Association*, *44*(1), 48–61. https://doi.org/10.1111/j.1752-1688.2007.00137.x

.

Appendices

Appendix A

Curriculum Vitae (CV)

1. Personal information

- Name Gebre Gelete Kebede
- Date of birth 01/02/1990
- Place of birth Andabet, South Gondar, Ethiopia
- Sex Male
- Marital status Single
- Nationality Ethiopian
- Address Mobile: +905338550396 or +251924093459

  Email: gegelete04@gmail.com

2. Educational Background

- Received MSc degree in Water Resources Engineering and Management (with **CGPA of 3.91 on 4.00 scale**) from Hawasa University on November, 2015.
- Receive BSc degree in soil resource and watershed management (with CGPA of **3.84 on 4.00 scale**) from Wondogenet college of Natural Resource, Hawasa University on July, 2011.
- Grade 9-12 Mekane eyessus secondary and preparatory school, Mekaneyesus, Ethiopia
- Grade 7-8 Jaragedo primary school, Jaragedo, Ethiopia
- Grade 1-6 Atsedemariam primary school, Ethiopia

3. Work experience:

- Lecturer at Arsi University, Ethiopia from November 2015 up to present
- Research assistant at Near east university, TRNC from September 2018-up to present
- Part-time lecturer at Near east university, TRNC from September 2018-2019
- Assistant Lecturer at Adama Science and Technology University from September, 2013 to October 2015 as

- Graduate Assistant **II** at Adama Science and Technology University, From September 2012 up to September 2013
- Graduate Assistant **I** at Adama science and technology University from September, 2011 to August, 2012

4. Award Received

- Certificate from Cech Republic Development Cooperation on Research Proposal Preparation (Jan, 2014).
- Certificate of higher diploma program (HDP)/ Pedagogical skills from Adama science and Technology University (2012).
- Certificate of paper presentation on 2nd International conference on Water problems in the Mediterranean Countries, Near East University, Cyprus. May, 2019

5. Language

Amharic (mother tongue) and English

6. Conferences Organized comitee member

- 2nd International conference on the environment survival and sustainability, 7 – 11 October 2019. Near East University, Nicosia, Cyprus.
- 2nd International conference on Water problems in the Mediterranean Countries (WPMC 2019), 06 – 10 May, 2019. Near East University, Nicosia, Cyprus.
- 2nd International conference on the Cyprus Issue: Past, Present and the Vision for the Future, 1 – 3 April, 2019. Near East University, Nicosia, Cyprus

7. Course given (from 2011-2022)

- Surveying and Mapping
- Hydrology
- Irrigation and drainage
- Water resources planning and management
- Soil and water conservation
- Sanitary engineering
- Water resources engineering

- Hydromechanics
- Strength of Materials
- Water treatment plant design

8. Computer skill

- Basic computer skill (Ms –Excel, word and PowerPoint)
- Advanced software's which are very important for water resource management and climate change such as HEC-HMS, SWAT, HBV, MATLAB, MODFLOW, Arc GIS, Machin learning, WEAP and ERDAS IMAGINE
- Epanet software for water supply distribution network design
- R- software
- SPSS and SAS

9. Training

- ➢ Diploma in Pedagogical Skill Improvement and support for teacher (PSIST) from Adama sciences and Technology University in 2012
- ➢ Certificate in Research Methodology from Hawasa University in 2014
- ➢ Certificate in SAS and SPSS software training from Arsi university in 2015
- ➢ Certificate in R software, from Arsi university in 2017

10. Publications

- Analysis of water balance and hydrodynamics of the Lake Beseka, Ethiopia (https://doi.org/10.2166/wcc.2022.323)
- Impact of climate change on the hydrology of Blue Nile basin, Ethiopia: a review (https://doi.org/10.2166/wcc.2019.014)
- Estimation of Suspended Sediment Load Using Artificial Intelligence-Based Ensemble Model (https://doi.org/10.1155/2021/6633760)
- Evaluating disinfection techniques of water treatment (https://www.deswater.com/DWT_articles/vol_177_papers/177_2020_408.pdf)
- Evaluation of different natural wastewater treatment alternatives by fuzzy PROMETHEE method (doi:10.5004/dwt.2020.25049)

- Ranking of Natural Wastewater Treatment Techniques by Multi-criteria Decision Making (MCDM) Methods (https://link.springer.com/chapter/10.1007/978-3-030-64765-0_11)
- The Economic Impact of Climate Change on Transportation Assets (https://pdfs.semanticscholar.org/484a/15b656fe7bb4b93b83d0d26efc0a9998c3ee.pdf)
- Evaluating Disinfection Techniques of Water Treatment Using Multi-criteria Decision-Making Method (https://link.springer.com/chapter/10.1007/978-3-030-64765-0_12
- Management strategy for safe drinking water in developing countries – A case study for Assela, Ethiopia (http://doi.org/10.5004/dwt.2020.25225)
- Ensemble conceptual semi-distributed models for the rainfall-runoff process (ongoing)
- Physically and artificial intelligence-based hybrid modeling for the rainfall-runoff-sediment process (ongoing)

Appendix B

Additional time series

Figure 38

Time Series of Suspended Sediment Load

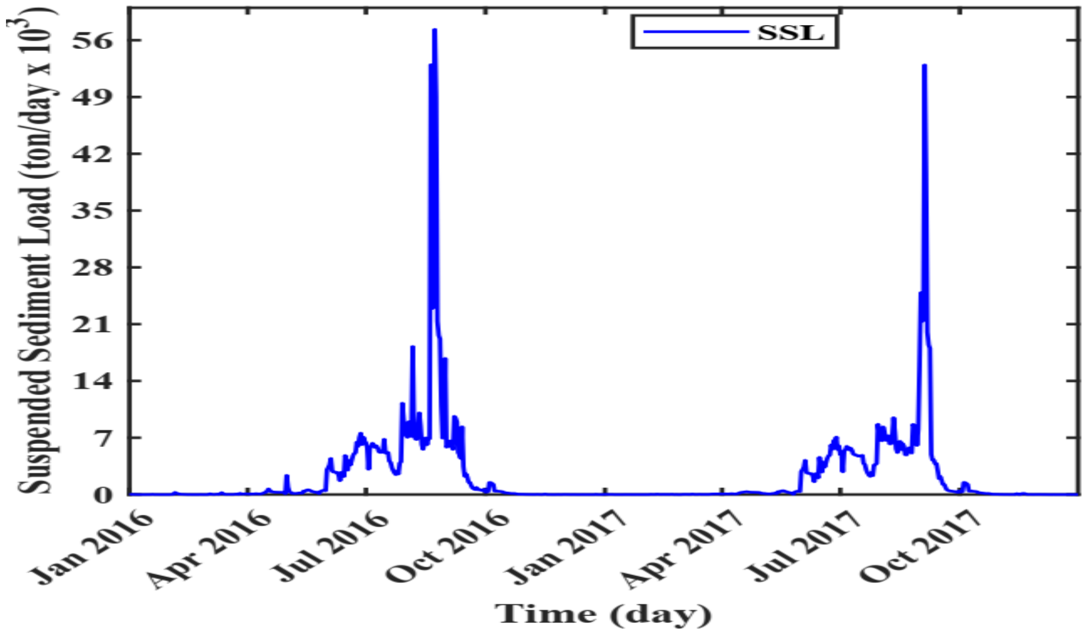


Figure 39

Time Series of Runoff from 2006-2017

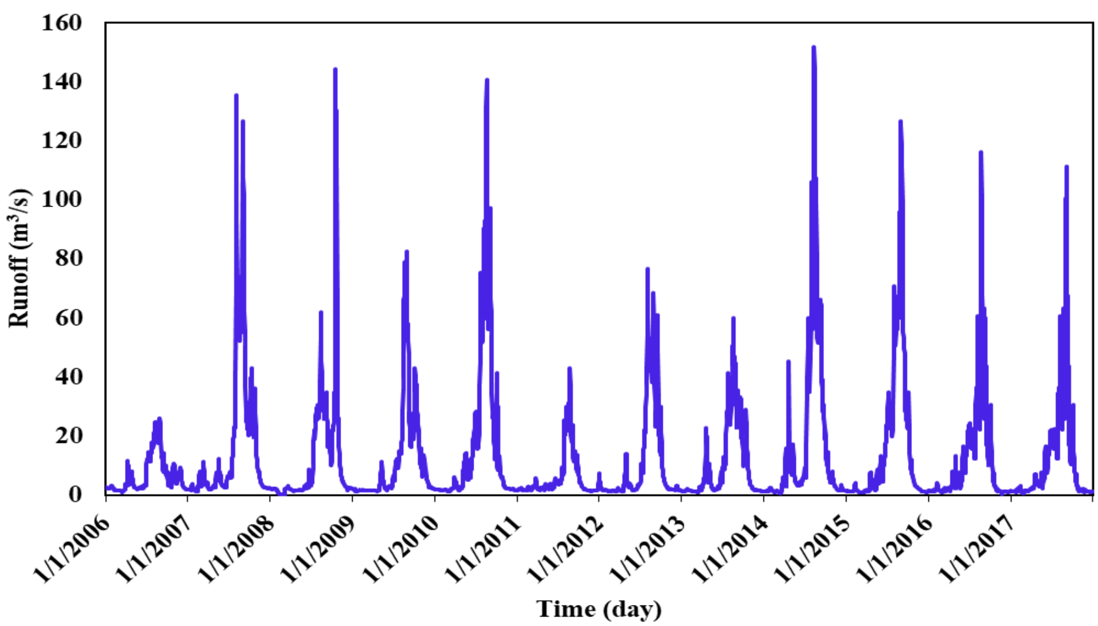


Figure 40

Time Series of the AI-based and Physically-based Models in the Calibration Phase

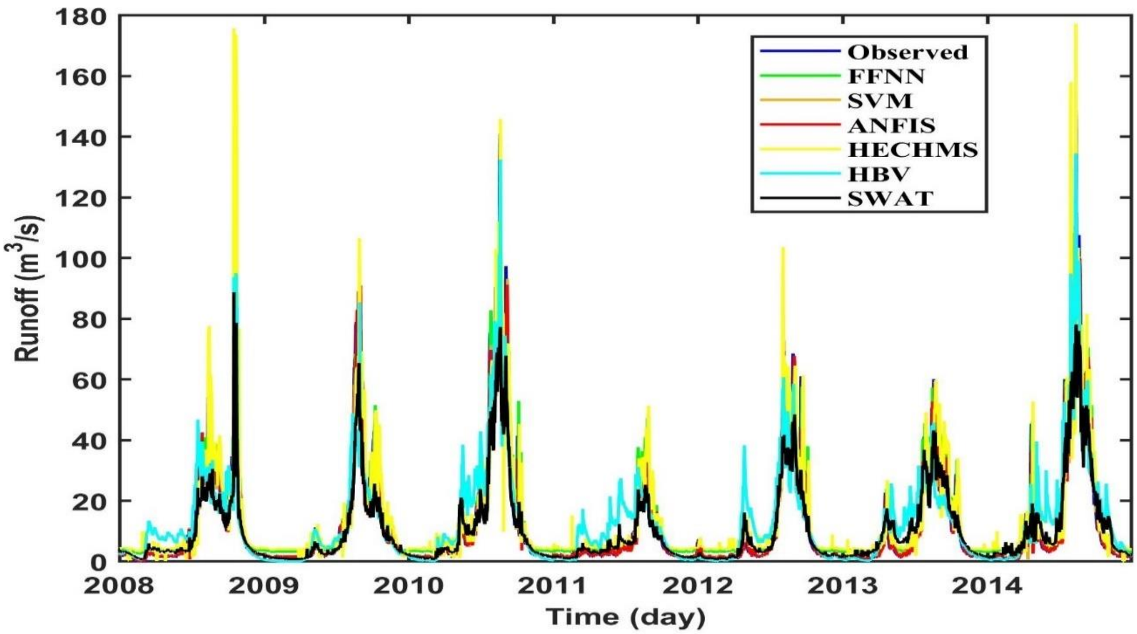
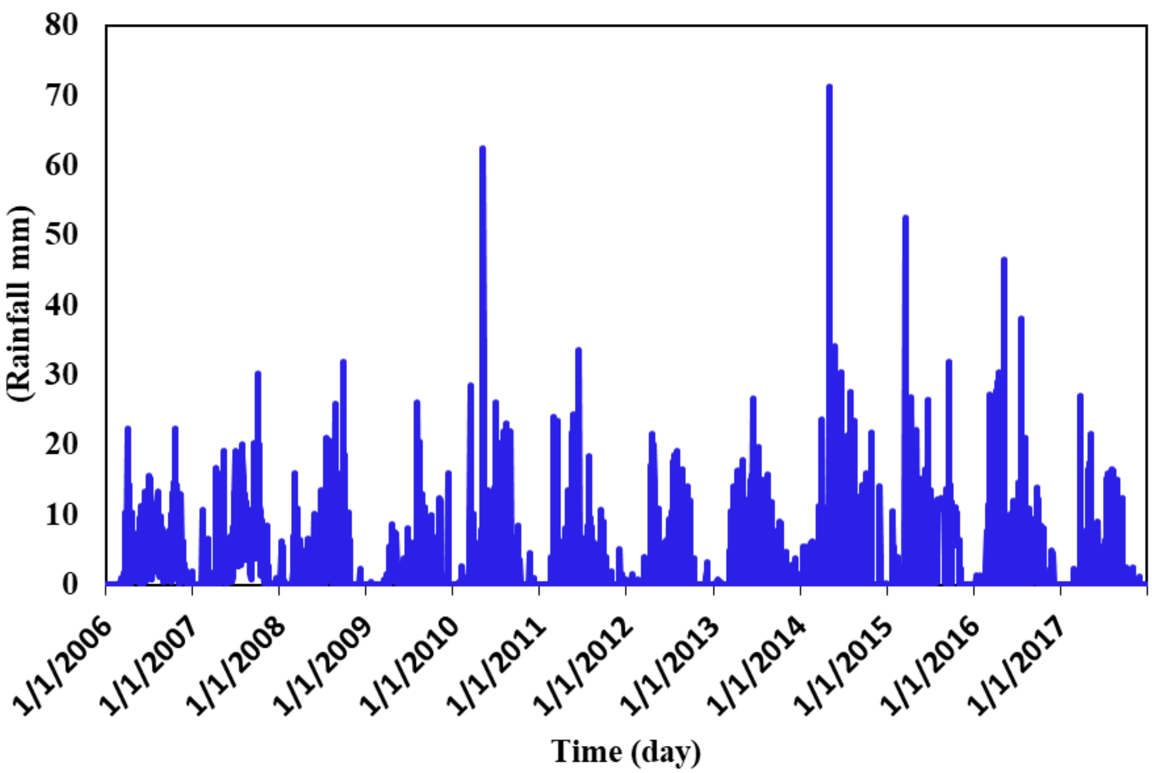


Figure 41

Time Series of the Theisen Polygon Average Rainfall



Appendix C

Ethical approval letter

To Institute of Graduate Studies

Reference: Gebre Gelete Kebede (20176898)

I would like to inform you that the above candidate is one of our postgraduate students in Civil Engineering Department. He is taking thesis under my supervision and the thesis title is: **“Hybrid Physical-artificial Intelligence-based Modeling for Rainfall-Runoff-Sediment Process, Case of Katar Catchment, Ethiopia”**

Since the researcher(s) will not collect primary data from humans, animals, plants or earth, this project does not need to go through the ethics committee.

Please do not hesitate to contact me if you have any further queries or questions.

Thank you very much indeed.

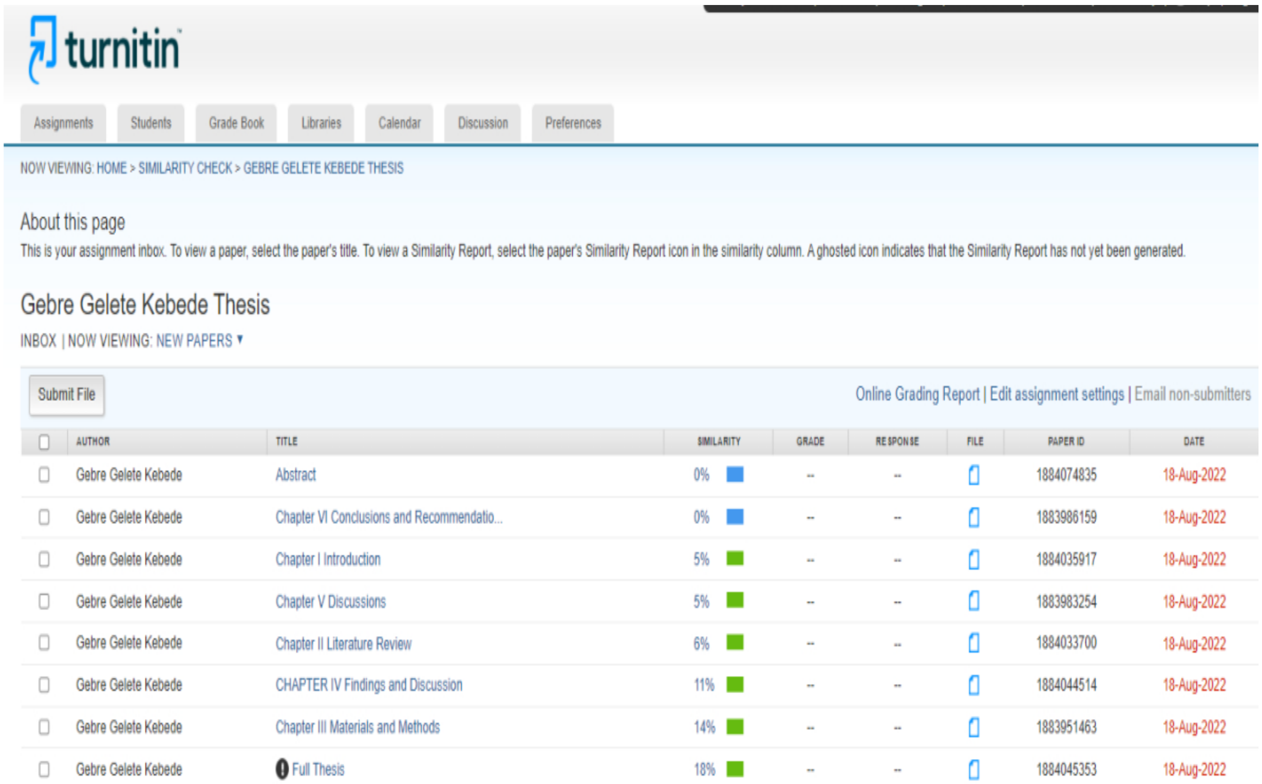
Best Regards.

Prof. Dr. Hüseyin Gokcekus
Dean, Faculty of Civil and Environmental Engineering,
Near East Boulevard, ZIP: 99138
Nicosia/TRNC, North Cyprus,

Mersin 10 – Turkey.
Email: huseyin.gokcekus@neu.edu.tr

Appendix D

Turnitin Similarity Report


turnitin

Assignments | Students | Grade Book | Libraries | Calendar | Discussion | Preferences

NOW VIEWING: HOME > SIMILARITY CHECK > GEBRE GELETE KEBEDE THESIS

About this page

This is your assignment inbox. To view a paper, select the paper's title. To view a Similarity Report, select the paper's Similarity Report icon in the similarity column. A ghosted icon indicates that the Similarity Report has not yet been generated.

Gebre Gelete Kebede Thesis

INBOX | NOW VIEWING: NEW PAPERS ▼

Submit File

Online Grading Report | Edit assignment settings | Email non-submitters

AUTHOR	TITLE	SIMILARITY	GRADE	RESPONSE	FILE	PAPER ID	DATE
Gebre Gelete Kebede	Abstract	0%	--	--		1884074835	18-Aug-2022
Gebre Gelete Kebede	Chapter VI Conclusions and Recommendatio...	0%	--	--		1883986159	18-Aug-2022
Gebre Gelete Kebede	Chapter I Introduction	5%	--	--		1884035917	18-Aug-2022
Gebre Gelete Kebede	Chapter V Discussions	5%	--	--		1883983254	18-Aug-2022
Gebre Gelete Kebede	Chapter II Literature Review	6%	--	--		1884033700	18-Aug-2022
Gebre Gelete Kebede	CHAPTER IV Findings and Discussion	11%	--	--		1884044514	18-Aug-2022
Gebre Gelete Kebede	Chapter III Materials and Methods	14%	--	--		1883951463	18-Aug-2022
Gebre Gelete Kebede	Full Thesis	18%	--	--		1884045353	18-Aug-2022

Prof. Dr. Hüseyin Gökçekuş