

ADDIS ABABA UNIVERSITY
ADDIS ABABA INSTITUTE OF TECHNOLOGY
SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING



**Real-Time Flood Forecasting Using Artificial Neural
Networks (ANN) and Flood Inundation Mapping**

A Thesis in Hydraulic Engineering

By: Habtamu Tamiru

ID No: GSR/5390/10

Adviser: Belete Berhanu (PhD)

June, 2019

Addis Ababa

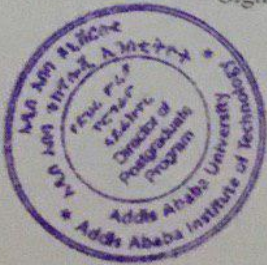
A Thesis

Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science

Real-Time Flood Forecasting Using Artificial Neural Networks (ANN) and Flood Inundation Mapping | 2019

The undersigned have examined the thesis entitled "Real-Time Flood Forecasting using Artificial Neural Network (ANN) and Flood inundation Mapping" presented by Habtamu Tamiru, a candidate for the degree of Master of Science and hereby certify that it is worthy of acceptance.

<u>Belete Berhane</u> Advisor	<u>[Signature]</u> Signature	<u>08/07/2019</u> Date
<u>Dereje Hailu</u> Internal Examiner	<u>Dereje Hailu</u> Signature	<u>08/07/2019</u> Date
<u>Agizew Nigussie</u> External Examiner	<u>[Signature]</u> Signature	<u>08/07/2019</u> Date
<u>Henok Fikre (Dr.)</u> A/Dean, School of Civil & Environmental Engineering	<u>[Signature]</u> Signature	<u>08/07/2019</u> Date
<u>Chair person</u>	<u>[Signature]</u> Signature	<u>08/07/2019</u> Date



AAU, Addis Ababa Institute of Technology (AAiT) | Page 1

UNDERTAKING

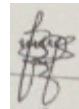
I certify that research work titled “**Real Time Flood Forecasting using Artificial Neural Network (ANN) and Flood Inundation mapping**” is my own work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged or referred.

Habtamu Tamiru

Email: habtemodel1345@gmail.com

Phone Number: +251917466191/0917792485

Signature:



Addis Ababa Institute of technology (AAiT)

Addis Ababa University (AAU)

CERTIFICATION

The undersigned certify that he has read the thesis entitled “**Real-Time Flood Forecasting using Artificial Neural Networks (ANN) and Flood Inundation Mapping**” The Case of *Baro River Basin, Itang special wereda* and hereby recommend for acceptance by the Addis Ababa University in partial fulfillment of the requirements for the degree of Master of Science.

Belete Berhanu (PhD)

(Advisor)

Date

ACKNOWLEDGMENTS

First of all I would like to praise almighty GOD for his incomparable help until the end of my work. Secondly, I would like to express my genuine gratitude to my advisor Belete Berhanu (PhD) for his dedication and giving me valuable guidance and continuous support from the beginning of this work to the end to reach this current level of success and I have been extremely lucky to have a such advisor who cared so much about my work, and who responded to my questions and queries so promptly.

My sincere appreciation also goes to Fitsume Teshome who helped me from the basic brotherly and of all my lovely classmates for their moral support, lastly my gratitude goes to all staff members of Civil and Environmental Engineering specially Hydraulic Engineering stream and others who helped me to carry out my thesis work through remarkable encouragement, advice, material support and who played a role in my academic accomplishments.

ABSTRACT

Flooding is one of the most destructive and harmful natural disasters occurring in many parts of the world and there is increasing evidence that losses are rising largely because more people are settling in flood prone areas. In many regions of the world, flood forecasting is one among the few feasible options to manage floods and Ethiopia has no exceptional. Flooding in the country is mainly linked with heavy rainfall and the topography of the highland mountains and lowland plains with river banks system formed by the major river basins such as Baro River.

This study presents Real Time Flood Forecasting system using Artificial Neural Network (ANN) and HEC-RAS integrated modeling in Baro River. ANN hydrological flood forecasting model set up using both deterministic and stochastic approach with Rainfall, Temperature and Topographic Wetness Index (TWI) as parametric inputs and trained random neurons weights as stochastic variable. The hydrological model trained and validated using 7 years (1999-2005) and three years (2006-2008) observed stream flow data respectively. And its performance also evaluated with 0.84 and 0.87 NSE values at calibration and validation period respectively. Similarly, for hydraulics modeling, using Normal Difference water Index (NDWI) revealed that both recorded flood events and flood extent area obtained from HEC-RAS are overlapped up to 96% during calibration and validation.

The Real time forecasting of flood and its inundation area also evaluated using forecasted daily rainfall and temperature for 3, 7 and 10-days during (May 27, 2019-June 05, 2019) rainy period and these results further compared with the real time condition after 3, 7 and 10 days and showed very good performance. In addition to these, three decades future flood affected areas with different climate change scenarios identified to warn the inhabitants and development investments.

Key words: Artificial Neural Networks (ANN), HEC-RAS, Inundation Mapping and Flood prone Areas, Normal Difference water index ,Real-time flood forecasting

TABLE OF CONTENTS

CERTIFICATION.....	III
ACKNOWLEDGMENTS	IV
ABSTRACT.....	V
TABLE OF CONTENTS	VI
LIST OF TABLES	XI
LIST OF FIGURES	XII
ABBREVIATIONS.....	XIV
1. INTRODUCTION	1
1.1 GENERAL INTRODUCTION	1
1.2 Statement of the problem	2
1.2.1 Research Questions	3
1.3 Objectives of the Research.....	4
1.3.1 General objective	4
1.3.2 Specific objectives	4
1.3.3 Significance of the Study	5
1.3.4 Scope of the study	6
2. LITERATURE REVIEW.....	7
2.1 General overview of flood.....	7
2.1.1 River Flooding	7
2.1.2 Surface Flooding.....	8
2.1.3 Surge (Flow) Flooding.....	8
2.2 Flood prediction techniques	8
2.2.1 Flood forecasting definition.....	8
2.3 Linear Models for Flood Prediction	9

2.3.1	Linear stochastic auto-regressive moving-average (ARMA) models.....	9
2.3.2	Non-Linear Models for Flood Prediction	9
2.3.3	Flood forecasting in Ethiopia.....	9
2.4	Application of Artificial Neural Networks in Hydrology	11
2.5	Introduction to Artificial Neural Networks.....	11
2.5.1	What Is an Artificial Neural Network.....	11
2.5.2	Models of artificial neural network.....	12
2.5.3	Neural network architectures	12
2.5.4	Selection of ANN architectures	12
2.5.5	Weights in Artificial Neural Networks	14
2.5.6	Activation functions.....	14
2.5.7	Different activation functions	14
2.5.8	Sigmoid activation function.....	15
2.5.9	Feed-forward networks	15
2.5.10	Training neural networks	15
2.5.11	Supervised learning.....	16
2.5.12	Unsupervised learning	16
2.5.13	Neural Network Training Software	16
2.5.14	Back to back propagation.....	16
2.6	ANNs as Rainfall-Runoff models	17
2.6.1	Real Time Flood Forecasting.....	17
2.6.2	Artificial Neural Networks for Real Time Flood Forecasting.....	18
2.7	Early warning systems	19
2.7.1	Meteorological and Hydrological Considerations	20
2.7.2	Aspects of flood forecasting and early warning systems.....	21

2.7.3	Elements of Flood Forecasting and Early Warning System	21
2.8	Global Climate Change	22
2.8.1	Climate Change of Africa	22
2.8.2	Climate change of Ethiopia.....	23
2.8.3	Current Climate Variability and Observed Trends	23
2.8.4	Temperature Variability and Trend	23
2.8.5	Climate Scenario	24
2.8.6	Representative Concentration Path way (RCP)	25
2.8.7	RCP4.5 (stabilization scenario)	25
2.8.8	RCP6 (stabilization scenario)	26
2.8.9	RCP8.5 (high emission scenario).....	26
2.8.10	Bias Correction	27
3.	MATERIAL AND METHRODOLOGY.....	28
3.1	MATERIALS AND METHODS	28
3.2	Description of Study Area.....	28
3.3	Software used in the study	30
3.4	Data used and processing	31
3.4.1	Data used and sources	31
3.5	Data processing	31
3.5.1	Topography	31
3.5.2	Meteorological Data Processing	32
3.5.3	Filling Missing data	33
3.5.4	Checking the consistency of data.....	34
3.5.5	Test for Outlier.....	35
3.6	Model setup	37

3.6.1	Hydrological Modeling using ANN in R studio	37
3.6.2	Input variables for Rainfall-Runoff models.....	37
3.6.3	Combinations of input variables	37
3.7	Data preparation	38
3.7.1	Pre-processing and post-processing data	38
3.7.2	ANN types and architectures	39
3.7.3	Choosing an ANN type.....	39
3.7.4	Finding an optimal ANN design	39
3.7.5	ANN training issues in R-R modeling.....	40
3.7.6	Initialization of network weights	40
3.7.7	Feed-forward networks	40
3.7.8	Training algorithm performance criteria.....	40
3.8	Hydraulic Modeling	40
3.8.1	The HEC-RAS model	40
3.8.2	Data preparation.....	41
3.8.3	Two-Dimensional (2D) Modeling in HEC-RAS	41
3.8.4	HEC-RAS Model Calibration and Validation	42
3.8.5	Climate change scenarios for flood prone areas identification.....	44
3.8.6	Schematic diagram of general method in the study	45
4.	RESULTS AND DISCUSSION.....	47
4.1	Rainfall-Runoff Modeling ANN Design in R studio	47
4.1.1	Neural network architectures	47
4.1.2	Pre-processing and post-processing.....	48
4.1.3	Initialization of network weights	48
4.1.4	Feed-forward networks	50

4.1.5	Back propagation Neural Networks.....	52
4.1.6	Model performance evaluation	53
4.2	Running Hydraulic Modeling.....	57
4.2.1	Data preparation.....	57
4.3	Running Hydraulic Modeling (HEC-RAS).....	60
4.4	Calibration and Validation of HEC-RAS Model	62
4.4.1	Calibration.....	62
4.4.2	HEC-RAS Model Validation	63
4.5	Real Time Forecasting at time-days ahead	64
4.5.1	Short term forecasting scenarios of early warning	65
4.6	Climate change scenarios	69
4.6.1	Climate Scenario	69
5.	CONCLUSION	72
6.	RECOMMENDATIONS	73
7.	REFERENCES	74
8.	APPENDICES	76
	Appendices A: Rainfall Data used in the study (after quality check)	76
	Appendices B: Double Mass Curves for all Rainfall stations	78
	Appendices C: River Geometries Baro River at different stations	82
	Appendices D: River cross section of Baro River at different stations.....	83

LIST OF TABLES

Table 3-1: Details of all software used in the study works.....	30
Table 3-2: Datasets detail and their sources with their purposes.....	31
Table 3-3: Meteorological Stations used in the study area	33
Table 4-1: initialized values of weights in R studio	49
Table 4-2: Results of weights after training is reached.....	54

LIST OF FIGURES

Figure 1-1: Flood events Itang Area and Prone Areas in Ethiopia	3
Figure 2-1 : Standard Neural Networks for Feed forward computation	13
Figure 2-2: Representative Concentration Pathway (RCP) from the fifth report (ARF5).....	27
Figure 3-1: Location and description of the study area in detail	29
Figure 3-2: Topography and the river networks in the study area	32
Table 3-3: Double Mass Curve (DMC) for checking data trend (Gambella station)	35
Figure3-4: Checking outlier for hydrological data	36
Figure 3-5: Daily stream flow data of Baro River at Gambella.....	36
Figure 3-6: HEC-RAS model Calibration and Validation framework	43
Figure 3-8: General Flow chart of the methodology	46
Figure 4-1: Neural networks architecture selected in the model	47
Figure 4-2: algorithm selection of best ANN architecture.....	48
Figure 4-3: Scaling or normalization of raw data before feed to network.....	48
Figure 4-4: Initialization of weights between nodes.....	49
Figure 4-5: Initial values of weights assigned to the networks.....	49
Figure 4-6: Feed Forward algorithm developed in R studio.....	50
Figure 4-7: Algorithms developed in R studio to apply activation function	50
Figure 4-8: Linear activation function at output node	51
Figure 4-9: Total error between output and target (actual) data	51
Figure 4-10: Result from ANN model before training	51
Figure 4-11: All Back-propagation algorithms developed using gradient descent.....	52
Figure 4-12 Model performance evaluation and stopping condition set in R studio.....	53
Figure4-13: Model performance Evaluation algorithm	54
Figure 4-14 : Results of weights (adjusted weights) assigned to the networks	55
Figure 4-15: ANN calibrated or trained daily flow result using Back-propagation algorithm.....	55
Figure 4-16: ANN result Validated for the year (2006-2008 G.c)	56
Figure 4-17: Model performance in R studio for validated ANN	56
Figure 4-18: 12.5m Digital Elevation (DEM) in RAS Mapper	57

Figure 4-19: Baro River geometries prepared in RAS Mapper	57
Figure 4-20: Sample cross-section for the River at station 365413.....	58
Figure 4-21: River geometries with 500m x 500m gridded 2D flood area.....	58
Figure 4-22: RAS Mapper with no terrain or other map layer	59
Figure 4-23: computational mesh with 500m x 500m gridded terrain	59
Figure 4-24: River geometries with 500m x 500m grid and Terrain Mapper	60
Figure 4-25: Baro River with terrain data and shade of contour interval 20m	60
Figure 4-26: Unsteady flow analysis boundary condition in HEC-RAS.....	61
Figure 4-27: Unsteady flow analysis time window adjusted to run.....	62
Figure 4-28: Outflow hydrograph at Itang areas (downstream boundary)	62
Figure 4-29: Comparison of Simulated inundation map and flood extent.....	63
Figure 4-30: Comparison of Simulated inundation map and flood extent.....	64
Figure 4-31: Flood forecasted at 3, 7 and 10-days ahead with depth range	65
Figure 4-32: Forecasted flood or Discharge for 3-days ahead.....	66
Figure 4-33: Flood inundation map for 3-days head flood forecasted.....	66
Figure 4-34: Forecasted flood or Discharge for 7-days ahead.....	67
Figure 4-35: Flood inundation map for 7-days head flood forecasted.....	67
Figure 4-36: Forecasted flood or Discharge for 7-days ahead.....	68
Figure 4-37: Flood inundation map for 10-days head flood forecasted.....	68
Figure 4-38:Figure: stream flow projected for the next 10-years	69
Figure 4-39: stream flow projected for the next 20-years.....	70
Figure4-40: stream flow projected for the next 30-years.....	70
Figure4-41: Flood prone area for the next 10-years (2020-2029)	71
Figure4-42: Flood prone area for the next 20-years (2030-2039)	71
Figure4-43: Flood prone area for the next 30-years (2040-2049)	71

ABBREVIATIONS

ANN	Artificial Neural Networks
ARF5	Fifth Assessment Report
BPNN	Back-Propagation Neural Network
GIS	Geographical Information System
GHG	Green House Gas
HEC-RAS	Hydrologic Engineering Center River Analysis and Simulation
IPPC	International Panel on Climate Change
MLP	Multiple Layer Perceptron
MSE	Mean Square Error
MWIE	Ministry of Water Irrigation and Electricity
MWR	Ministry of Water Resources
NDWI	Normalized Difference Water Index
NMA	National Meteorological Agency
NMSA	National Meteorological Service Agency
NOAA	National Organization for Atmospheric
NSE	Nash-Sutcliffe coefficient of Efficient
QPF	Qualitative Precipitation Forecast
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
SNNPRS	Southern Nations and Nationalities Peoples Regional
SPI	Standard Precipitation Index
SRES	Special Report on Emissions Scenarios
TWI	Topographical Wetness Index
USGS	United state Geographical Surveys
WMO	World Meteorological Organization

1. INTRODUCTION

1.1 GENERAL INTRODUCTION

Flooding is one of the destructive and harmful natural disasters occurring in many parts of the world and there is increasing evidence that losses are rising largely because more people are settling in areas that are prone to natural hazards, such as the flood plains areas of major rivers[1]. Flood forecasting (FF) is one the most challenging and difficult problems in hydrological modeling due to its critical contribution in reducing economic and life losses and mitigating the effects of floods can be accomplished using either structural or nonstructural measures, or by a combination of both.

In many regions of the world, flood forecasting is one among the few feasible options to manage floods at real time to cope community[2]. Real-time forecasting of stream flows is very important issue to provide reliable warnings of unusual flood conditions on major river[3]. Flood forecasting is an essential requirement for solving a wide range of scientific and management problems related to the societal and environmental issues that still waging war with human beings over the world particularly for developing countries like Ethiopia. The socio economic and environmental impacts of floods are large in many parts of the world due to lack of reliable flood early warning systems among other disasters. Real time Flood forecasting is not only important in preparing early warning system, but also in predicting its environmental impacts, such as the transport and health related issues of the community[4].

Real-time flood forecasting and warning has become an important component of flood risk management strategies that look for to mitigate the impacts of floods on communities at risk by issuing timely and accurate forecasts and warnings of coming flooding. The needs on Real time flood forecasting and warning for Africa and the existing gaps for future research according to [5] was clearly forwarded that in many parts of the continent are highly exposing of these problems. As recent study from different parts of the continent indicated that more flooding expected across East Africa predictions in some sorts of years in the future during rainy seasons specially from June to September which may result flooding.

Ethiopia has no exceptional and Flooding in the country is mainly linked with heavy rainfall and the topography of the highland mountains and lowland plains with natural drainage systems formed by the major river basins such as Baro River.

In most cases, floods occur in the country as a result of lengthy heavy rainfall causing rivers to overflow and inundate areas along the river banks in lowland plains as of Itanga wereda in Gambella Region, Ethiopia. Since the beginning of the regular rainy season which usually begins from June or July, the country has been experiencing unusually extended and widespread rainfalls resulting overflow of rivers[6]. Although floods in many parts of the country are a seasonal phenomenon, the magnitude of the current flooding that has been occurring since 2007 in Baro River is very serious issue. As a result of torrential and heavy rains in the upstream highlands rivers such as Birbir and Geba rivers are causing Baro River to swell or overflow, inundating or covering the surrounding fields which are mostly located in the river course.

1.2 Statement of the problem

Surface water of Baro-Akobo basin is exposed to intense rainfall sometimes responsive for flooding, causing damage to the community's properties and health. The rainy season in Ethiopia is intensive in four months from June to September and this intense rainfall in the highlands causes flooding of settlements close to any stretch of river courses of low-lying areas[7]. In the past years, flooding has been observed in many parts of the country, indicating that the frequency of flood is increasing from year to year. It is also obvious to understand that the impacts of flooded areas to the society and environment as whole and to solve this dominating problem the following research idea is formulated as follows in the figure below for the study area.

Flood can seriously affects public and personal transport by cutting off roads and public transporting lines, as well as communication links when telephone lines are damaged because of fallen trees and also disturb normal natural drainage systems in the areas. Floods can distribute large amounts of water and suspended sediment over large areas, covering valuable soil nutrients to agricultural lands which were clearly seen in Itang area in Baro River course as flood event of 2012 G.C as shown in figure 1-1.



a) Part of Itang Area inundated by the 2012 flood event[6] b) Flood Affected areas in Ethiopia

Figure 1-1: Flood events Itang Area and Prone Areas in Ethiopia

In other side, there is no any well organized flood forecasting system in the region as well in the country, to inform the people at earlier to the occurrence of the flood to save life and wealth at head of the flooding time. In Ethiopia, even though forecasts of rainfall by the National Meteorological Services Agency (NMA) are frequently used to issue warnings regarding the likelihood of flooding, there is no appropriate real-time flood forecasting system that helps in reducing the damage due to flooding and as a result of this Flood, the socio-economic problems are also seriously increasing. Many lives and properties have been lost in the last few years due to this disaster.

Therefore, in this work, a Real time flood forecasting system using the combined hydrological (ANN) and Hydraulics (HEC-RAS) modeling is presented.

1.2.1 Research Questions

To achieve the research objectives, it was tried to answer the following research questions:

- ❖ Is there a possibility to establish flood forecasting system using Artificial Neural Network (ANN) and HEC-RAS hydraulics modeling in River Baro, in Gambela Region?
- ❖ Is the model able to forecast the real time flood with 3-10 days ahead of occurrence?

- ❖ Can we identify the future flood affected areas using different climate change scenarios?

1.3 Objectives of the Research

1.3.1 General objective

- ❖ To develop a Real-Time flood Forecasting system on Baro River to warn residents of Itang special Wereda at ahead of flooding time.

1.3.2 Specific objectives

The specific objectives of this study which addressed in this study are to:

- ❖ To develop ANN and HEC-RAS integrated flood forecasting system on Baro River
- ❖ To forecast the real time flood at head to 3, 7, and 10 days
- ❖ To identify flood prone areas of the wereda with different climate change Scenarios

1.3.3 Significance of the Study

The study is very important and plays a vital role to the following concerns:

As the traditional way of flood forecasting system are causing many hazards on the community, as a result this study will be dedicated to Real-Time flood forecasting for habitant of Itang area in Baro River Basin. In addition to this thesis is also very significant to the following issues:

- ❖ A flood inundation map generated in this study area used as flood hazard zones identifying tool in planning and developing any water related projects along Baro River course crossing the area.
- ❖ Flood prone areas delineated at different climate scenarios also used to warn habitant Itang special wereda in the coming 30-years.
- ❖ The real time algorithms developed for this specific study area can also be easily used for other areas by simple adjustment of the algorithm.
- ❖ The results obtained in this thesis works can also be inputs for other study like social and economic impacts of flood damage that helps in knowing how the community was suffered by the flooding.
- ❖ Again the output of this work can also be as bench mark in knowing the impending flood from the upstream habitants to take measures for the downstream habitat ant in the next climate change scenarios develop.

1.3.4 Scope of the study

This study develops hydrological and Hydraulic models using Artificial Neural Networks (ANN) and HEC-RAS respectively for Real-Time Flood Forecasting in the Baro River that helps issue identifying for Itang special Wereda flood prone areas.

Even if Artificial Neural Networks (ANN) needs large data size to be trained in hydrological model and different factors (unavailability and quality problems) , only 7 years daily data were used in this thesis.

The study is limited to use only one feedforward Artificial Neural Networks type with only one hidden layer since the primary objective of this thesis is not comparing performance of different network architectures.

Hydraulic modeling for this specific study is limited to 1000m (1km) downstream of upstream boundary condition (outlet at Gambella town) and did not include up to the end of the Baro River due to unavailability of data.

The hydraulic modeling is also gives emphasis to Two-Dimensional (2D) flood area analysis rather than giving emphasis to One-Dimensional (1D) analysis since flood inundation mapping is the goal of this thesis work.

2. LITERATURE REVIEW

2.1 General overview of flood

Among all observed natural hazards, water-related disasters (floods or droughts) are the most frequent and cause major fear to people and socio-economic development in the world[6]. Floods are known as the most frequent and disturbing natural disasters in both developed and developing countries. Almost all of these flood events have significantly affected large parts of Ethiopia. Being one of the largest countries in East Africa, Ethiopia's topography characteristics has made the country attractive vulnerable to floods and resulting destruction and damage to life, economic, livelihoods, infrastructure, services and health system[8]. Since the beginning of the regular rainy season which usually begins in Ethiopia in June or July, the country has been experiencing unusually extended and widespread rainfalls resulting in flash floods or the overflow of rivers.

One of the keys to understand flood risk begins with knowing the type of flood. And there are several different kinds of flood, and each one accepts a different impact in terms of how it occurs, the damage it causes, and how it is forecasted.

2.1.1 River Flooding

This occurs when excessive rainfall over a given period of time causes a river to exceed its capacity and the rivers can overflow their banks to cause flooding. This happens when there is more water upstream than normal and as it flows downstream to the adjacent low-lying areas, there is a burst (busting the natural banks) and water gets into the land. There are two main types of river flooding:

- ❖ **Overbank flooding:** occurs when water level overflows over the boundaries of bank of a river or stream. This is the most common and can occur in any size channel from small streams to huge rivers.
- ❖ **Flash flooding:** is characterized by an intense, high velocity torrent of water that occurs in an existing river channel with little to no notice. Flash floods are very dangerous and

destructive not only because of the force of the water, but also the crashing debris that is often swept up in the flow.

In flatter areas, floodwater tends to rise more slowly and be shallower, and it often remains for days. In hilly or mountainous areas, floods can occur within minutes after a heavy rain. To determine the probability of river flooding, models consider past precipitation, forecasted precipitation.

2.1.2 Surface Flooding

Surface water flood is caused when heavy rainfall creates a flood event independent of an overflowing water body (raining rain overflow both the banks and nearby lands). One of the most common misconceptions about flood risk is that one must be located near a body of water to be at risk. Surface flooding exposes that it can happen in any urban area even higher elevation areas that lie above river floodplains. There are two common types of surface flooding:

- ❖ **Intense rain saturates an urban drainage system.** The drainage or banks become inundated and water flows out into streets and nearby structures.
- ❖ **Run-off.** Flowing water from rain falling on hillsides that are unable to absorb the water.

2.1.3 Surge (Flow) Flooding

This occurs in areas that lie on the seaside of a sea, ocean, or other large body of open water. It is typically the result of extreme tidal conditions caused by severe weather. Storm surge produced when high winds from hurricanes and other storms push water onshore is the leading cause of coastal flooding and often the greatest threat associated with a tropical storm. In this type of flood, water overwhelms low-lying land and often causes devastating loss of life and property.

2.2 Flood prediction techniques

2.2.1 Flood forecasting definition

Flood forecasting can be defined as a process of estimating and predicting the magnitude, timing duration and duration of flooding based on the known characteristics of river basin, with the aim to prevent damages to human life, properties and to the environment.

The type of technique used in Flood prediction can be classified according flood prediction parameters such as meteorological data (precipitation), climatological data (Temperature, humidity etc) and hydrological data (Gauged flow or stage). Among these key influencing flood variables, rainfall and the spatial examination of the hydrologic cycle had the most remarkable role in runoff and flood modeling[9]. This is the reason why rainfall prediction, including used for flood prediction, especially in the prediction of floods depths for short-term flood prediction is highly relied on the availability of data.

2.3 Linear Models for Flood Prediction

2.3.1 Linear stochastic auto-regressive moving-average (ARMA) models

Linear stochastic processes are among the most widely used time-series technique for modeling future water resources[10]. A stochastic process is a process with random outcomes in probability theory, and can be observed as the matching part to a deterministic process. A stochastic process considers many probable outcomes instead of dealing with only one possible reality of how the process might evolve over time. The Autoregressive Integrated Moving Average (ARIMA) model is frequently used as predictive model, and simple Autoregressive Moving Average (ARMA) models are referred to as Box-Jenkins models. Most of the time-series techniques traditionally used for modeling floods fall within the framework of the ARMA class of linear stochastic processes. In general, the ARMA model is a tool for understanding and predicting future values in a given time series of data and the application of low-order ARMA processes to model short-term precipitation values is normally used in flood prediction.

2.3.2 Non-Linear Models for Flood Prediction

This study focuses on non-linear time series analysis and prediction techniques for floods. An artificial Neural Network model is presented with some supportive issues in detail.

2.3.3 Flood forecasting in Ethiopia

Flood forecasting in Ethiopia is not done in scientific, operational and organized way. Ministry of Water Resources (MWR) of Ethiopia is not currently implementing an operational rainfall-runoff model for the purpose of flood forecasting[6].

Personal communication with the hydrology expert of MoWIE indicates that flood early warning system is done using radio in a very traditional way. The ministry receives water level information from stations in flood prone areas through radio communication. The hydrology staff in the ministry office visually analyzes the pattern of the discharge hydrograph. If flood is expected the coming days then a warning message will be sent to early warning and disaster prevention office in the flood prone areas. Finally the Woreda water office staffs or other concerned bodies directly disseminate the warning information to the community. This process is less accurate, not reliable and is time consuming.

According to [11] of concept note on Flood Forecasting and Early Warning System (FFEWS) an alternative technology for flood management system and damage reduction is very important in Ethiopia and also the author recommended that it is high time for Ethiopia to work towards developing proper flood management mechanism to cope with the future flood situations. As a result of this deficiency of flood management, more frightening assessment is that the trend of major flood disasters and the losses generated by them have increased drastically in recent years.

The study [12] evaluated Artificial Neural Network (ANN) for flood forecasting and early warning system in Upper Awash basin (UAB) and the result revealed that the model performance can further be improved using neural network prediction technique. Finally, the author concludes that the calibrated model can be used to forecasts flood events ahead of up to six days.

With regard to flood forecasting and early warning system, the best system for Ethiopia must be modified on the basis of various factors such as hydro-meteorological data availability (suitable to forecasting), the human skill, cost, communication infrastructure, etc. Overall system should be i) very simple but reliable ii) can be run with minimum set of available hydro-meteorological data iii) focused to highly flood prone areas of the country but general in its form to assume forecasting to other areas iv) can either utilize existing communication networks or minimum communication system can be immediately established using mobile or wireless technologies v) have 24 hour (standby) committed combination of highly skilled professionals, technicians and data readers.

2.4 Application of Artificial Neural Networks in Hydrology

2.5 Introduction to Artificial Neural Networks

2.5.1 What Is an Artificial Neural Network

There is no single definition for an artificial neural network. [13] defined a neural network as a class of mathematical algorithms, since a network can be regarded essentially as a graphic notation for a large class of algorithms. Such algorithms produce solutions to a number of specific problems and also it can be described as a network of simple but interconnected processing units called neurons (or neuronal units), which are able to automatically adjust to information and learn aspects of this information by storing it in the connection strengths, represented as weights between neurons.

Artificial Neural Networks (ANNs) have been motivated right from their beginning by the recognition that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, non-linear, and parallel computer (information-processing system). It has the capability to organize its structural constituents, known as neurons in a massively distributed and parallel network, so as to perform certain computations in many times quicker than the fastest digital computer in existence today [14]. Neural networks are stimulated by the way the human brain works. A human brain can process huge amounts of information using data sent by human senses (especially vision). The processing is done by neurons, which work on electrical signals passing through them and applying flip-flop logic, like opening and closing of the gates for signal to transmit through.

The development of artificial neural networks (ANNs) began approximately 50 years ago stimulated by a desire to understand the human brain and follow its functioning. Within the last decade, it has experienced a huge renaissance due to the development of more sophisticated algorithms and the emergence of powerful computation tools.

Wide research has been devoted to investigating the potential of artificial neural networks (ANNs) as computational tools that obtain, represent, and compute a mapping from one multivariate input space to another [15].

The ability to identify a relationship from given patterns make it possible for ANNs to solve large-scale complex problems such as pattern recognition, nonlinear modeling, classification, association, and control. Since the early nineties, ANNs have been successfully used in hydrology-related areas such as rainfall-runoff modeling, stream flow forecasting, ground-water modeling, water quality, water management policy, precipitation forecasting, hydrologic time series, and reservoir operations and the application of ANNs as an alternative modeling tool for certain hydrologic problems is the subject of the second part of the series[16].

2.5.2 Models of artificial neural network

Similar to the biological neuron structure, ANNs define the neuron as a central processing unit, which performs a mathematical operation to generate one output from a set of inputs. The output of a neuron is a function of the weighted sum of the inputs plus the bias. Each neuron performs a very simple operation that involves activating if the total amount of signal received exceeds an activation threshold. The ANN contains a large number of simple neuron-like processing elements and a large number of weighted connections between the elements. The weights of connections encode the knowledge embedded in the network.

2.5.3 Neural network architectures

One class of ANN architecture is the feed-forward network and is the simplest Neural Networks architecture in which inputs are pushed forward to simulate the model. For this class of ANN, data signals always propagate in one direction from the Input layer to the Output layer and without consideration of any time delays.

The other class of ANN architecture is the recurrent neural network, which contains feedback connections from units in subsequent layers to units in preceding layers[17].

2.5.4 Selection of ANN architectures

The determination of the best network architecture is one of the difficult tasks in the model building process but one of the most important step to be taken. The ANN models employed in this study are feed-forward networks and recurrent networks with hidden and special hidden layers of neurons. The following neural networks are commonly used for flood forecasting.

There are so many techniques by which ANN type can be selected for specific problem and sometimes it may takes many times to reach at the optimal ANN type if trial and error is used. In this thesis work the following algorithm was developed from the scratch to select the best ANN type for this study.

To come with the best ANN type first trial number of neurons in hidden layer is assigned and after the inputs data sets are partitioned according. For the first trial the algorithm will be run to the error between the output and the Target. Again the second trial will continued and the error now compared to the first trial, if the value of error (the difference between output and Target) increase the number neurons in the hidden are change further to see the effect.

Lastly, the best one is selected. The function of the entire neural network is simply the computation of the outputs of all the neurons, which is an entirely deterministic calculation. Essentially, ANN is a set of mathematical function approximations and any neural network processing a framework has the following architecture.

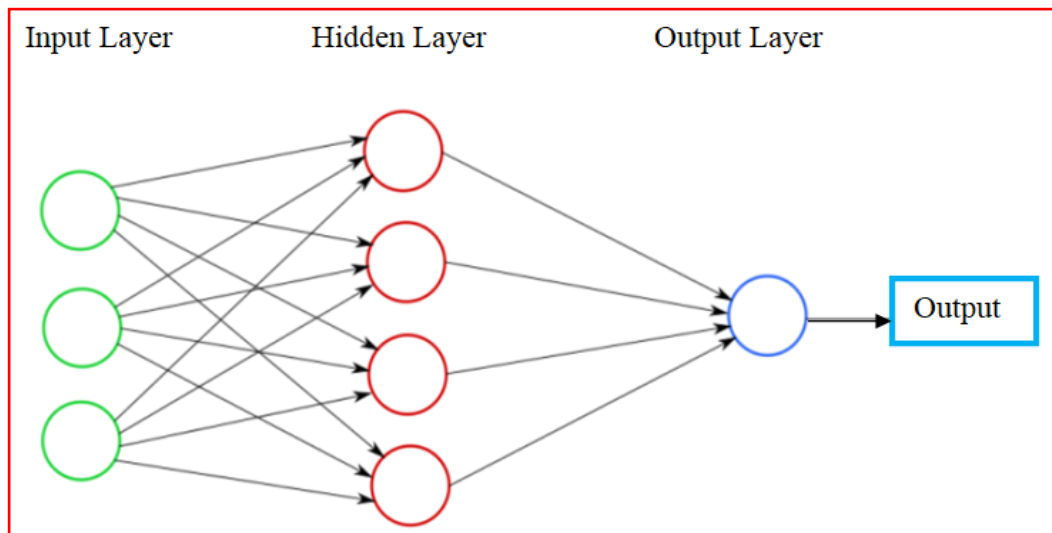


Figure 2-1 : Standard Neural Networks for Feed forward computation

There is a set of inputs, a processor, and a set of outputs. This layered approach is also followed in neural networks.

The inputs form the input layer, the middle layer(s) which performs the processing is called the hidden layer(s), and the output(s) forms the output layer. The hidden layer has the magic to convert the input to the desired output.

The understanding of the hidden layer requires knowledge of weights, bias, and activation functions, but in hydrological Models the bias is neglected[17].

2.5.5 Weights in Artificial Neural Networks

Weights in an ANN are the most important factor in converting an input to impact the output. This is similar to slope in linear regression, where a weight is multiplied to the input to add up to form the output. Weights are numerical parameters which determine how strongly each of the neurons affects the other. For a typical neuron, if the inputs are X_1 , X_2 , and X_3 , then the synaptic weights to be applied to them are denoted as w_1 , w_2 , and w_3 and the output is:

$$y = f(x) = \sum x_i w_i \quad \text{Equation 2-1}$$

The output along with the weighted sum of the inputs to the neuron of the processing done by a neuron is thus denoted as:

$$\text{Output} = \text{sum}(\text{weights} * \text{inputs}) \quad \text{Equation 2-2}$$

2.5.6 Activation functions

The concept of the processing of neural networks is mainly achieved through the activation functions. An activation function is a mathematical function which converts the input to an output, and adds the magic of neural network processing. Without activation functions, the working of neural networks will be like linear functions.

2.5.7 Different activation functions

There are many activation functions available for a neural network to use and they are listed as follows:

- ❖ Linear activation function
- ❖ Unit step activation function
- ❖ Sigmoid activation function
- ❖ Hyperbolic tangent activation function

❖ Rectified linear unit activation function

Given that neural networks are to support nonlinearity and more complexity, the activation function to be used has to be strong enough and to have to be capable in differentiation since chain rule is used in propagation of error.

The sigmoid is the most used activation function and was used in this study to convert input data from input layer to output layer through hidden layer in which this processing is taken place.

2.5.8 Sigmoid activation function

This function is a mathematical function that produces a sigmoid curve; a characteristic curve for its S shape. This is the earliest and often used activation function. This squashes the input to any value between 0 and 1, and makes the model logistic in nature. This function refers to a special case of logistic function defined by the following formula:

$$f(x) = \frac{1}{1+e^{-x}} \quad \text{Equation 2-3}$$

2.5.9 Feed-forward networks

The ANN models used in this study is feed forward networks with three input neurons in input layer having Rainfall (P), Temperature (T) and Topographical wetness Index (TWI) input neurons or nodes and four neurons in one hidden layer and one output layer with one neuron. The simplest way to define feed-forward network is that, all connections point in one direction from the input towards the output layer and the computation is processed in hidden layer using selected activation function for that specific problem.

2.5.10 Training neural networks

The process of optimizing the connection weights is known as training or learning. The network learns a function by adjusting the strength of its connection weights in response to the training examples presented (target) to it in accordance with a predefined learning law. ANNs are trained by applying an optimizing algorithm, which attempts to reduce the error in the network output by adjusting the matrix of network weights. There are two main types of training: supervised learning and unsupervised learning.

2.5.11 Supervised learning

In this training we supply the neural network with inputs and the desired outputs. Response of the network to the inputs is measured.

The weights are modified to reduce the difference between the actual and desired outputs (result from inputs) and this training method was applied in this thesis works since it is easier and used in hydrology in most of the cases.

2.5.12 Unsupervised learning

We only supply inputs and then the neural network adjusts its own weights, so that similar inputs cause similar outputs. The network identifies the patterns and differences in the inputs without any external assistance.

2.5.13 Neural Network Training Software

Many researchers are using some training software to manage or wisely use their time and to reduce the complexity in developing training algorithms. Neural network simulation software are programmed instructions that allow one to build, train, and evaluate neural networks, and are referred to as neural network simulators or can be trained using some training algorithms such Gradient descent in back propagation. The following software are widely used training software has been using by many researchers.

- ❖ The NeuroSolutions software Stuttgart Neural Network Simulator (SNNS) and
- ❖ Java Neural Network Simulator (Java NNS)
- ❖ MATLAB tools

It was not the purpose of this research to use any software to train the model rather training algorithms was developed based gradient descent from the scratch since built-in algorithms enforce the user to some limitations.

2.5.14 Back to back propagation

Forward propagation is used to push forward the inputs to get rough solution and does not take any account to reduce the error between desired and target output. Back propagation is one of the important concepts for understanding neural networks and it relies on calculus to update the weights in each layer. Back propagation of errors is similar to learning from mistakes. In this

process the developed algorithms can correct and adjust the mistakes in the results in all and every iteration until it reaches a point called convergence (minimum error).

The goal of back propagation is to adjust the weights in each layer and minimize the overall error at the output layer propagating from output node from output layer toward hidden layer until input nodes. Feedforward networks are sometimes referred to as with a name that is derived from the employed training algorithm. The most common learning rule is the back propagation algorithm. An ANN that uses this learning algorithm is consequently referred to as a back propagation network (BPN).

One must keep in mind, however, that different types of ANNs (other than feed forward networks) can also be trained using the back propagation algorithm. Neural network learning highly relies on back propagation in feed-forward networks.

2.6 ANNs as Rainfall-Runoff models

The high degree of temporal and spatial variability, issues of nonlinearity of physical processes, is very challenging issue that many hydrologists are facing today. As a result of these difficulties, and of a poor understanding of the real-world processes, empirical properties can play an important role in modeling of R-R and ANNs are typical examples of empirical models [18]. ANNs are considered as one of the most advanced black-box modeling techniques and are therefore nowadays frequently applied in R-R modeling and most studies report that ANNs have resulted in better performance as opposed to traditional empirical techniques [19].

This limitation of ANNs is even more obvious in comparison to physically based R-R modeling approaches and to reduce lumped properties of this model inputs are first distributed spatially. For this thesis works, inputs datasets (Rainfall, Temperature and Topographical wetness Index) were distributed over the 6km x 6km grid size of spatial partition to minimize the lumped characteristics of the ANN model.

2.6.1 Real Time Flood Forecasting

The real time flood forecasting is one of the most effective non-structural measures for flood management.

The process of estimating the future stages or flows and its time sequence at selected vulnerable points along the river course during floods is called Real Time Flood Forecasting. Real time flood forecasting systems are formulated for issuing the flood warning in real time in order to prepare the evacuation plan during the flood. The real time flooding forecasting is the logic of using forecasted precipitation at real time and using this as input data for forecasting of stream flow and the depth of water inundated over some extent. For formulating the flood forecast in the real time, the observed meteorological and flow data are transmitted to the forecasting station through the different means of data communication which include telephone, wireless and network of telemetry stations etc.

The collected meteorological and flow data in real time are then used into the calibrated & validated real time flood forecasting model to forecast the flood flow and corresponding water levels for different lead periods varying from few hours to few days depending on the size of catchment and purpose of the forecast. The structure of the model should be simple and it should not have excessive input requirements, but at the same time the forecasted flood must be as accurate as possible.

The effectiveness of real time flood forecasting systems in reducing flood damage would depend upon how accurately the estimation of future stages or flow of incoming flood and its time sequence at selected points along the river could be predicted and suitable real time flood forecasting techniques are required to forecast such floods. The accurate real time flood forecasts are required to be issued well in advance in order to provide sufficient time, known as lead time, for evacuating the people from the areas likely to be affected by the flood. The lead time available for flood forecasts are very small. It makes the implementation of evacuation plan very difficult during the flood.

2.6.2 Artificial Neural Networks for Real Time Flood Forecasting

Real-time forecasting of stream flows during storms provides an essential input to operational flood management. This work is usually very complex due to the uncertain and unpredictable nature of the original phenomena. The technique of neural networks therefore was applied to this study is to overcome some uncertainty in traditional techniques and to solve complex relationship between hydrological parameters such as Rainfall-Runoff.

Forecasting of flood values during storms with a lead time of one and more hours was made using a selected sequence of past flood values observed at a specific location[20]. Generally the idea of using ANN as real time forecasting is that the forecasted precipitation obtained from National meteorological Service Agency (NMSA) or from different online sources like NOAA is given to ANN as input data to simulate or transform it in to stream flow (hydrological modeling) and then the result from hydrological modeling is used as input to hydraulic modeling to generate depth of water at different points that relies on real time. Therefore, ANN model is used as tool to transfer the forecasted precipitation in to steam flow and while HEC-RAS is used to generate depths. Many of studies reveal that ANN can used as both precipitation and stream flow forecasting tool to use it as hydrological and hydraulic modeling, but in this thesis works only hydrological modeling was simulated using ANN and the hydraulic modeling was modeled by HEC-RAS software.

2.7 Early warning systems

Of all the natural hazards capable of producing a disaster, floods are the most common phenomenon that causes human suffering, inconvenience and widespread damage to buildings, structures, crops and infrastructures. Floods have been observed to disrupt personal, economic & social activities and set back a nations security & development by destroying roads, buildings and other assets. To form an effective, real-time Flood forecasting system, the basic structures need to be connected in an organized manner. According to [11]Flood disasters account for about a third of all natural disasters throughout the world and are responsible for more than half of the fatalities. Economically, floods are a leading course of losses from natural events.

The money spent worldwide on flood control through building dykes, reservoirs, barrage, etc. has been found to be far greater than that spent on protection of other impacts from nature. The occurrence of the current flood in Ethiopia can be characterized as national catastrophe. The flooding occurred in almost all parts of the country. In the North, localities in Tigray and in the northeast, Amhara region have been affected by emerging floods.

In the south and East, the major flood damage was registered with loss of huge number of human and animal lives, loss of property. In the South, the Baro River was swelling to create a flood situation. Non-structural measures are designed to modify the damage potential of the flood without interfering to the characteristics of the flood (magnitude, peak, duration, etc). Such methods focus on software and hardware technological aspects, such as flood proofing, flood warning system, land use control, etc. For instance through flood forecasting and early flood warning mechanism, the potential of flood damage to properties and human lives can be reduced. Early warning system can be implemented to evacuation the population and property at risk before the flood wave reaches to the flood prone area.

However, flood warning systems requires efficient communication network to relay information and message from observational stations to forecasting centre and from forecasting to response agencies and to potential flood affected area. For Instance, the flood of Omo River, Baro and other big rivers are affected by slowly rising floods and gives comparatively more chance of saving property and life than the rapid flash floods as the one occurred in Dire Dawa. As far as flood damage is concerned, a simplified flood warning and communication system suffices the purpose. Therefore through national flood mapping and zoning, one or combination of methods can be implemented to reduce the damages of flood in the country, however, before implementing measures, detail study and analysis on alternative options is a paramount importance.

However, the focus of this concept note is to introduce alternative measure application flood forecasting and early warning system technology as an alternative flood managements system in Ethiopia. With regard to Flood Forecasting and Early Warning System, the best system for Ethiopia must be adapted on the basis of various factors such as hydro-meteorological data availability (suitable to forecasting), the human skill, cost, communication infrastructure^[11].

2.7.1 Meteorological and Hydrological Considerations

Clearly the ability to forecast critical events in time, location and quantity is significantly valuable for Flood forecasting and warning. Meteorological knowledge associated with flood warning falls into two broad areas, namely the climatology behind flooding and the operational meteorology involved.

Understanding the types of weather systems from which flooding can originate contributes a great deal to making decisions about what sort of observational and forecast systems are required. Similarly, understanding the seasonality of rain-bearing systems such as monsoons in Asia and tropical storms in Africa and Central America is also operationally important since this understanding will affect staff assignments and the organization of alert and background working patterns. Hydrological information requirements for flood forecasting and warning systems are similar to those for meteorology in that it is necessary to understand the overall flood characteristics of the area as well as possessing real-time information for operations.

Key observation and data requirements target water levels in lakes and rivers, river discharge and in some cases groundwater table levels. Water level ranges at given points can be linked to various flooding extents, so a series of triggers can be set up to provide warning through telemetry. The upstream-downstream relationship between water levels is an important means of prediction. Early flood warning systems depend on comparing levels from a point upstream with resulting levels at a point of interest at the flood-risk site. It is also important to know the time it takes for water at a peak upstream to reach a point farther downstream.

2.7.2 Aspects of flood forecasting and early warning systems

Establishing a viable flood forecasting and warning system for communities at risk requires a combination of data, forecast tools, and trained forecasters. A flood forecast system must provide sufficient lead time for communities to respond. Increasing this lead time enhances the potential for limiting damages and loss of life. Forecasts must be sufficiently accurate to promote community confidence so that they will respond when warned. If forecasts are inaccurate, the credibility of the programme will be questioned and there will be no response.

2.7.3 Elements of Flood Forecasting and Early Warning System

An important element in developing flood warning systems is ensuring its robustness so that it can cope with the range of potential events. Flooding is a phenomenon subject to a wide variability of scale and severity. Flood warning systems must, therefore, be designed to forecast rare and severe events as well as less serious and more common ones. However, the uncertainties inherent in forecasting are likely to be magnified during extreme events and such scientific and technological limitations must be taken into account.

In 2006 the United Nations released its Global Survey of Early Warning Systems, which identified four elements in natural hazard early warning systems, including flood forecasting:

- ❖ Risk knowledge: systematic assessment of hazards and vulnerabilities, including mapping of their patterns and trends
- ❖ Monitoring and warning services: accurate and timely forecasting of hazards using reliable, scientific methods and technologies
- ❖ Dissemination and communication: clear and timely distribution of warnings to all those at risk
- ❖ Response capability: national and local capacities providing knowledge about how to act correctly when warnings are communicated.

2.8 Global Climate Change

Many factors can go into the making of a flood. There are weather events (heavy or prolonged rains, storm surge, sudden snowmelt), and then there are the human-driven elements, including how we manage our waterways (via dams, levees, and reservoirs) and the alterations we make to land. Increased urbanization, for example, adds pavement and other impermeable surfaces, alters natural drainage systems, and often leads to more homes being built on floodplains. In cities, under-maintained infrastructure can lead to urban flooding. More and more, flooding factors are also linked to climate change.

2.8.1 Climate Change of Africa

Africa has been identified as one of the parts of the world most vulnerable to the impacts of climate change[21]. African countries are more affected by climate change because of their dependence on agriculture as well as their lower financial, technical, and institutional capacity to adapt[22]. The African continent is expected to be the most affected by climate change, land degradation, and desertification. Though Africa is the lowest source of emissions from inhabited continents (due to low levels of industrial development), it is the most vulnerable to the effects of climate change[23]. The warming in Africa is likely to be somewhat larger than the global, annual mean warming throughout the continent and in all seasons, with drier subtropical regions (especially arid zones) warming more than the moister tropics.

Annual rainfall is very likely to decrease in much of North Africa and Northern Sahara, while winter rainfall will very likely decrease in much of Southern Africa. There will likely be an increase in annual mean rainfall in tropical and East Africa. Sub-Saharan Africa is considered to be the most vulnerable to the impacts of climate change because of its high dependence on agriculture and natural resources, warmer baseline climates, low precipitation, and limited ability to adapt. Several studies have shown that surface water and groundwater evolutions over the past decades in Sub-Saharan Africa have been strongly affected by rainfall variations[24].

2.8.2 Climate change of Ethiopia

Ethiopia is among those countries most vulnerable to climate risks in Africa. Its high vulnerability derives in large measure from the country's heavy dependence on rain-fed, subsistence agriculture.[25] Ethiopia is a country where about 80% of the population is engaged in the agricultural sector and the main source of income for rural communities. Consequently, agricultural and livestock production, natural disaster like flooding that has been occurring country also affecting the community and food security depend strongly on weather conditions mainly on rainfall patterns such as amounts and timing. Hence, a large share of Ethiopia's population is very vulnerable to climate change and in particular to its inter-annual variability.

2.8.3 Current Climate Variability and Observed Trends

2.8.3.1 Rainfall Variability and Trend

According to the study conducted by Ethiopian National Meteorological Services Agency and Ministry of water Irrigation and Electricity (NMSA and MoWIE, 2007 G.C) on the climate variability and trend for selected stations in the country , in such a way a baseline climate was developed using historical data of temperature and precipitation from 1971- 2000 G.C. The year-to year variation of rainfall over the country expressed in terms of normalized rainfall anomaly averaged for 42, stations shows the country has experienced both dry and wet years over the last fifty five years (1951-2006GC).

2.8.4 Temperature Variability and Trend

The year to year variation of annual minimum temperatures expressed in terms of temperature differences from the mean and averaged over 40 stations shows the country has experienced both

warm and cool years over the last 55 years. However, the recent years are the warmest compared to the early years. The Figure 2-2 and 2-3 below clearly reveals that there has been a warming trend in the annual minimum and maximum temperature over the past 55 years. It has been increasing by about 0.370C every ten years. Between 1960GC and 2006GC, the mean annual temperature increased by 1.3°C, at an average rate of 0.28°C per decade (NMSA and MoWIE, 2007).

2.8.5 Climate Scenario

Scenarios have been used by decision makers and planners to analyze the situations where outcomes are uncertain[26]. In climate change research, they have become an important element as they allow researchers to understand the long-term consequences and describe reasonable pathways of climatic condition and other aspects of future[27].

Many factors have to be taken into account when trying to predict how future global warming will contribute to climate change. The amount of future greenhouse gas emissions is a key variable. Developments in technology, changes in energy generation and land use, global and regional economic circumstances and population growth must also be considered. So that research between different groups is complementary and comparable, a standard set of scenarios are used to ensure that starting conditions, historical data and projections are employed consistently across the various branches of climate science.

The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) findings will be based on a new set of scenarios that replace the Special Report on Emissions Scenarios (SRES) standards employed in two previous reports. The new scenarios are called Representative Concentration Pathways (RCPs). There are four pathways: RCP8.5, RCP6, RCP4.5 and RCP2.6 - the last is also referred to as RCP3-PD. (The numbers refer to forcing for each RCP; PD stands for Peak and Decline).

The name “representative concentration pathways” was chosen to emphasize the rationale behind their use. RCPs are referred to as pathways in order to emphasize that their primary purpose is to provide time-dependent projections of atmospheric greenhouse gas (GHG) concentrations.

In addition, the term pathway is meant to emphasize that it is not only a specific long-term concentration or radiative forcing outcome, such as a stabilization level that is of interest but also the trajectory that is taken over time to reach that outcome. They are representative in that they are one of several different scenarios that have similar radiative forcing and emissions characteristics".

2.8.6 Representative Concentration Path way (RCP)

RCPs are time and space dependent trajectories of concentrations and emission of greenhouse gases and pollutants resulting from human activities, including changes in land use. RCPs provide a quantitative description of concentrations of the climate change pollutants in the atmosphere over time, as well as their radiative forcing in 2100. RCP is the latest generation of scenarios that provide input to climate models in climate research. The RCPs were developed by combined efforts of the researchers from different disciplines involved in climate research.

A total of four pathways RCP2.6, RCP4.5, RCP6 and RCP8.5 were developed. They were named based on the radiative forcing target levels of 2.6, 4.5, 6 and 8.5 Watt/m², by the end of 21st century. The estimation of radiative forcing is based on the forcing of GHGs and other agents. All these four pathways were considered to be the representative of all the literature pertinent to change in climate and each RCPs defines a specific emissions trajectory and subsequent radiative forcing[28].

2.8.7 RCP4.5 (stabilization scenario)

The RCP 4.5 was developed by the GCAM modeling group at the Pacific Northwest National Laboratory Joint Global Change Research Institute (JGCRI) in the United States.

It is the stabilization scenario[28] in which radiative forcing stabilizes at 4.5W/m² (approximately 650 ppm CO₂-equivalent) in 2100 without ever exceeding that value. However, it does not mean that the GHG emissions and concentrations are stable. The major assumptions of this scenario are the global population reaches a maximum of 9 billion by 2065 and then declines to 8.7 billion in 2100, declines in energy consumption, increase in fossil fuel consumption, substantial increase in renewable energy and nuclear energy use, and large increase in forest area as a mitigation strategy.

2.8.8 RCP6 (stabilization scenario)

The RCP6 was developed by National Institute for Environmental Studies (NIES) and Japan Agency for Marine-Earth Science and Technology in Japan by using Asia-Pacific Integrated Model (AIM) modeling. It is also stabilization scenario like RCP4.5 but here radiative forcing stabilizes at 6.0 W/m^2 in the year 2100 without exceeding that value in prior years.

It is climate policy intervention scenario in which climate policies are implemented to restrain radiative forcing not to exceed 6.0 W/m^2 . In this scenario, the GHG emissions will be the highest in 2060 and then decline thereafter.

The primary assumptions of this RCP are increase in energy demand, shift for non-fossil fuel energy type and increase in population and economic growth in urban area, expansion of cropland and forest area, and decrease in grassland.

2.8.9 RCP8.5 (high emission scenario)

The RCP8.5 was developed by Integrated Assessment Framework by the International Institute for Applied System Analysis (IIASA) using MESSAGE model[28]. This RCP is representative of high emission scenarios in the literature and characterized by increasing GHG emission over time.

It is consistent with future with no change in climate policy to reduce emissions[15]. This pathway is also called as baseline scenario without including any mitigation target or without explicit climate policy. The GHG emissions increase significantly over time leading to 8.5 W/m^2 of radiative forcing by the end of 21st century.

The important assumptions in this pathway are continuous increase in global population reaching 12 billion by 2100, slow income growth with modest rates of technological progress, long-term high energy demand, moving towards coal intensive technologies and high emission in the absence of climate change policies[29].

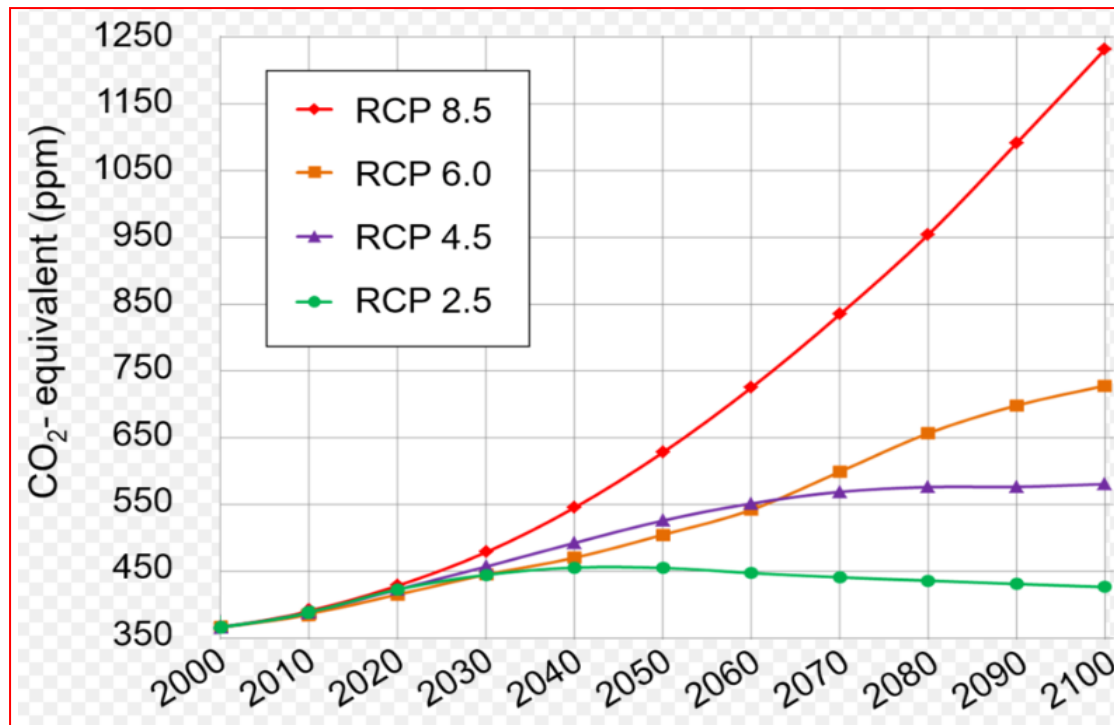


Figure 2-2: Representative Concentration Pathway (RCP) from the fifth report (ARF5)

2.8.10 Bias Correction

Despite high resolution data provision of RCM models, its limitations are systematic errors during 1st data correction. The theoretical and practical limitations may cause bias and should be corrected by bias correction methods. Bias correction should be applied to compensate for any tendency to overestimate or underestimate the mean of downscaled variables. Bias correction factors are computed from the statistics of observed and historical simulated variables for the same duration. Bias correction methods are assumed to be stationary, i.e. the correction algorithm and its parameterization for current climate conditions are assumed to be valid for future conditions as well. According to [30] the correction method used in the study was the linear scaling method (LS)

3. MATERIAL AND METHRODOLOGY

3.1 MATERIALS AND METHODS

3.2 Description of Study Area

The Baro Akobo basin is located in the southwestern part of Ethiopia. It covers approximately an area of 74,100km². This area includes all or part of the four administrative regions: SNNPRS (Southern Nations & Nationalities People Regional State) in the south, Oromiya in the northeast, Gambela in the central western part and Benishangul Gumuz in the northwestern extremity.

The Baro-Akobo basin is the fourth largest basin in the country, next to the Wabi Shebelle, Abbay and Tekeze river basins. The western, north western and south western side of the basin is bordered with the Sudan, while in the northern and north east it is bordered by the Abbay river basin and in the east and south east it is bordered by the Omo-Ghibe river basin. Geographically, it is located, between latitudes 5° 31" and 10° 54" north and longitude 33° and 36° 17" east.

It originates from the highlands in the southwest part of Ethiopia and flows across the low lying plains in the Gambela region of Ethiopia into the Republic of South Sudan, where it is known as the Sobat, before flowing into the White Nile River[6]. Itang town is located on the banks of the Baro River at a road distance of 53 kilometers west of Gambella town. Access through a road following the Baro on its northern side is particularly difficult during the rainy season allowing passage by long base vehicles and short-haul trucks only. Even these vehicles are facing the risk of getting stuck in one of the many mud pools on the way. A traveling time of two hours to cover the 53 kilometers can be considered as expeditious.

The most recent flood period (2008 G.C) in Itang forced around 2,000 peoples out of their homes[7]. In addition, many people made use of their social networks, for example to access financial resources to make small-scale productive investments.

This helped them through the extended flood period, during which they could not farm because the lands were inundated.

Many flood-affected respondents, however, were worried about draining their social network, which suggests there are limitations to people's access to social capital.

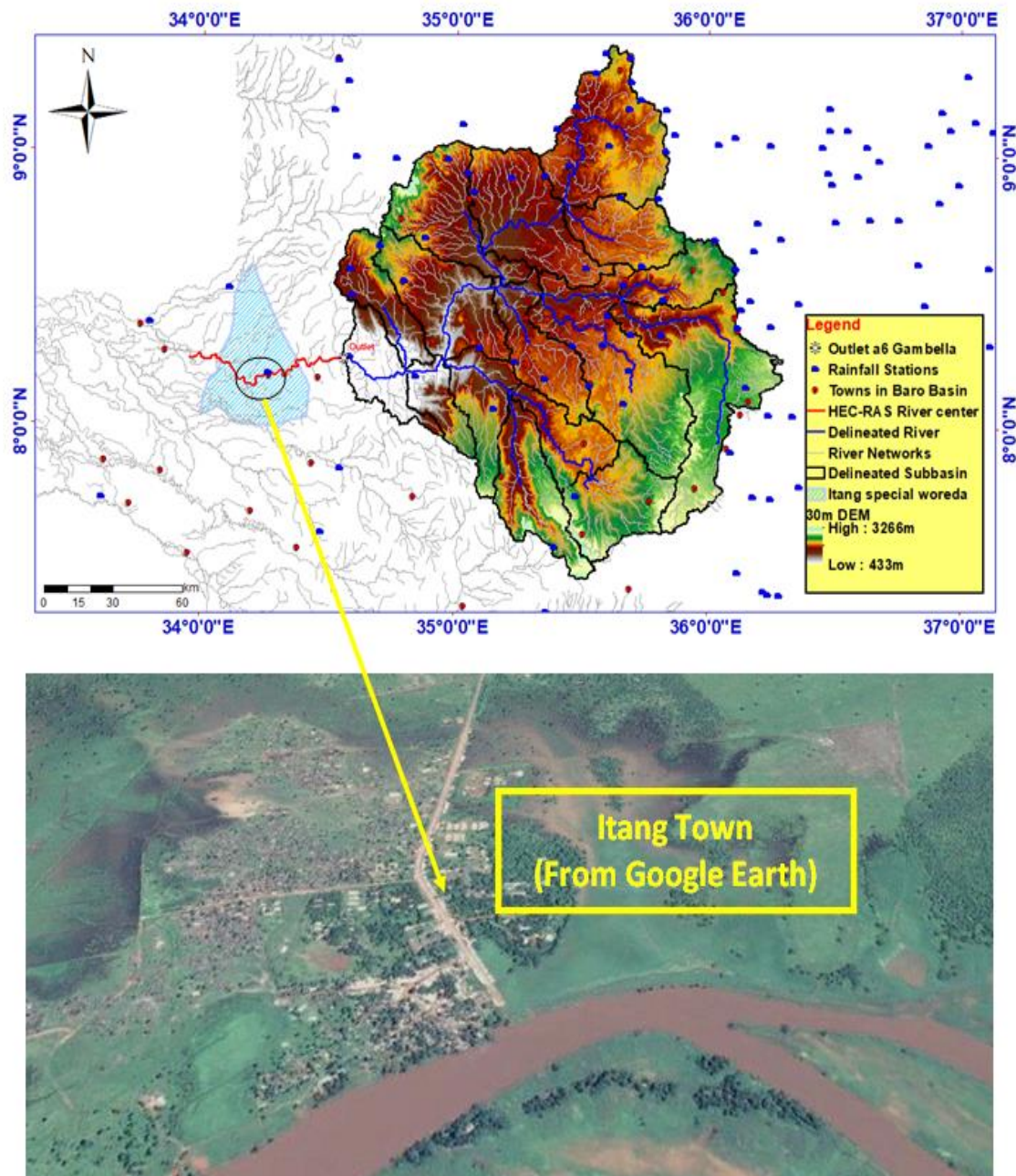


Figure 3-1: Location and description of the study area in detail

3.3 Software used in the study

Table 3-1: Details of all software used in the study works

NAME	PURPOSES	SOURCES
ArcGIS 10.4	- To prepare study area of the map - To generate and prepare spatially distributed inputs for ANN model - To overlay inundation map result with base map imagery to check the reality on the ground - To prepare river geometry for hydraulic modeling	Student trial licenses, sources from AAU FTP portal
HEC-RAS 5.05	- To generate 2D flood area - To generate inundation map - To simulate unsteady flow analysis	https://www.hec.usace.army.mil/software/hecras/downloads.aspx
R studio	- For hydrological modeling using ANN - Model evaluation of the trained values of ANN results using RMSE and NSE	https://www.rstudio.com/products/rstudio/download/
Neural Designer	To prepare Neural networks architecture and visualize the networks	https://www.neuraldesigner.com/free-trial
Mendeley Desktop	To organize all Journals used in this thesis work and insert citation	https://www.mendeley.com/download-desktop/
CMhyd	To extract and bias correction with ground data in CORDEX data processing	https://swat.tamu.edu/software/cmhyd/

3.4 Data used and processing

3.4.1 Data used and sources

The data used in this study were summarized on the table below with their sources.

Table 3-2: Datasets detail and their sources with their purposes

Category Of The Data	Specific Data Name	Sources	Purposes
Hydrological data	Gauged flow	MoWR	To train the ANN model
Meteorological data	Rainfall	NMA	ANN Rainfall runoff modeling
Climate data	Temperature	NMA	ANN Rainfall runoff modeling
Topographic data	❖ Digital Elevation Model (30m DEM) ❖ Digital Elevation Model (12.5mDEM)	❖ SARTM ❖ Alaska University facility	❖ Delineation ❖ River simulation
River networks	River for the basin	EthGIS-II	Delineation
Weather Research and Forecasting	Forecasted Rainfall	NMA	Real Time stream flow forecasting

3.5 Data processing

3.5.1 Topography

The majority of the area as shown in the delineated sub basin lies below 2885m altitude and its highest elevation, mainly the western part, exceed 2000m. The Baro-Akobo River basin is partially part of the south western Ethiopian Plateau, which is characterized by rolling and hilly morphology. But towards west this rolling and hilly morphology abruptly changes into dominant long chain of sharp escarpments and lowland plain. The highlands of the upper part of this Basin make a good condition to cause flooding for the downstream low-lying floodplain areas.

The attitude or elevation of the area that is obtained from high accuracy digital elevation model (DEM) revealed that there is a big difference between the highest elevation and lowest elevation.

From the northern east of the Basin, majority of the elevation are greater than 1000m while the western part are totally flat low-lying having the altitude of 370m as seen the figure below.

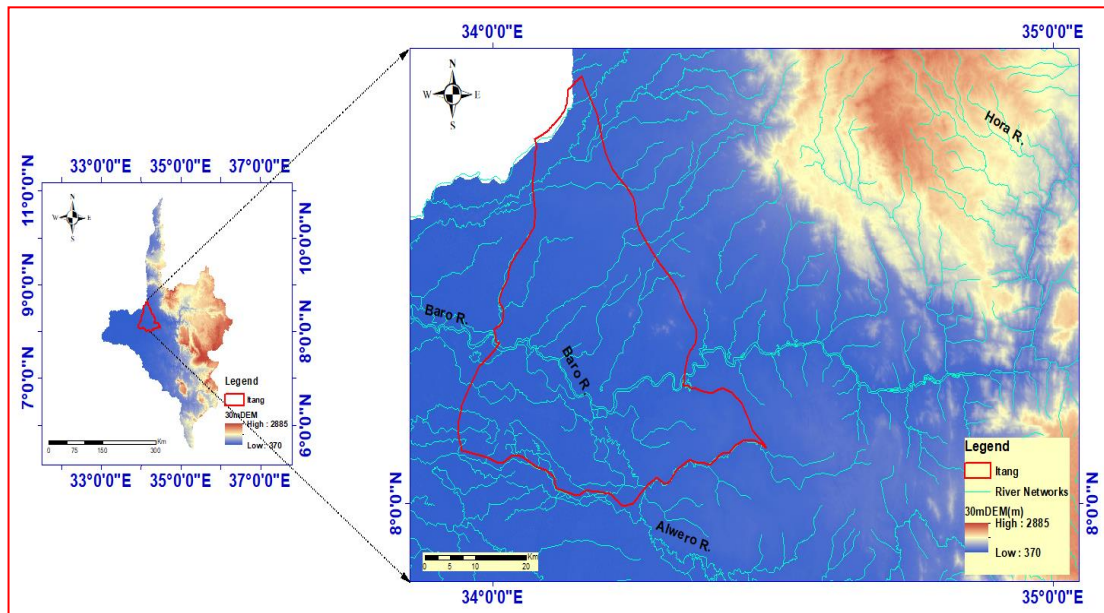


Figure 3-2: Topography and the river networks in the study area

3.5.2 Meteorological Data Processing

One of the most significant aspects of hydrometeorology has to do with the prediction and attempt to mitigate the effects of high precipitation events. Beginning point of flood forecasting, starts with using metrological data as a major inputs and this is the primary issue to model when forecasting.

A major component of hydrometeorology is mitigating the risk associated with flooding and other hydrological threats. First, there has to be knowledge of the possible hydrological threats that are expected within a specific region. After analyzing the possible threats, warning systems are put in place to quickly alert people and communicate to them the identity and magnitude of the threat. Many nations have their own specific regional hydro meteorological centers that communicate threats to the public.

Finally, there has to be proper response protocols in place to protect the public during a dangerous event. In Ethiopia, the source of raw metrological data is the National metrological agency (NMA). A request for daily rainfall and temperature data of 7 years from (1999-2005 G.C) periods of 26 stations was and only 14 stations were extracted based on the availability and quality of the data.

From the entire available automatic recording stations those which are in or nearby to the sub basin considered for the research work were selected.

As a result, a total of 14 stations for both rainfall and temperature were selected to use in the research work. The rainfall records that obtained from NMA covered the length of (1999-2005 G.C) years depending on the available rainfall records particular to catchment being considered.

Table 3-3: Meteorological Stations used in the study area

Station name	Longitude (deg)	Latitude(deg)	Elevation(m)	years of data used	Anu_Rain(mm)
Abdela	36.25	8.37	1859.90	1999-2005	2009.68
Alge	35.74	8.59	1807.02	1999-2005	1828.75
Bila	35.59	9.37	1911.82	1999-2005	1945.74
Bonga	34.85	8.18	519.23	1999-2005	1186.85
Bure	35.10	8.28	1600.60	1999-2005	1706.10
Dusta	36.18	7.75	2328.71	1999-2005	1936.07
Gambela	34.59	8.25	517.49	1999-2005	1095.85
Gatira	36.24	8.05	2203.02	1999-2005	2221.12
Gecha	35.40	7.56	2203.40	1999-2005	2091.86
Gimbi	35.83	9.16	1940.37	1999-2005	1897.69
Gore	35.53	8.15	1802.98	1999-2005	2080.38
Guliso	35.48	9.17	1606.56	1999-2005	1645.91
Metu	35.59	8.30	1736.55	1999-2005	1832.52
RobGebya	34.88	8.69	1791.29	1999-2005	1652.00

3.5.3 Filling Missing data

Missing data is a common problem in hydrology. To perform hydrological analysis and simulation using data of long time series, filling in missing data is very important.

The missing data can be completed using metrological and/or hydrological stations located in the nearby, provided that the stations are located in hydrological homogenous region. The rainfall and temperature stations in the study area had missing data in their records and it is necessary to estimate the values to keep the continuous time series of the data.

The normal-ratio and quadrant methods provide a weighted mean annual rainfall at each gauge and the latter having weights that depend on the distance between the gauges where recorded data are available and the point where a value is required.

The station average method for filling missing data is conceptually the same as the station average method for estimating a mean precipitation. This method may not be accurate when the total annual rainfall at any of the in region gauges differs from the annual rainfall at the point of interest by more than 10% , with the former basing the weights on the mean.

The normal-ratio method is conceptually simple; it differs from the station-average method of that the average annual rainfall is used in deriving weights. If the total annual rainfall at any of the n region gauges differs from the annual rainfall at the point of interest by more than 10%, the normal-ratio method is preferable. Because the normal-ratio method is more advanced than station average method and simple; this thesis uses this method for filling the missing rainfall data.

The general formula for computing P is:

$$Px = \frac{Nx}{N} \left(\frac{P1}{N1} + \frac{P2}{N2} + \frac{P3}{N3} \dots + \frac{Pn}{Nn} \right) \quad \text{Equation 3-1}$$

Where, PX =Missing value of precipitation to be computed.

Nx = Average value of rainfall for the station in question for recording period.

N1, N2.....Nn= Average value of rainfall for the neighboring station.

P1, P2....Pn = Rainfall of neighboring station during missing period

N= Number of stations used in the computation.

3.5.4 Checking the consistency of data

3.5.4.1 Meteorological data

Filled data still need to check for trend that may suffer the data for unusual trend. The rainfall recording of the rain gauge stations has under gone a significant change during the period of record with various reasons; inconsistency would arise in the rainfall data of that station. This inconsistency of a record will be done by the double mass curve technique.

If the conditions relevant to the recording of a rain gauge station have undergone a significant change during the period of record, inconsistency would arise in the rainfall data of that station. This inconsistency would be felt from the time the significant change took place. The checking for inconsistency of a record is done by double mass curve technique[31]. The accumulated total of the individual gauge is compared with the corresponding totals for a representative group of nearby gauge. If a decided change in the regime of the curve is observed it should be corrected. However, as all the selected stations in this study were consistent and there is no need of further correction. Double mass curve for Gambella station is presented as example below and detail for the others stations were attached to the appendices section.

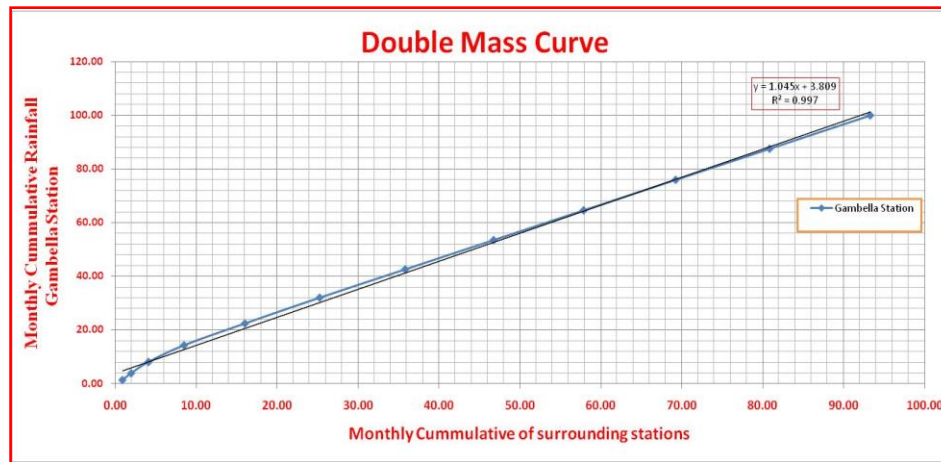


Table 3-3: Double Mass Curve (DMC) for checking data trend (Gambella station)

3.5.5 Test for Outlier

As outliers affect the statistics, especially higher order statistics, is recommended to test for outliers and eliminating the higher and lower data before using it in the flood estimation researches and the method used in this thesis work is based on [32] .

$$KN = -3.62201N^{\frac{1}{2}} + 6.28446N^{\frac{1}{4}} - 2.4983N^{\frac{1}{2}} + 0.491436N^{\frac{3}{4}} - 0.03791 * N$$

Equation 3-2

$$XH = e^{(X_{mean} + KN * SD)}$$

Equation 3-3

$$XL = e^{(X_{mean} - KN * SD)}$$

Equation 3-4

Where N is the number of data
XH the highest data in the time series
XL the lowest data in the time series
SD is standard deviation

No	Year	Q(max)	Y=logQ	KN	1.839798054
1	1999	1285.53	7.16		
2	2000	1196.35	7.09	XH	1350.13
3	2001	1170.19	7.06	XL	991.90
4	2002	1015.43	6.92	since the values of the Maximum Discharge are found between XH and XL , the data is OK for outlier	
5	2003	1108.56	7.01		
6	2004	1070.86	6.98		
7	2005	1241.87	7.12		
1	Xmean	1155.541429	7.049336262		
2	SD	95.95049286	0.083743912		

Figure3-4: Checking outlier for hydrological data

3.5.5.1 Hydrological Data

Hydrological data collected in this research was 7 years(1999-2005 G.C) daily flow gauged at Gambella town and the purpose of this data was calibrate the ANN model during the training of historical data of the same years used in hydrological modeling. The hydrologic gauging stations in the Baro-Akobo basin with automatic water level recordings are very limited.

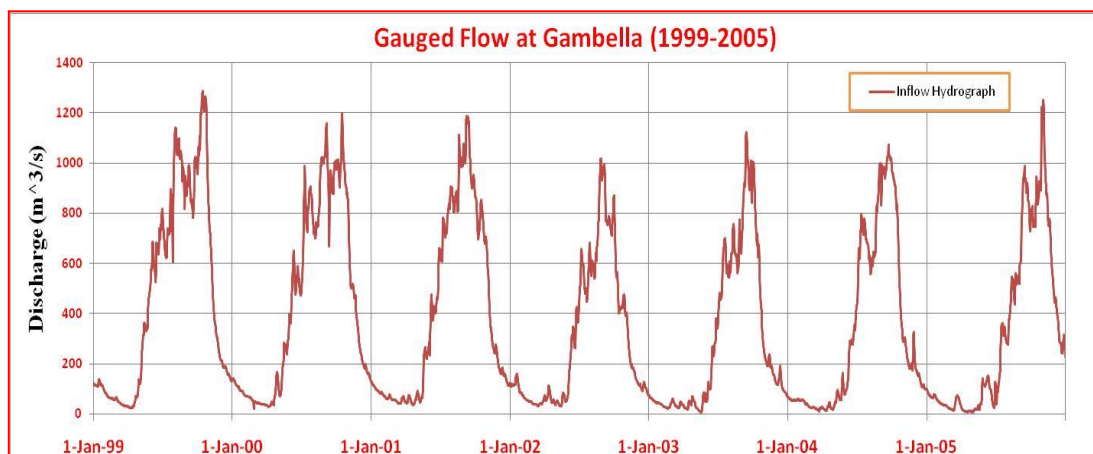


Figure 3-5: Daily stream flow data of Baro River at Gambella

3.6 Model setup

3.6.1 Hydrological Modeling using ANN in R studio

ANNs are often criticized for their black-box nature, as they are unable to reveal any explanation regarding how the model was built.

According to ASCE Task Committee (2000b), For ANNs to gain wider acceptability, it is increasingly important that they have some explanation capability after training has been completed. Most ANN applications have been unable to explain in a comprehensibly meaningful way the basic process by which ANNs arrive at a decision if training algorithms are libraries or tool in given software. It is highly attractive that ANNs be capable of telling an explanation, even if only a partial one, as an integral part of its function. In this thesis, in order to obtain some explanation from trained feed-forward MLP ANN training algorithms were developed in R studio from the scratch.

3.6.2 Input variables for Rainfall-Runoff models

The variables that have influence on catchment runoff or hydrological modeling are numerous. In this thesis works variables that used as ANN model inputs were presented, Rainfall, Temperature and Topographical wetness. When dealing with the hydrological situation where rainfall is the driving force behind runoff generation (another possibility climate data like temperature), rainfall input seems the most logical variable to present to an ANN.

3.6.3 Combinations of input variables

The variables mentioned above, in this thesis works are based on the availability of the data and way of treating the catchment as distributed hydrology in Ethiopia context. Basically, choosing the best input variables for an ANN model depends on the governing runoff processes in the catchment and highly relies on what is the driving force behind runoff in the catchment rainfall and other factors and these are just a few issues that should be considered when choosing input variables for ANN R-R models.

3.7 Data preparation

Since empirical modeling is data-driven modeling the importance of data quality is not to be miscalculated and to make more acceptable ways of preparing is critical. The input-output patterns, which are used to make the network learn during the training phase, are to be chosen in such a way that a good ANN model will be able to generate enough information from them to manage in the networks operational phase. Important aspects should be considered are quality and quantity of the inputs.

3.7.1 Pre-processing and post-processing data

The data that is used to train an ANN is generally not raw hydrological data (not the measurement values of field or laboratory experiments). After a data set is analyzed and found to be appropriate (quality and consistency are checked), additional processing such normalization of the data can take place. Implementation of one or more of the following pre-processing techniques that are discussed below can be an important tool for improving the training process efficiency. If a network uses a transformation function such as sigmoid function, the saturation limits are 0 and 1.

If the training patterns have extreme values compared to these limits, the non-linear activation functions could be operating almost exclusively in a saturated mode and thus not allow the network to train[33]. The training data, consisting of input patterns and output values, should be scaled to a certain range to prevent this problem. This is called scaling pre-processing the data. This method tends to have a smoothing effect on the model and averages out some of the noise effects of the data.

The type of scaling data normal scaling the input or output variables can be divided the maximum value present in the pattern, thereby linearly scaling the data to a range of 0 to 1 and this scaling to a range of 0 to 1 implies the assumption that the training data contains the full range of possible outcomes for the training data.

$$\mathbf{X_{scaled}} = \frac{\mathbf{X - X_{min}}}{\mathbf{X_{max} - X_{min}}} \quad \text{Equation 3-5}$$

Where X is raw data sets

3.7.2 ANN types and architectures

This section briefly discusses the problems and solutions when choosing an ANN type and ANN architecture.

3.7.3 Choosing an ANN type

Each problem has its own unique solution and its own method of reaching that solution. For different types of problems different types of ANNs exist, which are best fit for modeling that problem. It is, however, most doubtful that there will be only one right answer. Some common mapping types of ANN commonly used in R-R modeling are:

- ❖ Standard feed forward ANNs
- ❖ Radial Basis Function (RBF) networks and
- ❖ Different types of dynamic ANNs.

From the variety of ANNs a selection can be made based on certain ANN type characteristics that can aid in solving a specific problem. Detailed examination of the performance of different types of ANNs is often too time-consuming. Previous applications of ANNs in R-R modeling may also prove useful when making this selection. However, since no two models and data samples are the same, historical applications provide no certainty at all about future applications.

3.7.4 Finding an optimal ANN design

Not only the type of network, but also the design of that network determines its performance in terms of quality and speed. One of the main concerns of ANN design is finding a good ANN architecture. A good ANN architecture may be considered one yielding good performance in terms of error minimization, while keeping a simple and squash structure. The number of input units and output neurons are problem dependant, but the difficulty lies in determining the optimal structure of a network in terms of hidden neurons and layers, which can be chosen freely. Unfortunately, there is no universal rule for the design of such ANN architecture. Generally, a trial-and-error procedure is applied in order to find an appropriate architecture for a problem. Other possibilities besides trial and error include the use of algorithms that feature a combination of training and ANN architecture optimization.

3.7.5 ANN training issues in R-R modeling

For training a given ANN model in R-R modeling problems, following are starting point of the training and the criteria for training algorithm performance.

3.7.6 Initialization of network weights

The starting point of ANN training is determined by the values of the internal parameters of the network after their initialization. This initial weight matrix (as double matrix or vector) in combination with its accompanying initial network error can be visualized as a point on the error surface of the network, from which the training algorithm will try to find a minimum. By randomizing this starting point one can prevent the training algorithm getting stuck in the same minimum every time the ANN is trained.

3.7.7 Feed-forward networks

Once the inputs data and target output were prepared and given to ANN networks, then computation inside the networks can applied either using different libraries or tools or use own algorithms in which inputs and weights multiplied and summed together to obtain the rough solution.

3.7.8 Training algorithm performance criteria

The algorithm used for training a network can be easily altered, which makes the choice of learning algorithm a useful tool for guiding the speed versus accuracy performance of an ANN. This investigation will use model accuracy as the number one criterion for evaluation of algorithms. Modern personal computers are fast enough to let any training algorithm find an error minimum within acceptable time limits provided that the network architecture is not exorbitantly complex (which is often not the case in ANN R-R modeling).

3.8 Hydraulic Modeling

3.8.1 The HEC-RAS model

The Hydrologic Engineering Center River Analysis System (HEC-RAS) is a simulation software developed by the US Army Corps of Engineers and has been developed to manage

ivers and other public works under their authority. The HEC-RAS software has found wide acceptance among hydraulic engineers and researchers due to its robust channel flow analysis capabilities and its ability to simulate unsteady flood wave propagation and identifies flood prone areas as the areas where the ground is lower than the computed water elevation and allows the user to visualize the flood propagation in real time, thus making the software ideal for dam breach modeling.

3.8.2 Data preparation

The stream centerlines layer, bank lines layer, flow path layer, cross sectional cut line layer were created at the beginning. The River geometries created in HEC-RAS with their definitions are shown below.

- ❖ **Baro River centerline:** Used to identify the river or streamline and connectivity of the river network and assign river stations to computation points.
- ❖ **Cross-sectional cut lines:** Used to extract elevation transects from the DEM at specified locations and other cross-sectional properties.
- ❖ **Bank lines:** Used in conjunction with the cut lines to identify the main channel from overbank areas to understand the cross section of the River
- ❖ **Flow path centerlines:** Used to identify the center of mass of flow in the main channel and overbanks to compute the downstream reach lengths between cross sections.

Among these four layers the flow path layer need to be identified as being in the left overbank, right overbank or main channel and the stream centerline should be given river description. All cross sections were taken at an approximate interval of 200m. Elevation data then were extracted from 12.5m DEM and imported to HEC-RAS. As a rule each cross-section should be perpendicular to flow direction, and can intersect the main channel only once and may not intersect another cross section. The cross section cut lines should be long enough for the flood to attenuate and to include points of interest.

3.8.3 Two-Dimensional (2D) Modeling in HEC-RAS

HEC-RAS has added the ability to perform two-dimensional (2D) hydrodynamic routing within the unsteady flow analysis portion of HEC-RAS as one -dimensional (1D) unsteady-flow modeling, Two-dimensional (2D) unsteady-flow modeling and Combined 1D and 2D unsteady flow modeling.

The difference between 1D and 2D unsteady flow modeling is that in 1D flow modeling, only river geometries such as River stream line, banks, flow paths and the river cross-sections are used without considering the two-dimensional flood areas and feature is considered in 2D modeling. The main objective of 1D unsteady flow modeling is simply routing the inflow in the upstream to the effects at downstream and the channel or river cross-sections and different river stations. RAS Mapper in HEC-RAS was added to generate the 2D flow areas to enables the modeler to add the flow areas by drawing polygon developing the 2D flow computation mesh with different size based the interest of the objective of the modeling.

3.8.4 HEC-RAS Model Calibration and Validation

Calibration of HEC-RAS is done by changing the values of manning coefficient and normal depth roughness comparing the inundation flood extent result with flood event of August 21, 2005GC generated by Remote sensing analysis in GIS. First the imagery of the event is taken and then Normalized Difference Water Index (NDWI) is done to delineate the open water body in the study area of the same date as of the event.

Therefore, the inundated map result simulated by HEC-RAS is tuned to the flood extent generated by NDWI through changing the values of manning roughness coefficient and normal depth roughness until the both flood extent is overlapped. For validation, the same period is used as of hydrologic modeling for hydraulic modeling that the adjusted values of manning roughness coefficient and normal depth roughness are used in HEC-RAS to generate the inundation map, and then NDWI is delineated using flood event of August 27, 2008 G.C is used to compare the inundated flood extent obtained from HEC-RAS. The evaluation for this comparison is done by the overlapped areas of both flood extent of NDWI and HEC-RAS result. According to [38], if the two flood extent (NDWI and HEC-RAS) areas overlapped up to 95% (the ratio of the total area of the flood extent) it is considered as validated model.

Since this way of calibrating and validating of hydraulic modeling is new emerging ideas of Remote sensing application of GIS and HEC-RAS techniques for flood extent validation based on Landsat imagery, no statistical evaluation is added yet.

Normalize Difference Water Index (NDWI): Normalize Difference Water Index (NDWI) is used for the water body analysis. The index uses Green (Band-2) and near infra-red (Band-4) bands of remote sensing images. The NDWI can develop water information efficiently in most cases. It is sensitive to build-up land and result in over-estimated water bodies. NDWI can be calculated by following formula:

$$NDWI = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$

Where NIR is Near Infrared
SWIR is Short Wave Infrared

For Landsat 7 data, NDWI = (Band 4 – Band 5) / (Band 4 + Band 5)

For Landsat 8 data, NDWI = (Band 5 – Band 6) / (Band 5 + Band 6)

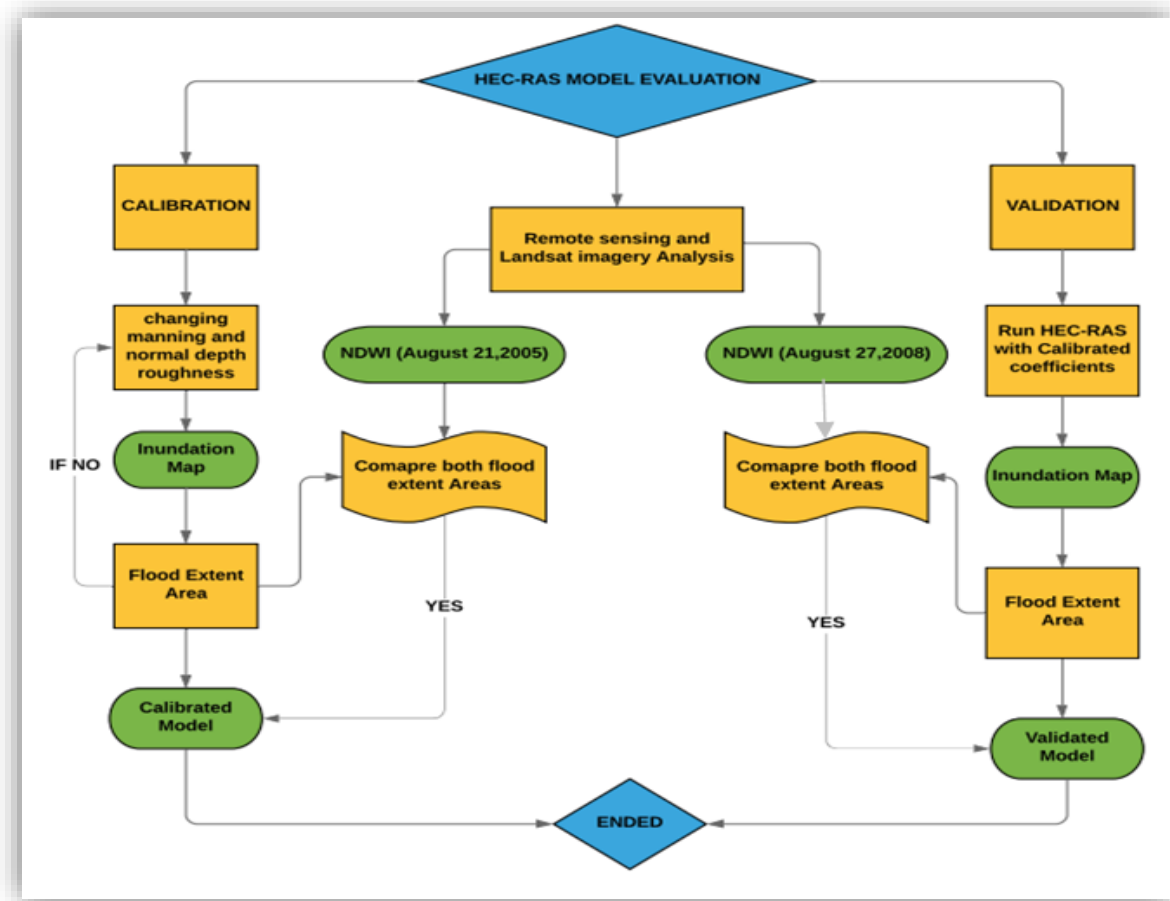


Figure 3-6: HEC-RAS model Calibration and Validation framework

3.8.5 Climate change scenarios for flood prone areas identification

Climate change is expected to increase both the magnitude and frequency of extreme precipitation events, which may lead to more intense and frequent river flooding. This study aims to assess the flood hazard areas identification under climate change scenarios in Baro River, Itang Special wereda, Ethiopia. RCP8.5 is considered since the climate scenario gives information about high emissions of radioactive (which our worst cases in hydrology). Floods have been experienced with greater frequency and more severity under global climate change. To understand the flood hazard and its variation in the future, the current and future flood hazards in the 21st century in Ethiopia for this specific wereda is presented. Floods and their trends are assessed using precipitation during heavy rainfall process and the temperature, which are calculated based on historical meteorological observations under Representative Concentration Pathway (RCP 8.5) scenario. The flood-causing the projection results indicate that the flood hazards could increase under RCP8.5 during the 21st century (2021–2050).

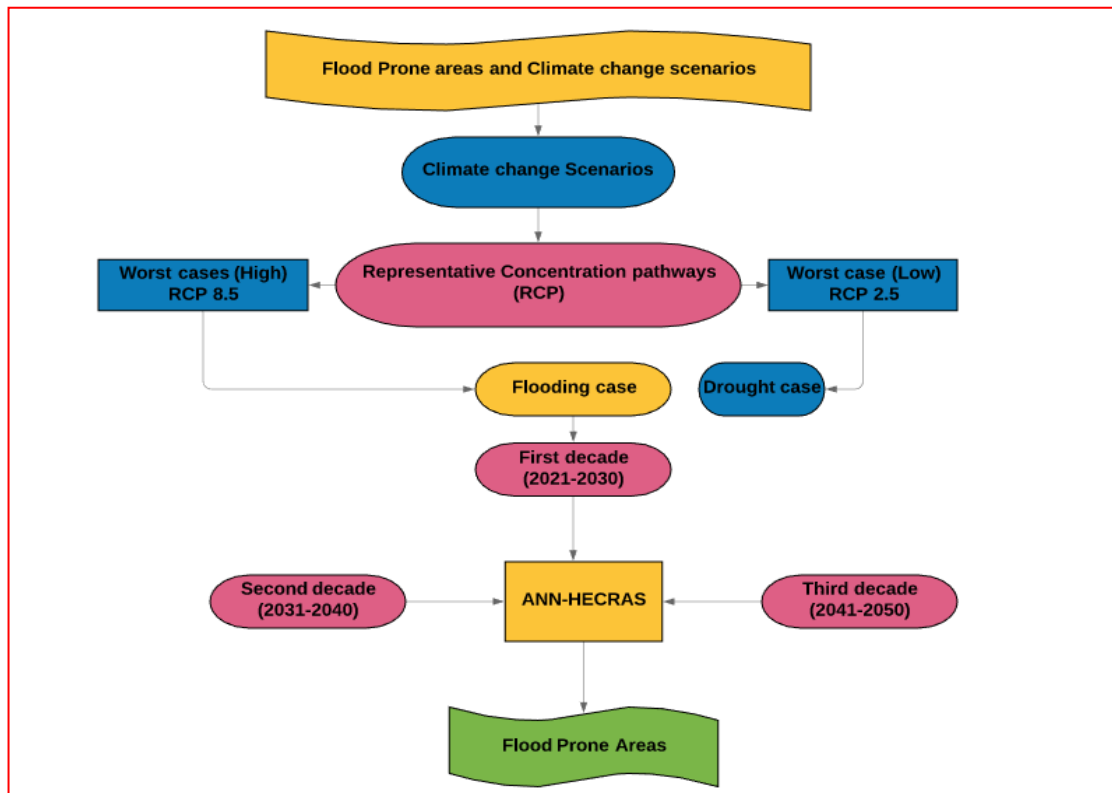


Figure 3-7: Climate change scenarios for flood prone area identification

According to the accepted climate change scenarios (RCP8.5), the future rainfall and temperature in the selected study area is expected to increase in the coming three decades. The expected increase in rainfall and temperature leads to an increase of runoff that is directly flooding that will cause disaster. It is necessary to accurately estimate the future frequency and severity of floods, considering increasing rainfall according to different climate change scenarios. Future flood risks due to relative hydrological risk also increased by in the coming 30-years (three decades) and the special attention must be given to the areas under flood risk. Data obtained from RCP8.5 for both rainfall and temperature are processed in ANN-HECRAS models for both hydrological and hydraulic modeling.

3.8.6 Schematic diagram of general method in the study

As mentioned in the above section, the general method used in this thesis works classified in two models (hydrological model and hydraulic model). The general steps in schematic of the method are shown below.

The two models (Hydrological modeling using Artificial Neural Networks (ANN) and Hydraulic modeling using HEC-RAS) are modeled first accomplishing the hydrological modeling fixing outlet at Gambella to prepare the flow hydrograph which is as input for upstream boundary condition in HEC-RAS, and then the result from hydraulic model is used as flood inundation mapping to know identify the flood risk zones in the area. ANN hydrological modeling is done using historical and forecasted rainfall and temperature for training and forecasting stream flow respectively. Weather research and forecasting data obtained from National Meteorological Agency (NMA) of early warning and meteorological forecast are used as input for ANN to forecast flow at real-time while the results from the ANN again used as input in HEC-RAS to generate flood inundation mapping.

The two models (hydrological and hydraulic) are integrated first to know the stream flow and then to know the depth of the resulted stream flow. The general schematic shown below is that the both models are integrated using weather Research and forecasting data obtained from NMA as intermediate. The general framework that shows the calibration and validation is also shown in the figure 3-8 above for HEC-RAS.

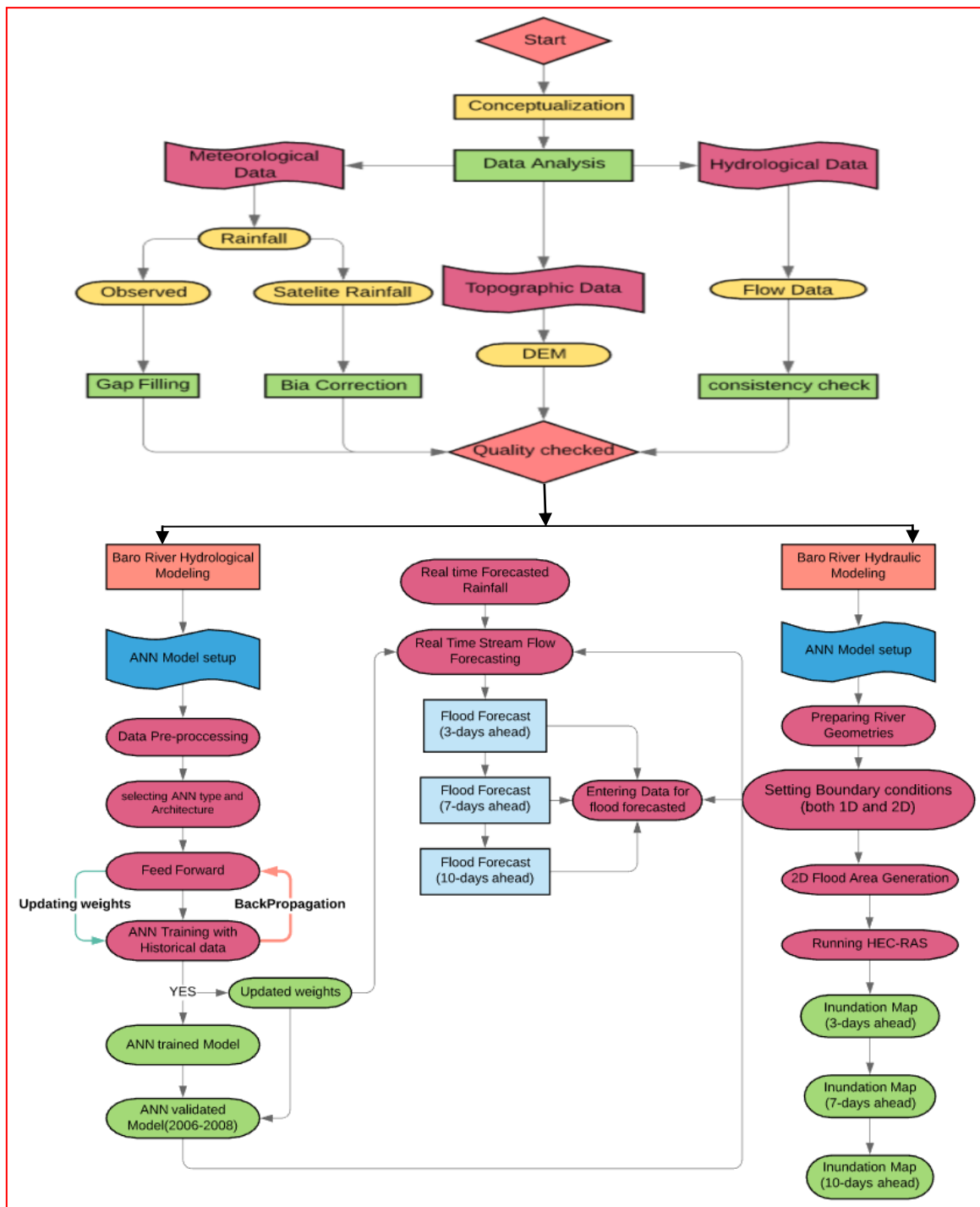


Figure 3-9: General Flow chart of the methodology

4. RESULTS AND DISCUSSION

4.1 Rainfall-Runoff Modeling ANN Design in R studio

4.1.1 Neural network architectures

Feedforward network is selected in this study. For this class of ANN architecture, input data from input nodes propagate in one direction from the Input layer to the Output layer and rough result reached. The input data used were Rainfall, Temperature and Topographical wetness Index (TWI), these data were converted to gridded (3km x 3km) datasets to reduce the lumped property of ANN modeling.

Time series data of (1999-2005) daily time period were prepared using weight factors obtained from Inverse Distance Weights (IDW) in ArcGis in which nearest point rainfall values and altitude were used to calculate weights in each stations, then these values are used in generating gridded datasets before feeding to the network.

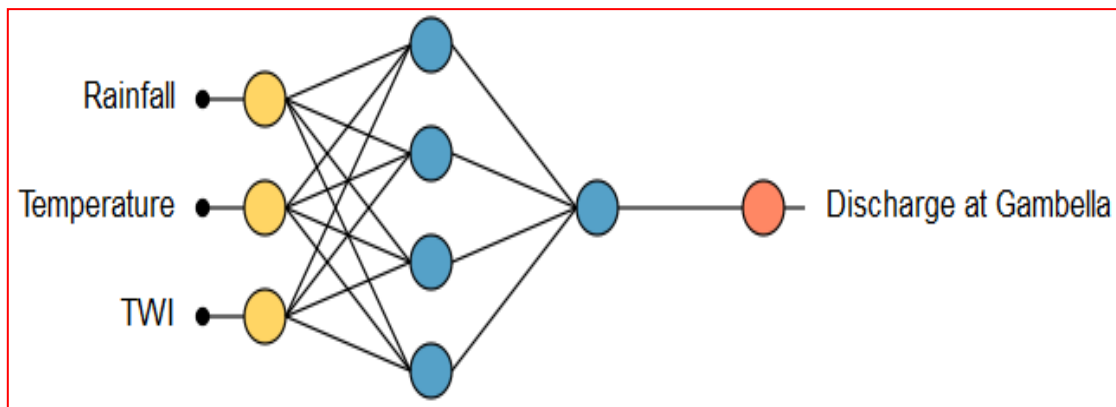


Figure 4-1: Neural networks architecture selected in the model

To reach at the best network type, trial and error can be made changing the number of nodes in the hidden layer, propagation algorithm, learning rate, and threshold until the best one selected based on the error calculated. Figure 4-2 below show that the best ANN type was reached after the above factors are set as seen in the algorithm.

In this study, three nodes one input layer, four hidden nodes in hidden layer and one node in output layer network type is selected.

```
### Algorithm developed to select the best ANN network type
library(neuralnet)
ANN_Gambella <- neuralnet(Discharge ~ P + T + TWI,
  data = train,
  hidden = 4,
  err.fct = "ce",
  learningrate = 0.5,
  threshold = 0.001,
  algorithm = 'backprop',
  stepmax = 100000,
  linear.output = FALSE,
  lifesign = 'full',
  rep = 1)
plot(ANN_Gambella, rep = 1)
```

Figure 4-2: algorithm selection of best ANN architecture

4.1.2 Pre-processing and post-processing

ANN is generally cannot use raw data, so it must be changed to usable way of format before feed to the network which is so called normalization or scaling. The type of scaling data of normal scaling the input or output variables can be divided the maximum value present in the pattern, thereby linearly scaling the data to a range of 0 to 1 and this scaling to a range of 0 to 1 implies the assumption that the training data contains the full range of possible outcomes for the training data.

```
## Statistics of the inputs data P, T, QO and TWI
min(P)
min(T)
min(TWI)
min(Qo)
max(P)
max(T)
max(TWI)
max(Qo)

## scaling or Normalisation of the inputs data P, T, QO and TWI
P_scaled <- (P-min(P))/(max(P)-min(P))
T_scaled <- (T-min(T))/(max(T)-min(T))
TWI_scaled <- (TWI-min(TWI))/(max(TWI)-min(TWI))
Qo_scaled <- (Qo-min(Qo))/(max(Qo)-min(Qo))
```

Figure 4-3: Scaling or normalization of raw data before feed to network

4.1.3 Initialization of network weights

In R studio, weights were randomized or initialized declaring float numbers for each weight that is used in the feedforward input propagation.

This initial weight vector in combination with its associated initial network shows initially that the synaptic or the strength between each node randomly, but the true values of these weights are reached after training of the network.

The weights of artificial neural networks must be initialized to small random numbers, because this is an expectation of the backpropagation algorithm used to train the model fast[34],[35].

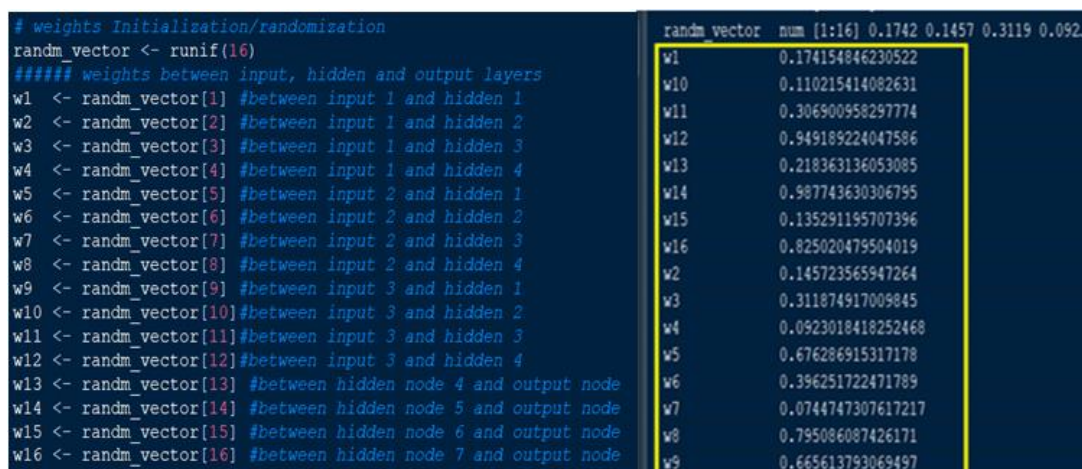


Figure 4-4: Initialization of weights between nodes

Table 4-1: initialized values of weights in R studio

W1	0.174	W5	0.676	w9	0.666	w13	0.218
W2	0.146	W6	0.396	w10	0.110	w14	0.988
W3	0.312	W7	0.074	w11	0.307	w15	0.135
W4	0.092	W8	0.795	w12	0.949	w16	0.825

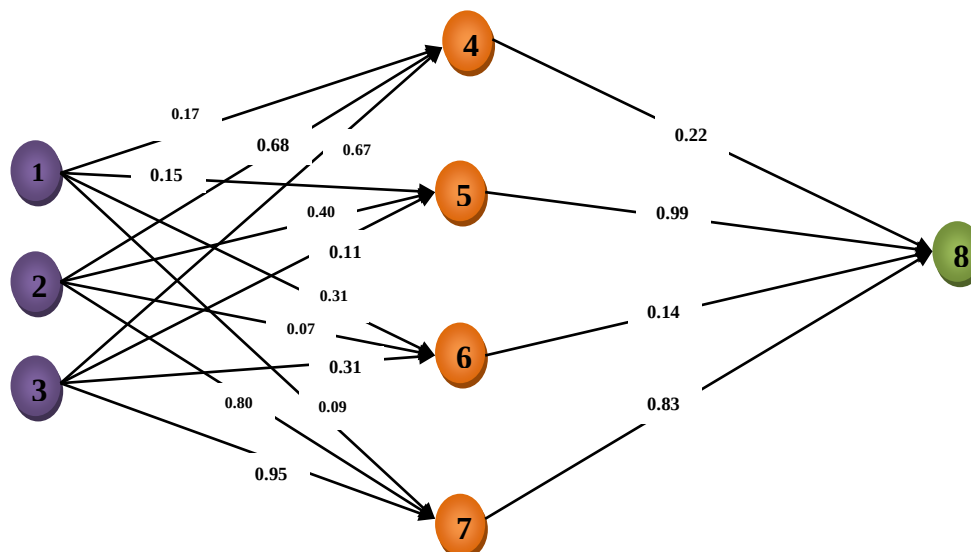


Figure 4-5: Initial values of weights assigned to the networks

4.1.4 Feed-forward networks

Feedforward propagation starts with assigning randomized weights using input data and target output to ANN networks once, then computation inside the networks can be applied either using different libraries or tools or use own algorithms in which inputs and weights are multiplied and summed together to obtain the rough solution.

```
# Feed Forward or forward propagation and net inputs to all nodes N4,N5, N6 and N7
for (i in 1:nrow(P_scaled)) {
  for (j in 1:ncol(P_scaled)) {
    N4 <- w1*(P_scaled) + w5*(T_Scaled) + w9*(TWI_Scaled)
    N5 <- w2*(P_scaled) + w6*(T_Scaled) + w10*(TWI_Scaled)
    N6 <- w3*(P_scaled) + w7*(T_Scaled) + w11*(TWI_Scaled)
    N7 <- w4*(P_scaled) + w8*(T_Scaled) + w12*(TWI_Scaled)
    next(i)
  }
  next(j)
}
```

Figure 4-6: Feed Forward algorithm developed in R studio

This value is passed to other neurons in the network. This process is summarized in the schematic presented in figure 4-6 below. A neuron is connected to other neurons via its input and output links. Each incoming neuron has an activation value and each connection has a weight associated with it. The neuron sums the incoming weighted values, representing the input from the neuron.

```
### Applying activation function for N4, N5, N6 and N7
for (i in 1:nrow(N4)) {
  for (j in 1:ncol(N4)) {
    O4 <- ((1)/(1+exp(-N4)))
    O5 <- ((1)/(1+exp(-N5)))
    O6 <- ((1)/(1+exp(-N6)))
    O7 <- ((1)/(1+exp(-N7)))
    next(i)
  }
  next(j)
}
```

Figure 4-7: Algorithms developed in R studio to apply activation function

Again with the same fashion the activated values or outputs from each hidden nodes are multiplied by respective weights and summed up together to give the output node as input and will be activated linearly and changed in to rough output of the networks at the output node as shown below.

The difference between activation between input and hidden nodes, hidden and output nodes is that linear activation function can be applied between hidden and output nodes since computation is linear relatively.

```
#### Applying linear transformation
for (i in 1:nrow(O4)) {
  O8 <- O4*w13 + O5*w14 + O6*w15 + O7*w16
  output <- ((1)/(1+exp(-O8)))
  next(i)
}
```

Figure 4-8: Linear activation function at output node

Feedforward ended when computation steps reach output node. Now, with the training data, the total error between rough result and target values is to be minimized. The total error (E) is computed by subtracting network output from the target (actual).

```
# The total of the errors is arrived at by using the following formula

E <- 0.5*(Qo_scaled - output)^2
```

Figure 4-9: Total error between output and target (actual) data

The rough solution to the networks before any training was made, the following result of ANN and the observed or target hydrograph was taken.

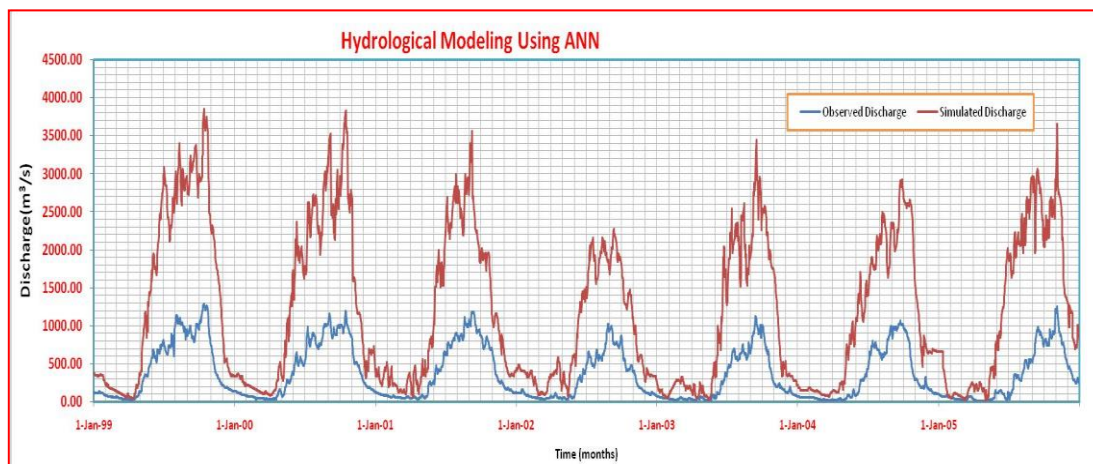


Figure 4-10: Result from ANN model before training

4.1.5 Back propagation Neural Networks

Back propagation of errors is similar to learning from mistakes to modify the result and accounts the error comes from feedforward propagation. The main idea of backpropagation is to minimize the magnitude of total error between output and target. The total error is propagated to the output first and then passes to the nodes in hidden layer until input nodes of input layer.

```
#### Backpropagation by Computing the gradient for Mean Squared Error function

w1_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w13 * 04 * (1 - 04) * output
w2_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w14 * 05 * (1 - 05) * output
w3_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w15 * 06 * (1 - 06) * output
w4_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w16 * 07 * (1 - 07) * output
w5_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w13 * 04 * (1 - 04) * output
w6_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w14 * 05 * (1 - 05) * output
w7_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w15 * 06 * (1 - 06) * output
w8_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w16 * 07 * (1 - 07) * output
w9_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w13 * 04 * (1 - 04) * output
w10_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w14 * 05 * (1 - 05) * output
w11_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w15 * 06 * (1 - 06) * output
w12_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * w16 * 07 * (1 - 07) * output
w13_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * 04
w14_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * 05
w15_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * 06
w16_error <- (output - Qo_scaled) * Qo_scaled * (1 - Qo_scaled) * 07
learningrate <- 0.5
new_w1 <- w1 - learningrate * w1_error
new_w2 <- w2 - learningrate * w2_error
new_w3 <- w3 - learningrate * w3_error
new_w4 <- w4 - learningrate * w4_error
new_w5 <- w5 - learningrate * w5_error
new_w6 <- w6 - learningrate * w6_error
new_w7 <- w7 - learningrate * w7_error
new_w8 <- w8 - learningrate * w8_error
new_w9 <- w9 - learningrate * w9_error
new_w10 <- w10 - learningrate * w10_error
new_w11 <- w11 - learningrate * w11_error
new_w12 <- w12 - learningrate * w12_error
new_w13 <- w13 - learningrate * w13_error
new_w14 <- w14 - learningrate * w14_error
new_w15 <- w15 - learningrate * w15_error
new_w16 <- w16 - learningrate * w16_error
```

Figure 4-11: All Back-propagation algorithms developed using gradient descent

After the total error is propagated, new weights are calculated to run the network again using the updated weights. Feedforward is repeated whenever the error is propagated from output to input nodes. In these training codes, model performance evaluation and stopping conditions are provided for the network. To govern the iterations in the computation either user defined number of iteration (epoch) or stopping condition is given to the network, then it finish or stop according the command.

In most of the cases choosing iteration number (epoch) is less effective since stopping condition (model performance evaluation as stopping condition) is preferable, because the goal of the computation is use the network until the best degree of accuracy is reached rather than computing many times. In this study, model performance evaluation (NSE) is set at 0.87 (which a best model) as stopping condition, therefore, the network stopped when NSE=0.87 immediately.

```
# Replace all update values of weights
new_N4 <- matrix((new_w1[1,1]*P[i,j])) + ((new_w5[1,1]*(T[i,j])) + (new_w9[1,1]*(TWI[i,j]))), nrow = 2557, ncol = 1)
new_N5 <- matrix((new_w2[1,1]*P[i,j])) + ((new_w6[1,1]*(T[i,j])) + (new_w10[1,1]*(TWI[i,j]))), nrow = 2557, ncol = 1)
new_N6 <- matrix((new_w3[1,1]*P[i,j])) + ((new_w7[1,1]*(T[i,j])) + (new_w11[1,1]*(TWI[i,j]))), nrow = 2557, ncol = 1)
new_N7 <- matrix((new_w4[1,1]*P[i,j])) + ((new_w8[1,1]*(T[i,j])) + (new_w12[1,1]*(TWI[i,j]))), nrow = 2557, ncol = 1)
new_O4<- ((1)/(1+exp(-new_N4)))
new_O5<- ((1)/(1+exp(-new_N5)))
new_O6<- ((1)/(1+exp(-new_N6)))
new_O7<- ((1)/(1+exp(-new_N7)))

new_O8<- O4*new_w13[1,1] + O5*new_w14[1,1] + O6*new_w15[1,1] + O7*new_w16[1,1]
new_output <- ((1)/(1+exp(-O8)))
output_ANN<- output

NSE <- 1 - sum((Qo_scaled - output_ANN)^2)/sum((Qo_scaled - Qo_mean)^2)
RMSE <- sqrt((sum(Qo_scaled - output_ANN)^2/2557))
if(NSE == 0.87 && E == 0.03 ){
  break
}
}
```

Figure 4-12 Model performance evaluation and stopping condition set in R studio

These steps are repeated until the error converges of very low error term or a specified number of times. All the steps are taken care of internally in the R packages available. To speed up the iteration learning rate can be supplied along with various other parameters.

4.1.6 Model performance evaluation

Model performance evaluation indicators are used to check the how good the model is working. Generally the Nash-Sutcliffe Efficiency (NSE) is used by most modelers as an overall performance measure. For hydrological forecasting (such as real-time flood forecasting) purpose, criteria like the Nash Sutcliffe model efficiency (NSE), RMSE, and mean absolute error are widely used, with NSE being most popular[36].

As shown in figure 4-16 the statistically computed value of Nash-Sutcliffe Efficiency (NSE) is 0.87, which revealed that ANN is a powerful technique to Real time flood forecasting applied for this specific study.

The ANN model performance evaluation is adjusted with NSE at the above value to stop the iteration in the computation.

```

99 # Model performance Evaluation using NSE
100 Qo_mean <- sum(Qo_scaled)/2557
101 E <- sum(0.5*(Qo_scaled - output)^2)
102 NSE <- 1 - sum((Qo_scaled - Qo_mean)^2)/sum((Qo_scaled - output)^2)
103
104
105
106
90:33 Loading inputs data (Precipitation(P), Temperature(T), Observed Discharge at Gambella(Qo) and Topographic wetness index(TW)) :
Console ~/
NSE
1) 0.87

```

Figure4-13: Model performance Evaluation algorithm

At the end of training, the following trained values of weights (Table 4-2) were obtained from the networks. These trained values of the networks are used in validation purpose for other sample data out of the data used in training.

Table 4-2: Results of weights after training is reached

W1= 0.61	W5=0.09	W9=0.48	W13=0.19
W2=0.54	W6=0.71	W10=0.09	W14=0.06
W3=0.68	W7=0.87	W11=0.32	W15=0.30
W4=0.64	W8=0.27	W12=0.31	W16=0.30

The main objective of fixing or updating values of weights is that to use them again in network diagram in validation or forecasting purposes. The figure 4-13 shows that the trained or updated values of the weights were assigned again in the network diagram or architecture. These trained values of weights are used for both real-time flow forecasting and flood prone areas identification in climate change scenarios.

The values of the trained weights further used in comparing different real time flood forecasting for 3-days, 7-days and 10-days ahead to get floods and corresponding depths.

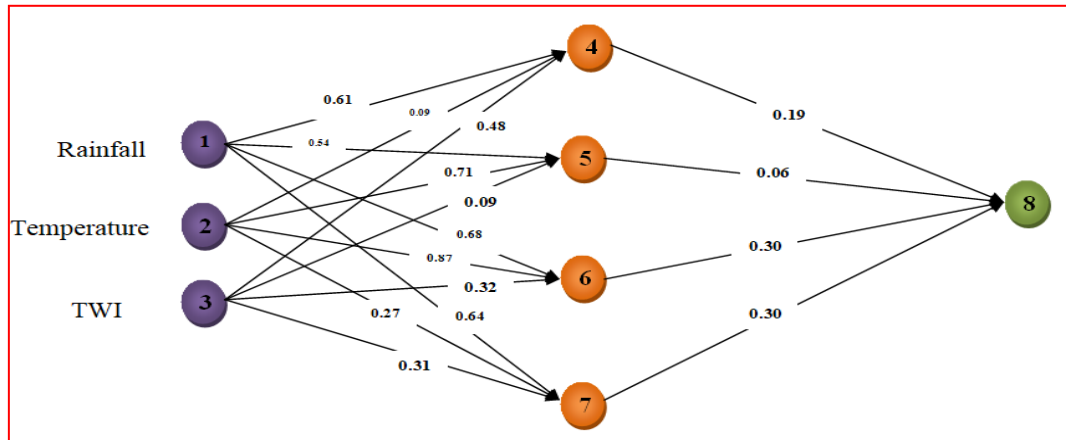


Figure 4-14 : Results of weights (adjusted weights) assigned to the networks

Results relating to the 7 years (1999-2005) for the Baro River based on the precipitation, temperature and topographical wetness index (TWI) that is trained (calibrated) is shown in figure 4-14. The analysis shown that, application of Artificial Neural Networks (ANN) in R-R modeling overcomes the difficulties due to non-linearity and found that the result ANN model gave high accuracy for flood forecasting. In general, both visual (graphical) and statistical (NSE) model performance evaluation is done and in both criteria best result were obtained. For graphical evaluation, visual inspection is made to see whether the two hydrographs are matched to some extent. In figure 4-14 below the blue line hydrograph is the target or observed while the red one is the result from Artificial Neural Networks (ANN).

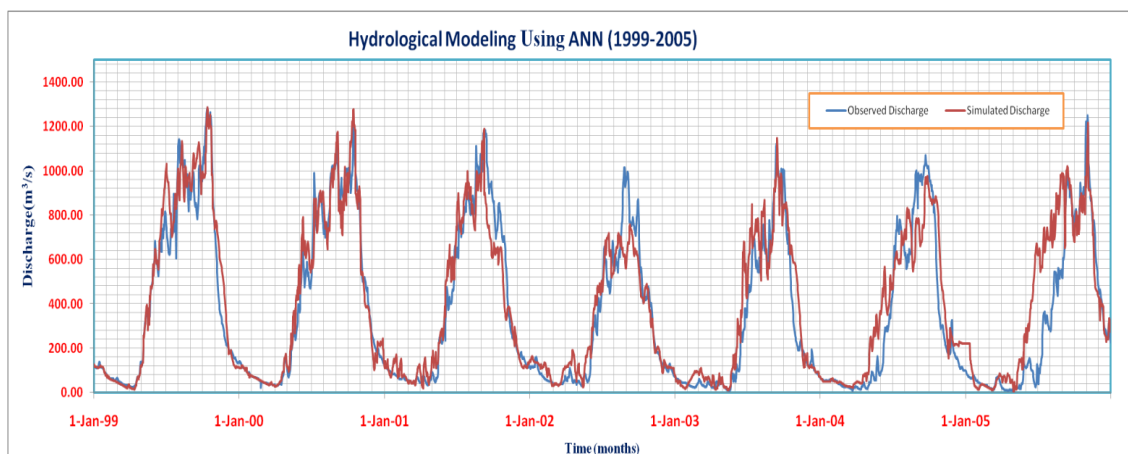


Figure 4-15: ANN calibrated or trained daily flow result using Back-propagation algorithm

For the above calibrated ANN (trained) model of 7 years daily data from 1999-2005, the validation was done with sample data of 2006-2008. Based on the model evaluation made (both model performance and efficiency), RMSE and NSE resulted values of 22.83 and 0.87 respectively during calibration (training) is checked for other sample data of 2006-2008 for validation, the results for both model performance and efficiency revealed that trained ANN model for validation is best with RMSE 1.89 and NSE 0.84 values.

For validation purpose the values of weights were taken from the trained model and these values are given to the developed ANN model to run. In this simulation fixed and trained values of weights were used and the same procedures as of the above were done to get the output.

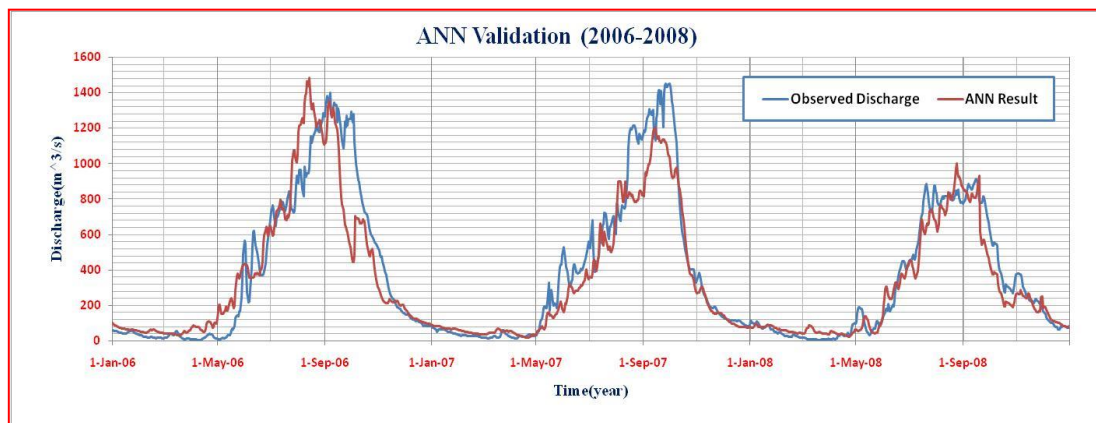


Figure 4-16: ANN result Validated for the year (2006-2008 G.c)

```

82 # statistics of the simulated (for Validated ANN model)
83 Qo_mean <- sum(Qo)/1096
84 NSE <- 1 - sum((Qo - output)^2)/sum((Qo - Qo_mean)^2)
85 options(scipen = 999,digits = 4)
86
87
88
78:1 (Top Level)
Console C:/Users/AAiT/Desktop/R/ANN in R/Vaidation/Validation/
> NSE
[1] 0.8204

```

Figure 4-17: Model performance in R studio for validated ANN

4.2 Running Hydraulic Modeling

4.2.1 Data preparation

All geometries of Baro River were generated using high resolution DEM to show stream centerlines, bank lines, flow paths, and cross-sectional lines. Since the objective of this study was to prepare flood inundation area mapping at Itang area, 2D flood areas and all parameters needed for this purpose were developed using Terrain data. RAS Mapper window of the HEC-RAS for the latest version is powerful to prepare both river geometries and flood areas in 1D and 2D unsteady analysis.

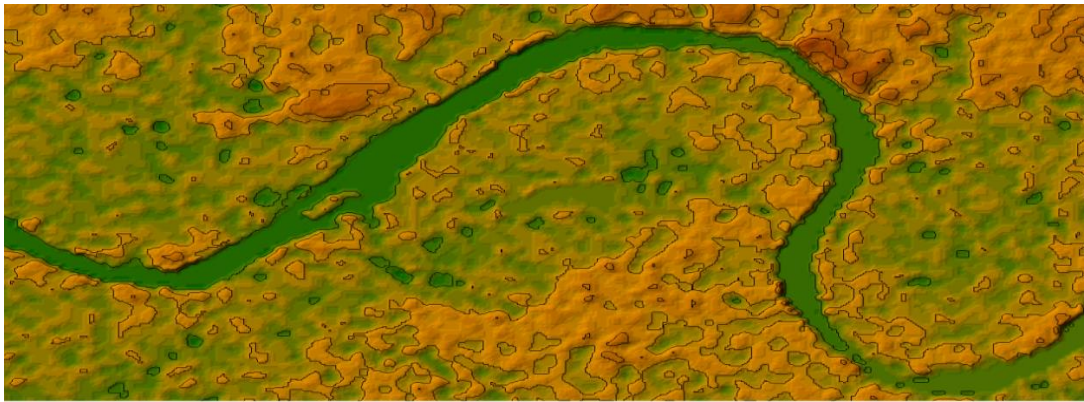


Figure 4-18: 12.5m Digital Elevation (DEM) in RAS Mapper

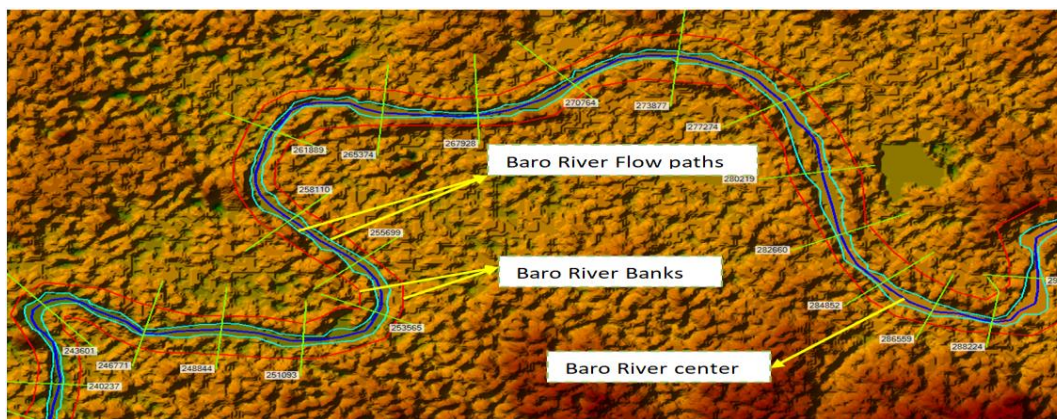


Figure 4-19: Baro River geometries prepared in RAS Mapper

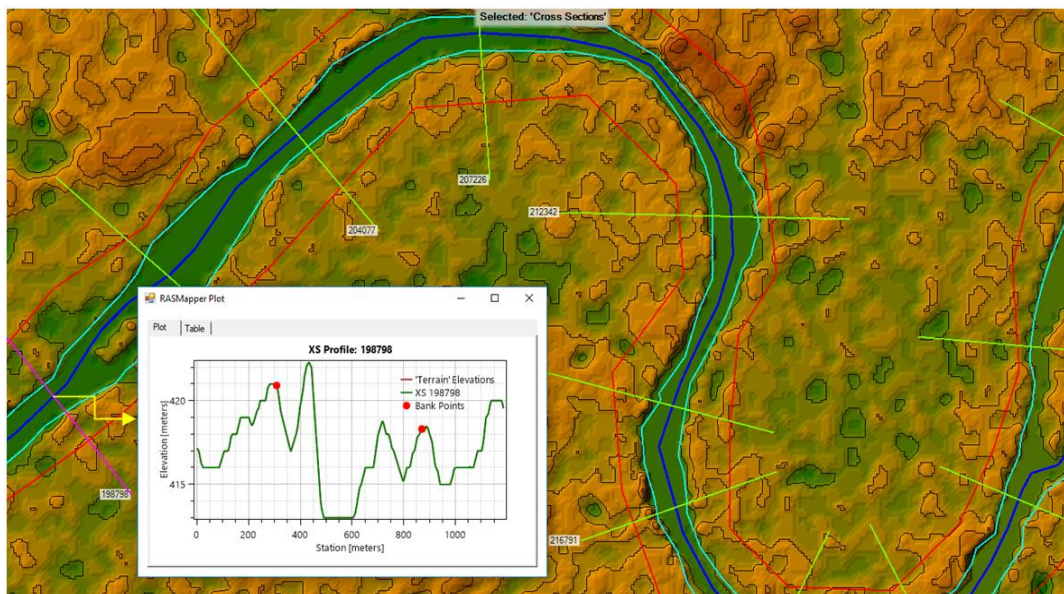


Figure 4-20: Sample cross-section for the River at station 365413

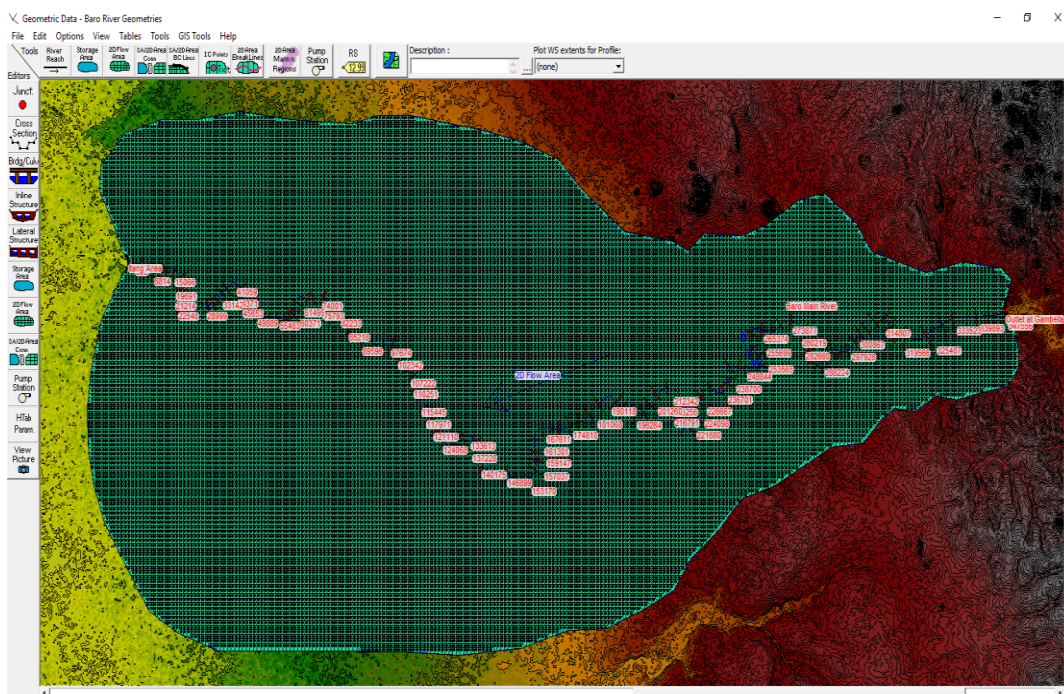


Figure 4-21: River geometries with 500m x 500m gridded 2D flood area

Real-Time Flood Forecasting Using Artificial Neural Networks (ANN) and Flood Inundation Mapping

2019

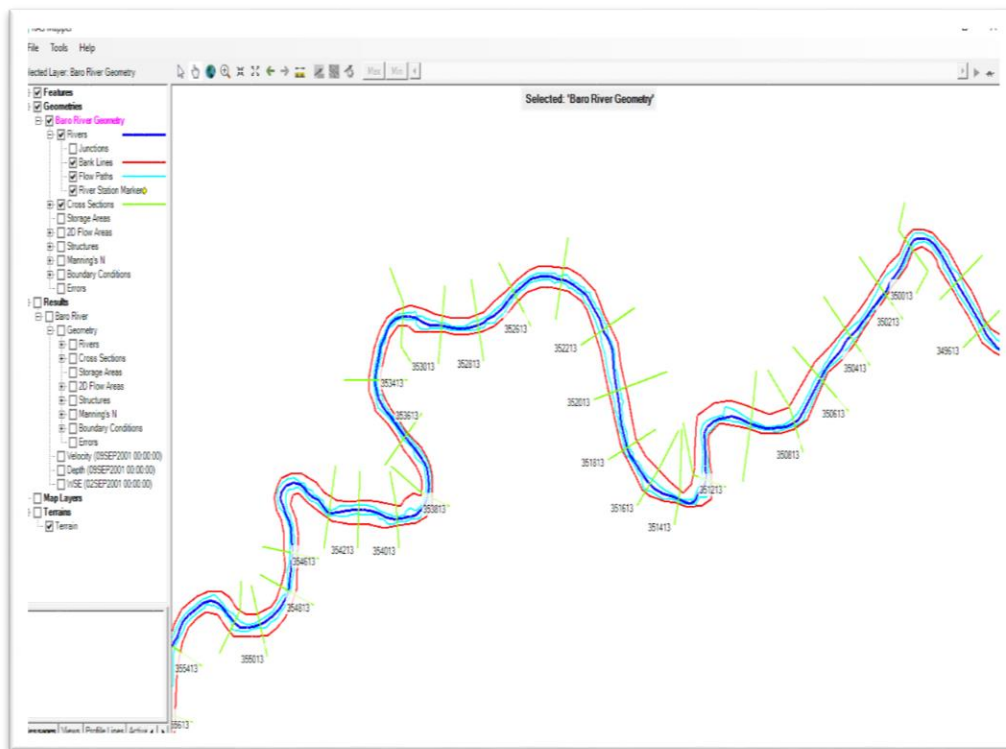


Figure 4-22: RAS Mapper with no terrain or other map layer

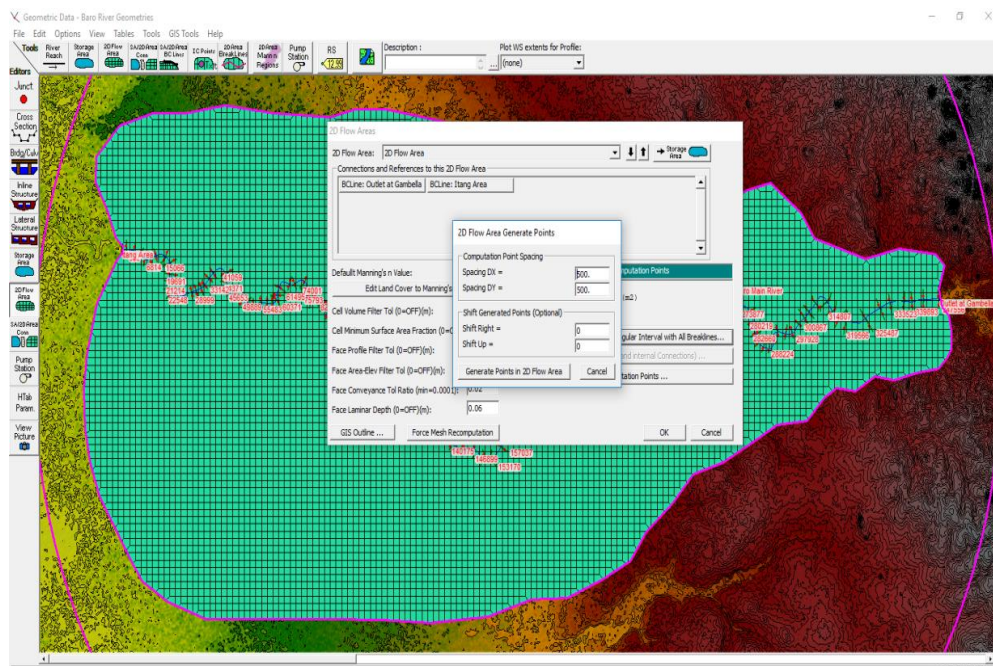


Figure 4-23: computational mesh with 500m x 500m gridded terrain

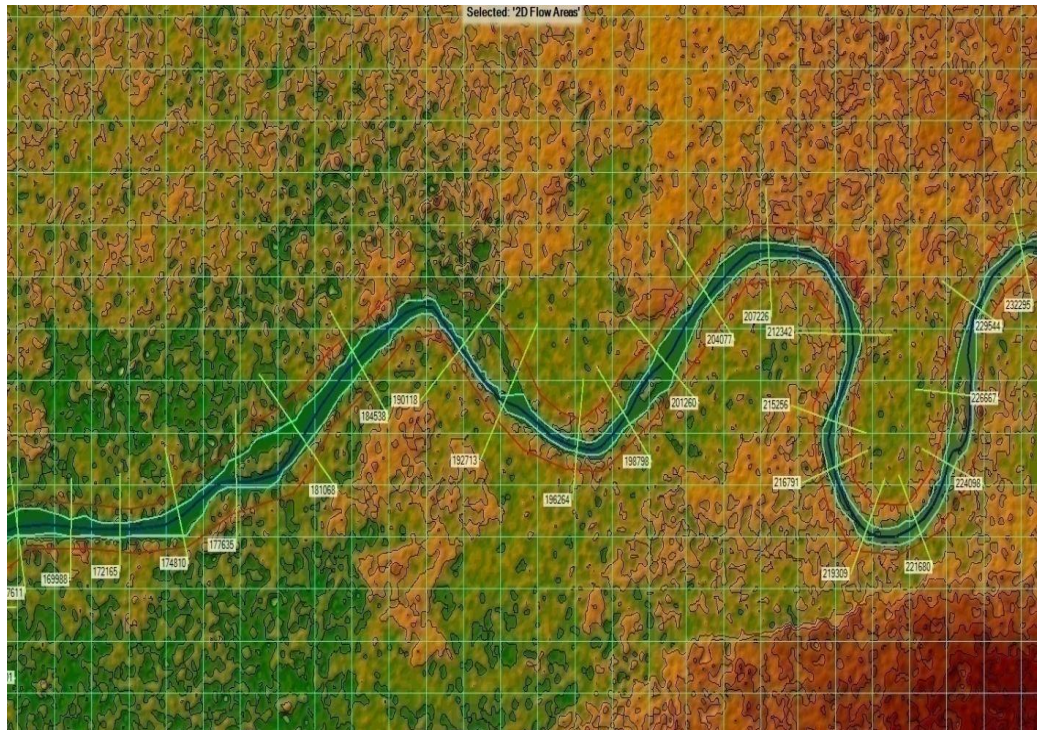


Figure 4-24: River geometries with 500m x 500m grid and Terrain Mapper



Figure 4-25: Baro River with terrain data and shade of contour interval 20m

4.3 Running Hydraulic Modeling (HEC-RAS)

After all data and river geometries were prepared, boundary conditions were set to enter data where needed. In this thesis work, outlet at Gambella town and Itang areas were selected as

upstream and downstream boundary conditions. The inflow hydrograph obtained from ANN model is given to the model as upstream hydrograph where normal depth roughness is used for downstream.

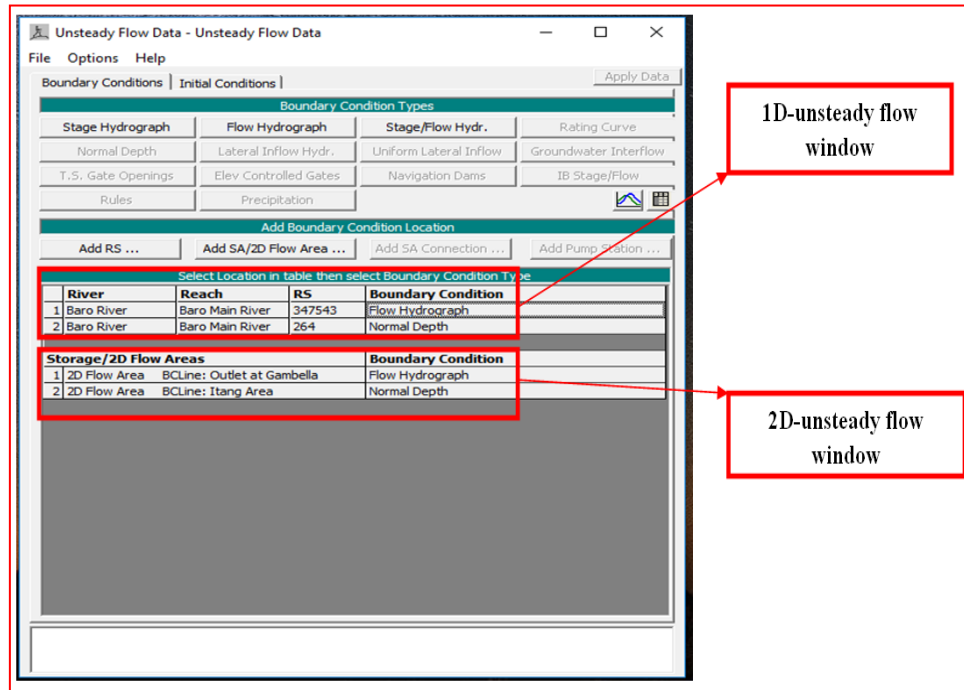


Figure 4-26: Unsteady flow analysis boundary condition in HEC-RAS

Before entering all data needed in both boundary conditions, the simulation time is set first and the adjustment of simulation or computation time highly affects the result of HEC-RAS, therefore, it should be set carefully. According to [37] reducing the computation time increases the accuracy of model or result, but takes time to complete the simulation, while increasing computation time speed up the time to complete.

In addition to computational time, normal depth (roughness) and manning coefficient are the other parameters which can affect the shape of hydrograph (outflow), the peak of the result and the shape of hydrograph. The values of these parameters can be fixed through trial and error using different techniques.

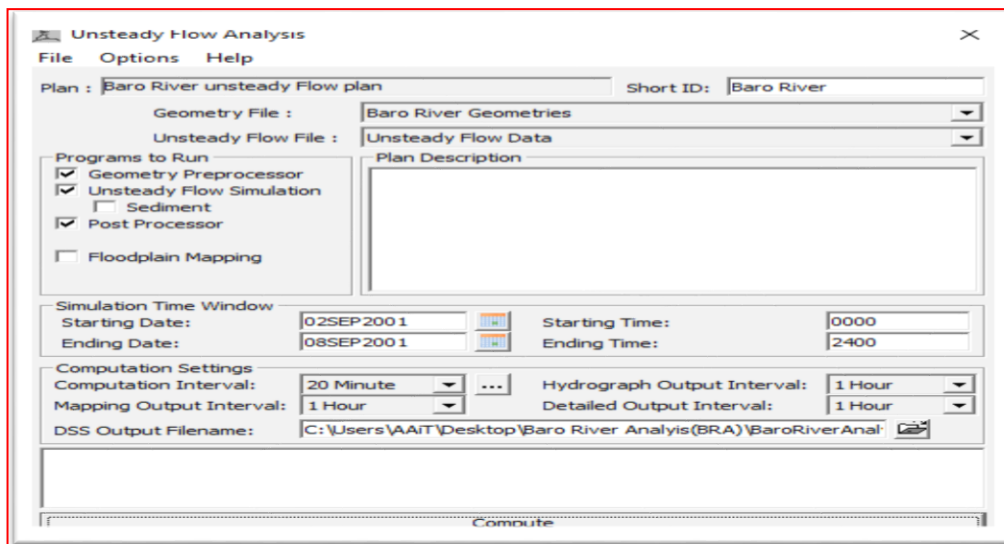


Figure 4-27: Unsteady flow analysis time window adjusted to run

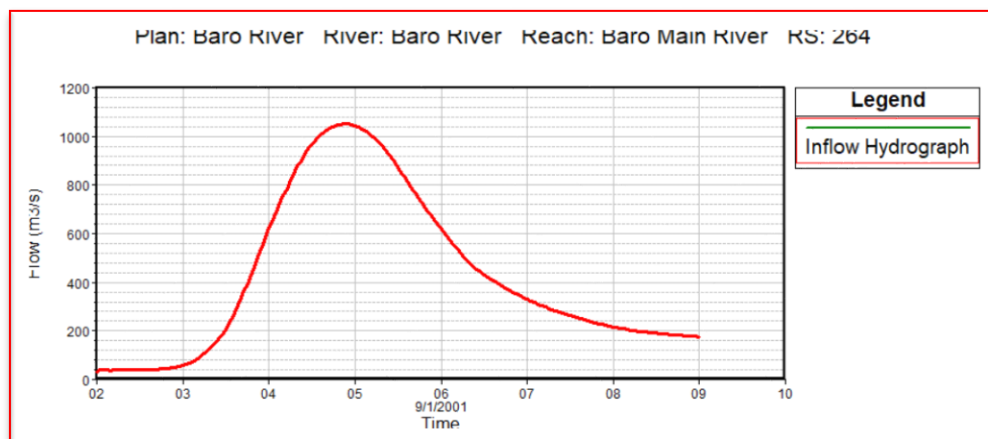


Figure 4-28: Outflow hydrograph at Itang areas (downstream boundary)

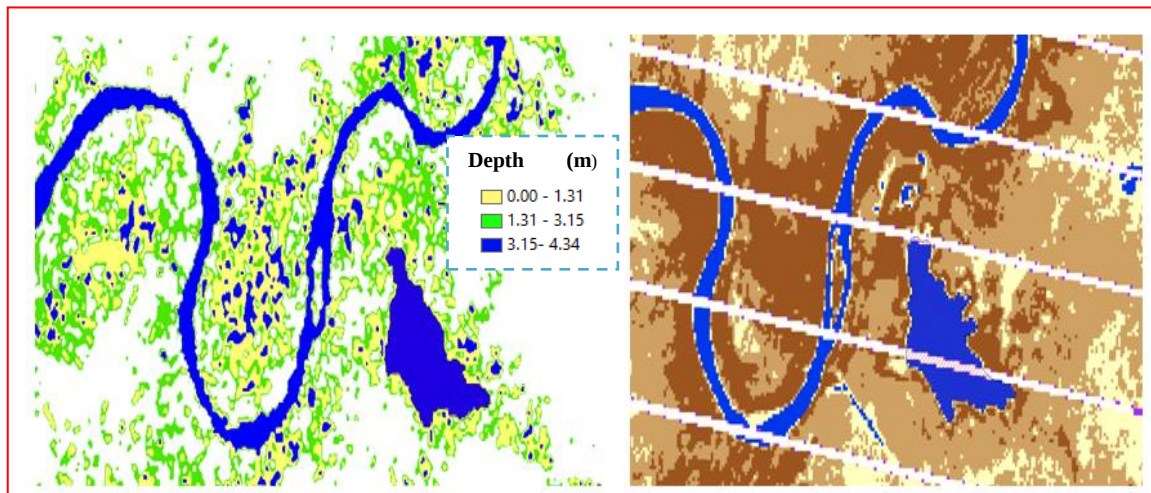
4.4 Calibration and Validation of HEC-RAS Model

4.4.1 Calibration

If observed or measured data such as flow hydrograph, water level, water depth, flood extent of the case study are available during flood event, it can be simple to calibrate and validate HEC-RAS result of inundated map, unless situations may difficult in both cases if the above all data are missed or not available, instead calibration and validation may follow other options like remote sensing analysis of the event and needs surveying the historical event.

In such cases, the modeler is forced to use trial and error to change manning roughness coefficient for calibration until the inundation map resulted from HEC-RAS and the real flood event extent (area) became resembled and remote sensing analysis for validation.

In this thesis works these two logics were applied. The result of inundation map from HEC-RAS was calibrated using Flood event of (August 21, 2005) by changing the values of manning coefficient roughness and normal depth roughness[38].



a) Inundated Flood extent of simulated (1999-2005) b) Image of Flood Extent (21 August 2005) (NDWI)

Figure 4-29: Comparison of Simulated inundation map and flood extent

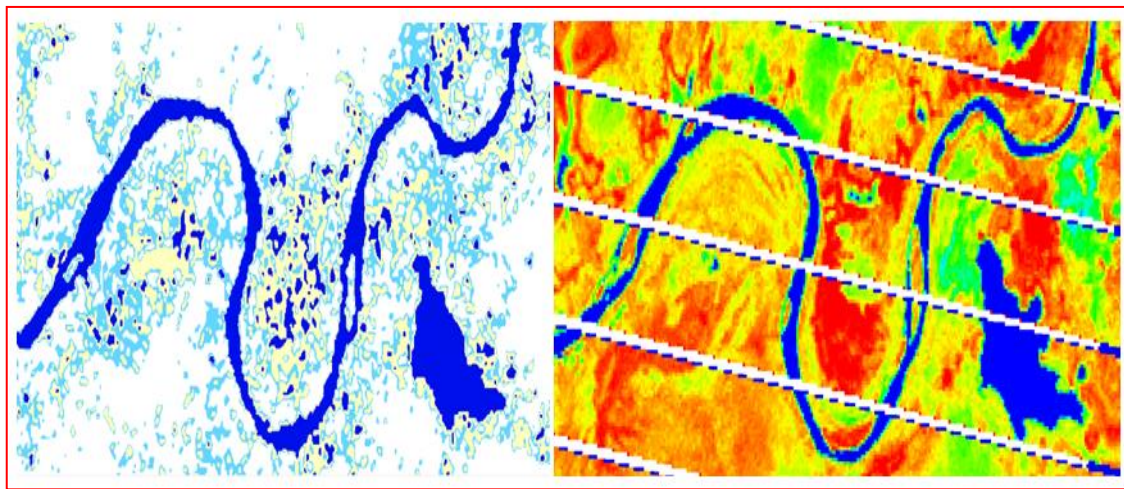
4.4.2 HEC-RAS Model Validation

In this Thesis works, the satellite imagery of good resolution for flood event (27 August 2008) was downloaded LANDSAT 7geotiff image of Band-4 and Bans-5 for analysis of Normalized Difference Water Index (NDWI).

Normalized Difference Water Index (NDWI) used for both calibration and validation in which events of (21, August 2005 and 27 August 2008) were compared with HEC-RAS flood extent results of 7 years (1999-2005) and 3 years (2006-2008) respectively. The figure shows the general frame work of calibration and validation of HEC-RAS model using flood events of different periods.

Normalize Difference Water Index (NDWI) is used for the water body analysis. The index uses Green (Band-2) and near infra-red (Band-4) bands of remote sensing images. The NDWI can develop water information efficiently in most cases. It is sensitive to build-up land and result in over-estimated water bodies.

Inundated flood extent of the same year about 96% of the areas are overlapped and this indicates that the inundated food extent obtained from HEC-RAS was promised and therefore it is validated according to NDWI map of flood extent during the event according to[38].



a) Inundated Flood extent of simulated (1999-2005) b) Image of Flood Extent (27 August 2008) (NDWI)

Figure 4-30: Comparison of Simulated inundation map and flood extent

4.5 Real Time Forecasting at time-days ahead

To form an effective, real-time flood forecasting system, the basic structures need to be connected in an organized manner. This requires: (a) providing specific rainfall forecasts (both quantity and timing) using Weather Research and Forecasting; (b) establishing a network of to compute the inputs to convert to floods and depths and (c) flood forecasting model software connected to real time to get the result we need as transformation tool. Since the main objective of real time flood forecasting is knowing the flood impending and related time ahead, in this study three short term forecasting scenarios were presented at 3-days, 7-days and 10-days ahead and the depth of flood (inundation map) related to these forecasting scenarios were presented

also. In order to improve the real time forecasting of foods, this paper proposes a short-term forecasting scenarios for 3, 7 and 10-days ahead are presented. The objective of this study is to present an ANN-based real-time forecasting model to improve predictions of both flood and depth of the flood, and also to find the corresponding leading time in terms of providing both high accuracy and satisfactory performance.

For this study area the lead-time obtained in the development of the forecasting model is from 1 to 3 h in each short-term forecasting developed. The reliability of forecasting results will build confidence in the forecasting model that is developed.

4.5.1 Short term forecasting scenarios of early warning

Once the ANN model is trained and validated to forecast flood, then forecasted rainfall and temperature at a head time obtained from NMSA are given to the ANN model to obtain stream flow at the different a head time based on the input time scenarios, in this study 3-days, 7-days and 10-days forecasted rainfall an temperature data were used to generate stream flow at same time scenarios (3-days, 7-days and 10-days).

For this case the forecasted real time data started from May 27, 2019 to May 29, 2019 G.C for both rainfall and temperature. After running HEC-RAS at three hour (3-hr) hydrograph computation time, the result of HEC-RAS model for each time scenarios revealed that, for the flood coming at three, seven and ten days ahead have magnitude of 1402.97 m³/s, 353.68 m³/s and 179.52 m³/s. According to these results no need to warn the habitants or residents of Itang area since it showed any risk since the maximum depth of water inundated the area for the time scenarios could not show any damage when compared to the common water depth seen in the area. The detail results for flood projections under RCP8.5 climate change scenarios for the three periods (decades) are indicated in figures 4.38 to 4:43.

Figure 4-31: Flood forecasted at 3, 7 and 10-days ahead with depth range

Time window	Time scenarios	Leading time	Flood depth
May 27-29, 2019	3-days ahead	May 28, 2019 09:00PM	0.00-0.52 (m)
May 27-June 2, 2019	7-days ahead	June 1, 2019 03:00AM	0.00-24 (m)
May 27- June 5, 2019	10-days ahead	June 3, 2019 12:00 PM	0.00-0.82 (m)

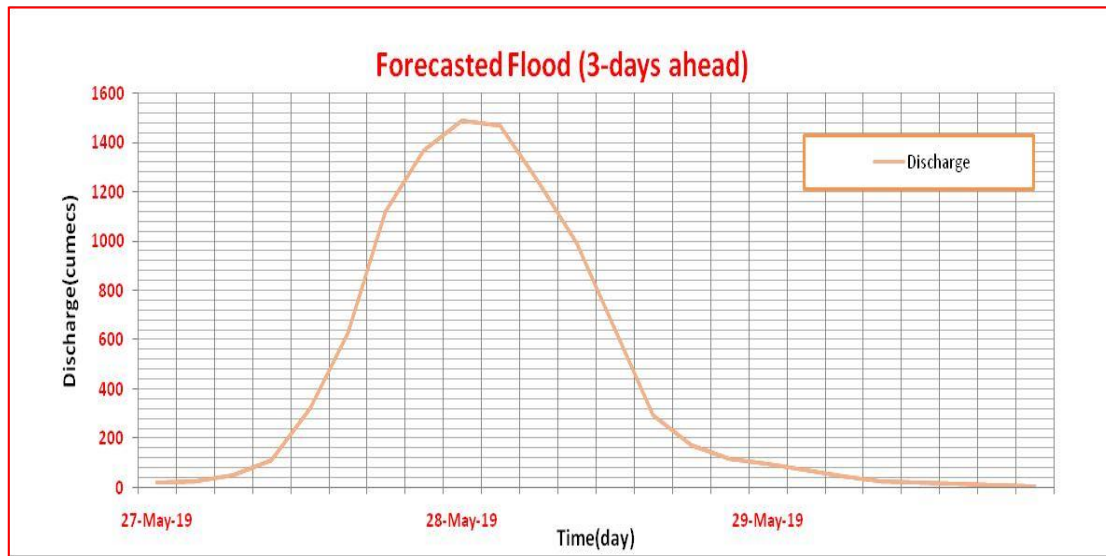


Figure 4-32: Forecasted flood or Discharge for 3-days ahead

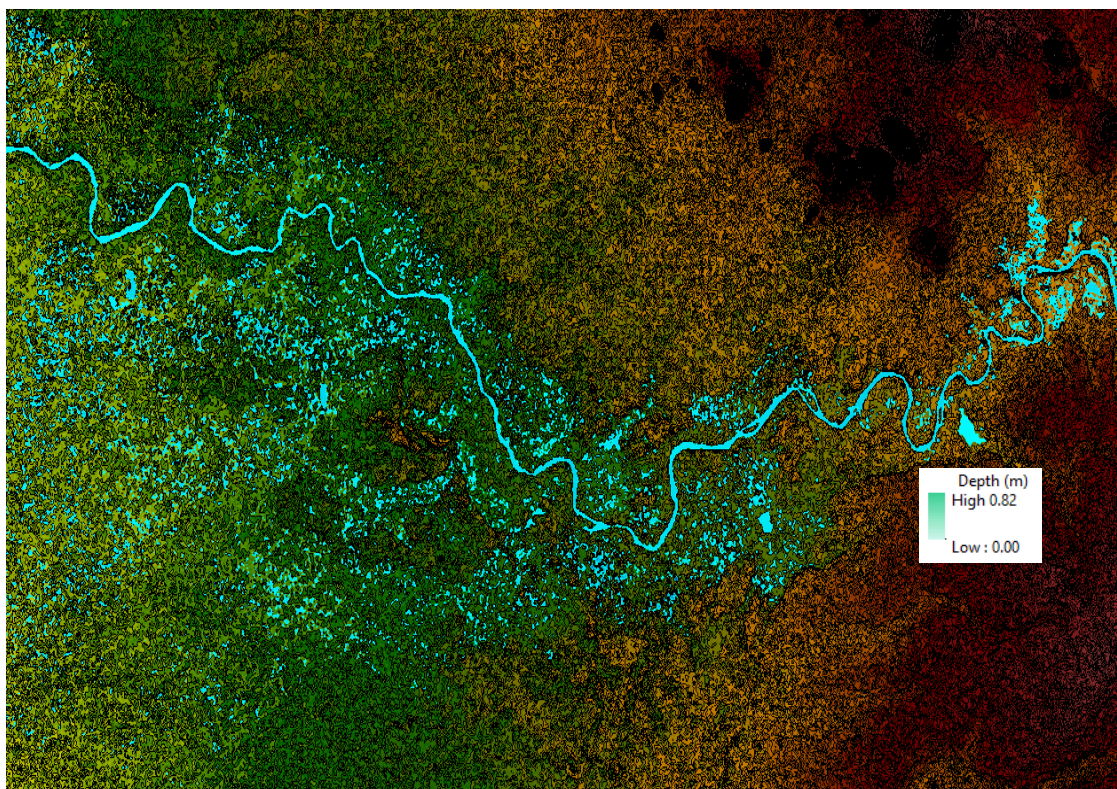


Figure 4-33: Flood inundation map for 3-days head flood forecasted

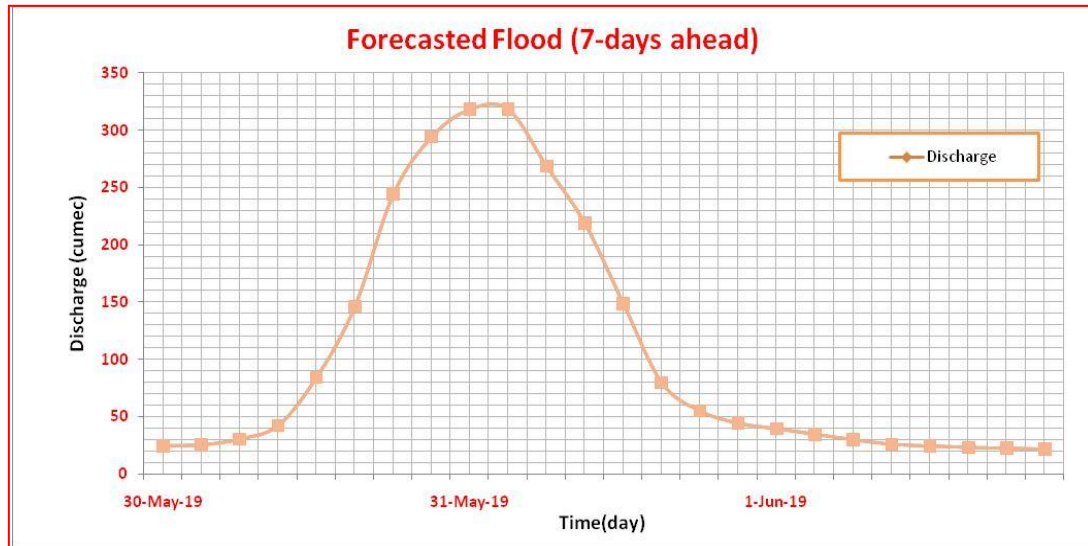


Figure 4-34: Forecasted flood or Discharge for 7-days ahead

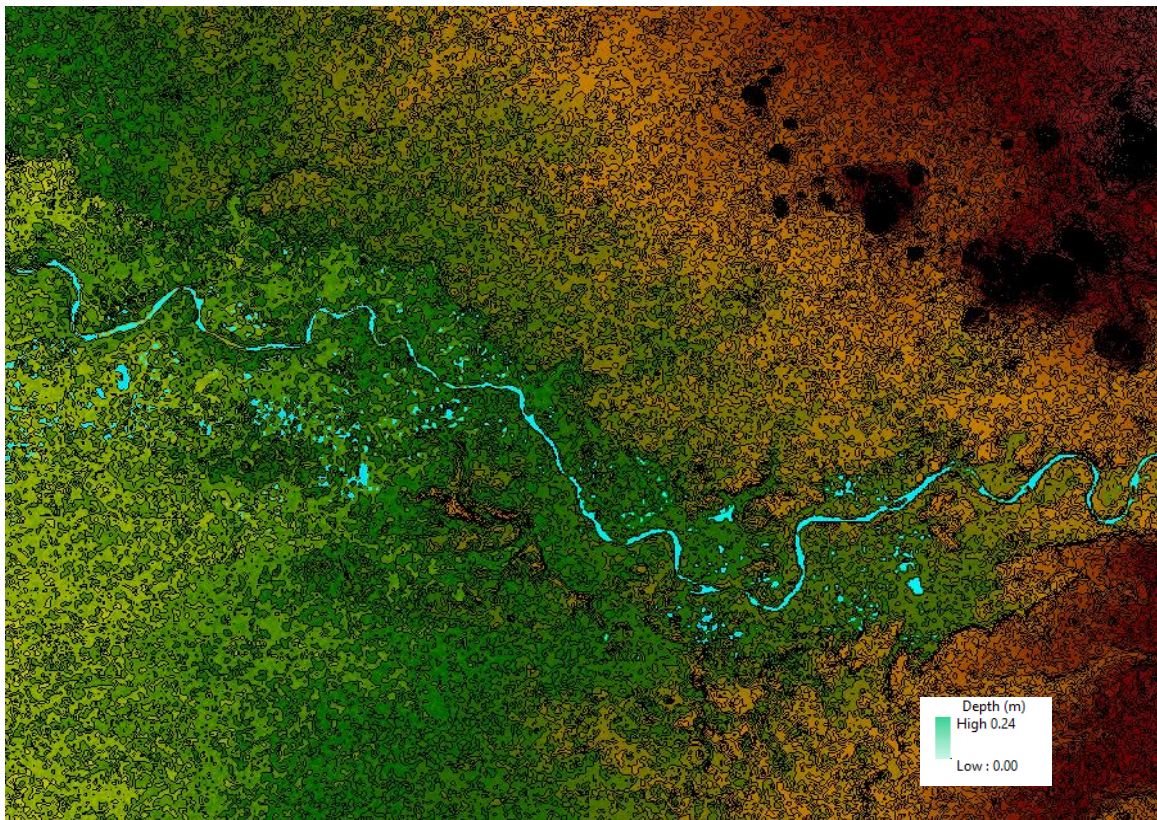


Figure 4-35: Flood inundation map for 7-days head flood forecasted

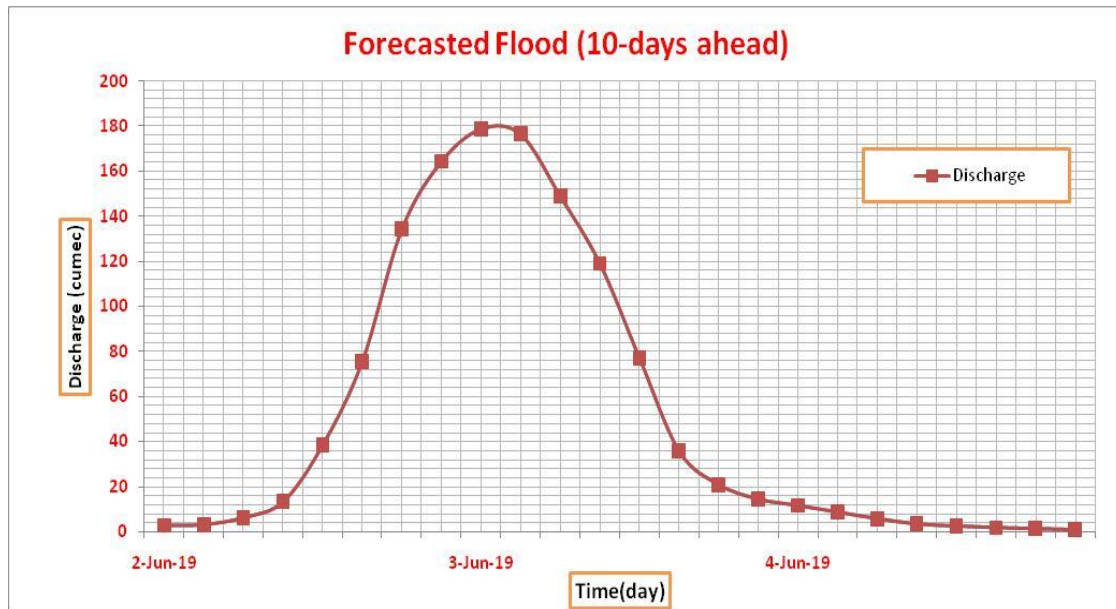


Figure 4-36: Forecasted flood or Discharge for 7-days ahead

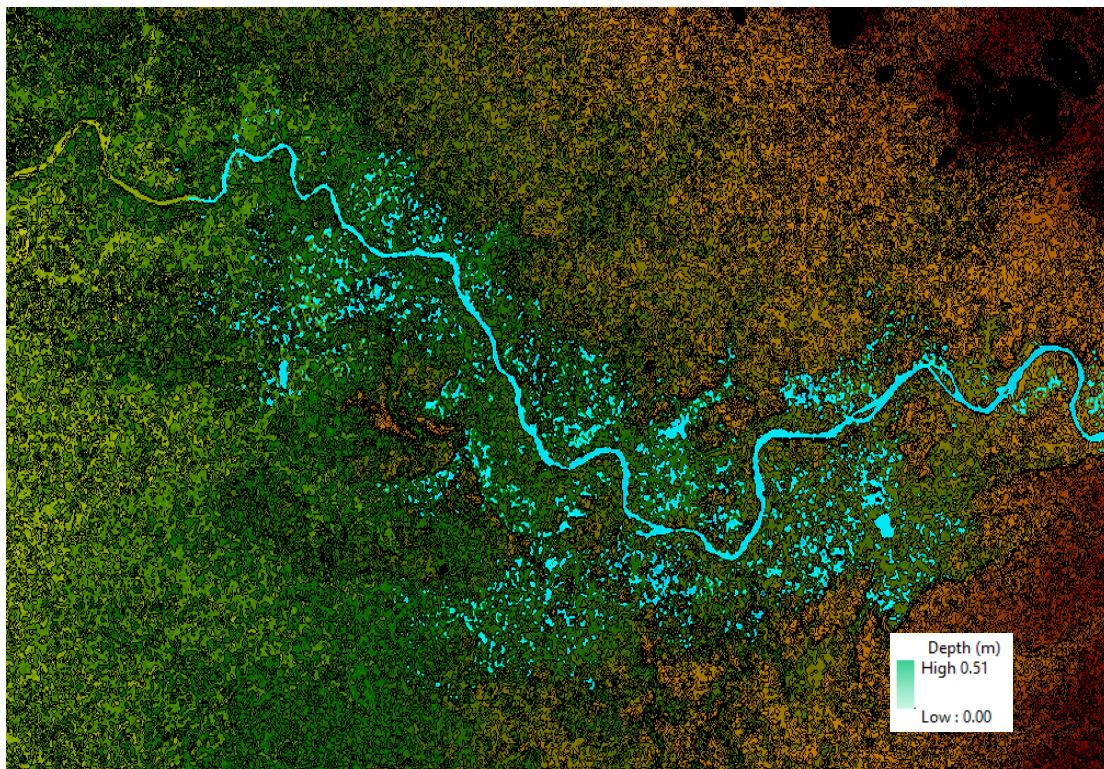


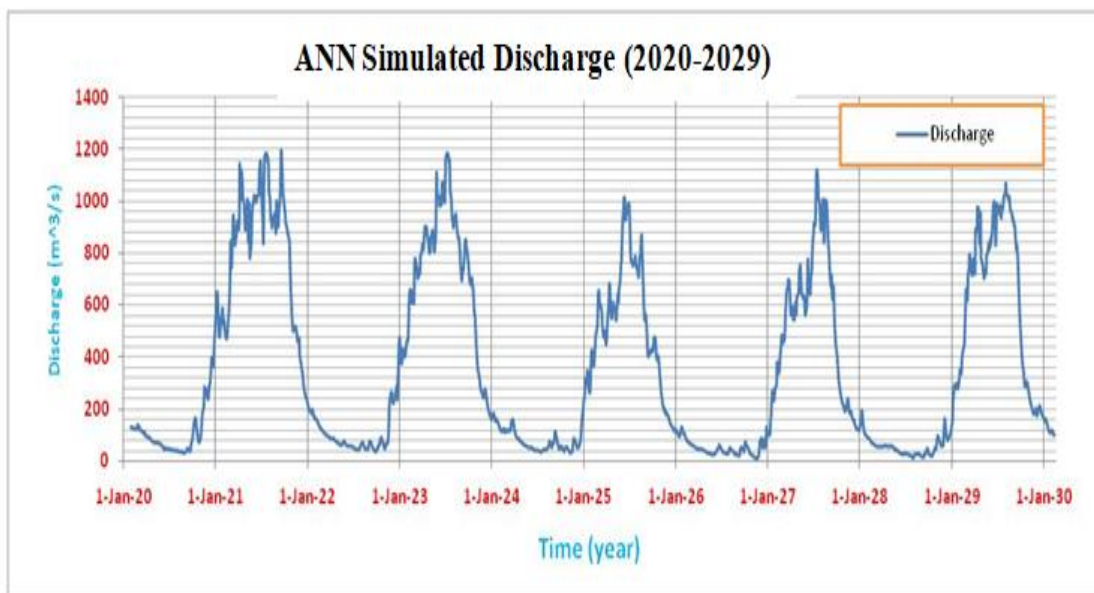
Figure 4-37: Flood inundation map for 10-days head flood forecasted

4.6 Climate change scenarios

4.6.1 Climate Scenario

In flood management prediction climate change is core issue and to prepare future flood risk areas 30-years climate scenarios were developed with three 2020-2029, 2030-2039 and 2040-2050 decadal categories. To prepare data for CMhyd gauges or observed data are saved in individual files, all of which are listed in a location file. Separate location files are required for precipitation and temperature. The NAME fields in the location files point to the corresponding data files and the fields LAT and LON specify the location of the gauges. In the data files, the first line is reserved for the starting date of the time series, while each of the following lines represents one day. The data file names have to match the names specified in the NAME field of the location file. All files have the extension txt to be readable for the software

According to these projected values of stream flow for next 30 years, the maximum values of stream flow of first 10, 20 and 30 years are $1189.42\text{m}^3/\text{s}$, $1374.57\text{m}^3/\text{s}$, $1855.39\text{m}^3/\text{s}$ respectively. Flood prone areas of these stream flow the area (Itang) will have the probability to be damaged and the details of these results for each climate scenarios for the next 30 years were summarized on the table below.



Figure

4-38:Figure: stream flow projected for the next 10-years

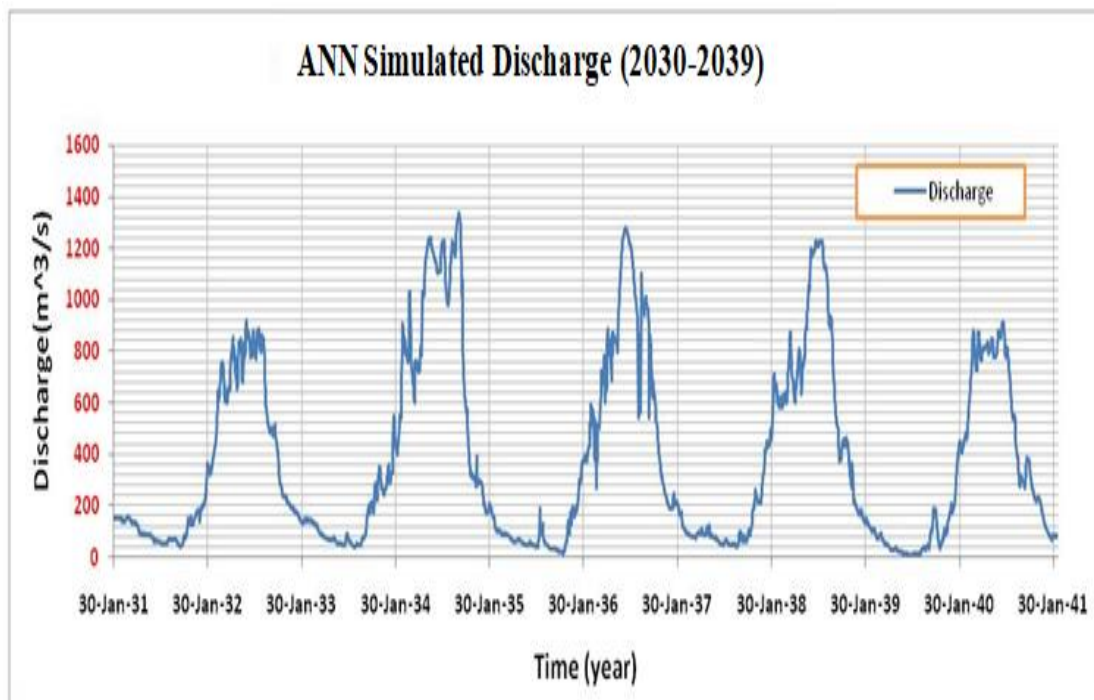


Figure 4-39: stream flow projected for the next 20-years

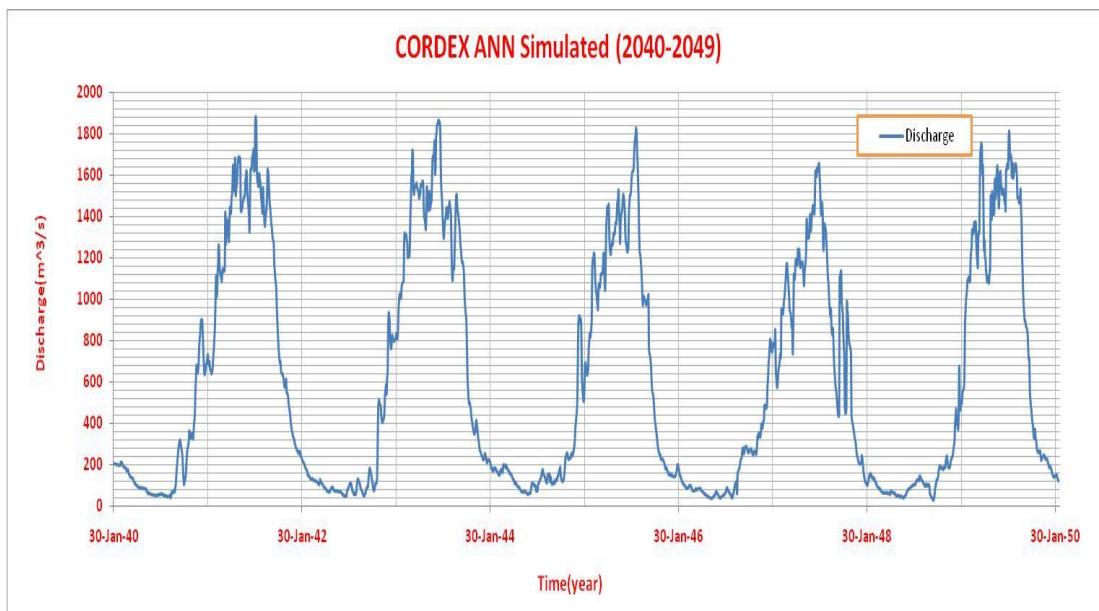


Figure4-40: stream flow projected for the next 30-years

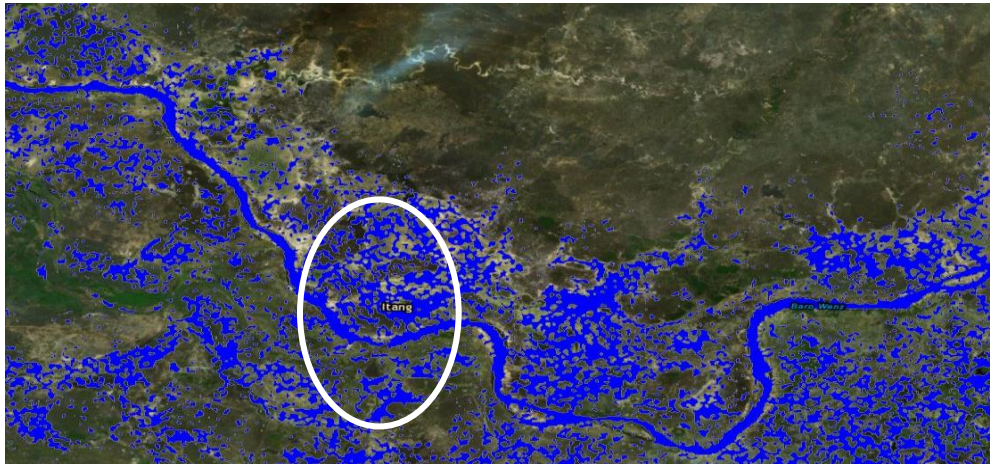


Figure4-41: Flood prone area for the next 10-years (2020-2029)



Figure4-42: Flood prone area for the next 20-years (2030-2039)

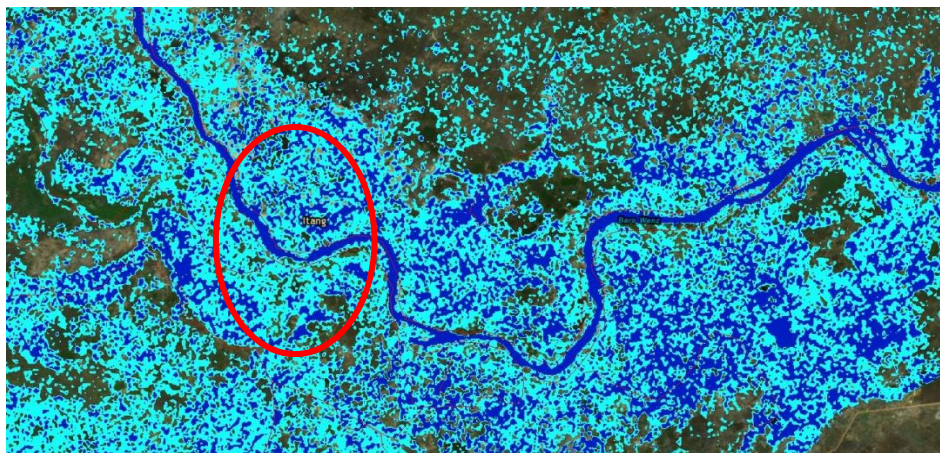


Figure4-43: Flood prone area for the next 30-years (2040-2049)

5. CONCLUSION

This thesis work tried to cover hydrological and hydraulic modeling using Artificial Neural Networks (ANN) and HEC-RAS respectively. ANN model for this specific work revealed that the techniques are powerful for Real time flood forecasting. The ANN forecasting model tried to integrate the deterministic and stochastic concepts of the hydrological analysis with taking Rainfall, Temperature, and Topographic Wetness Index (TWI) as major inputs and random weights of the neurons as stochastic variables. The iterative training nature of the ANN process also support it to capture the reality easily.

The hydrological modeling calibrated, through training of the ANN using backpropagation for 7 years (1999-2005) daily datasets (Precipitation, Temperature and Topographical Wetness Index) in R studio and validated using another 3 years (2006-2008) daily datasets with trained values of weights. It is very good performance justified with NSE values of 0.85 and 0.87 for training (calibration) and validation respectively. Similarly, the hydraulic model also calibrated and validated using flood extent of events recorded on August 21, 2005 and August 27, 2008 respectively. Above 95% overlapping of the computed flood affected area with observed flood area in the events, justified the ability of the model to capture the reality.

The real time forecasting capacity of the model also verified by using 3, 7 and 10 days forecasted rainfall and temperature on May 27, 2019 to June 5, 2019 and floods were forecasted at Real time ahead of 3, 7 and 10-days with maximum Discharges of 1402.97 m³/s, 353.68 m³/s and 179.52 m³/s respectively and flood inundation maps these three floods were also generated, resulting that the maximum of the flood depths were 0.82m, 0.24m and 0.51m respectively.

In addition the flood prone areas for the next three decades in relation with different climate change scenarios also identified using the model to warn the downstream communities and development investments in the area. Finally, the study wanted to conclude that the flood forecasting system developed with the integration ANN-HECRAS as hydrological and hydraulics modeling, to be a state-of-art flood forecasting system to warn inhabitants and development investments in flood prone areas.

6. RECOMMENDATIONS

This study was confined with one type ANN architecture (feedforward) and one training algorithm (Backpropagation) only. Several other neural network architectures, such as **Recurrent Neural Networks** could also be modifying ANN result. It is also possible to use different training algorithms, because the result of any ANN model can be modified through changing either neural network architectures or using different training algorithms such as conjugate and Levenberg-Marquardt algorithms to increase the accuracy of the model further. Generally, the following points are forwarded:

- ❖ As flood prone areas of climate change scenarios revealed that some areas will probably be damaged , therefore, early warning system should be established to cope the community
- ❖ Even if training of Artificial Neural Networks (ANN) needs a large data size, only 7 years daily data were used due to data scarcity, and increasing the data size it possible the training performance of the ANN model

7. REFERENCES

- [1] M. Woube, “Flooding and sustainable land-water management in the lower Baro-Akobo river basin, Ethiopia”, *Appl. Geogr.*, vol 19, no 3, bll 235–251, 1999.
- [2] S. K. Jain *et al.*, “A Brief review of flood forecasting techniques and their applications”, *Int. J. River Basin Manag.*, vol 16, no 3, bll 329–344, 2018.
- [3] M. Mimikou, H. Skaltsas, en T. Methanis, “A real-time flood forecasting technique”, *Water Int.*, vol 9, no 3, bll 127–135, 1984.
- [4] D. T. Mai en F. De Smedt, “A combined hydrological and hydraulic model for flood prediction in Vietnam applied to the Huong river basin as a test case study”, *Water (Switzerland)*, vol 9, no 11, 2017.
- [5] R. Society, “Advances in Real-Time Flood Forecasting Author (s): Peter C . Young Source : Philosophical Transactions : Mathematical , Physical and Engineering Sciences , Vol . 360 , No . 1796 , Flood Risk in a Changing Climate (Jul . 15 , 2002), pp . 1433-1450 Pub”, vol 360, no 1796, bll 1433–1450, 2016.
- [6] M. E. A. Dr. Alemseged Tamiru, Dr. Negash Wagesho, “Impact of Flooding on Human Settlement in Rural”, 2014.
- [7] A. Ababa, “Flood Alert # 4”, no August, 2018.
- [8] L. Y. Worku, “Climate change impact on variability of rainfall intensity in the Upper Blue Nile Basin”, *IAHS-AISH Proc. Reports*, vol 366, no June 2014, bll 135–136, 2015.
- [9] A. Mosavi, P. Ozturk, en K. W. Chau, “Flood prediction using machine learning models: Literature review”, *Water (Switzerland)*, vol 10, no 11, bll 1–40, 2018.
- [10] M. Campolo, A. Soldati, en P. Andreussi, “Artificial neural network approach to flood forecasting in the River Arno”, *Hydrol. Sci. J.*, vol 48, no 3, bll 381–398, 2003.
- [11] S. A. Moges, “Flood forecasting and early warning system (FFEWS). An alternative technology for flood management system and damage reduction in Ethiopia: A concept Note”, bll 36–41, 2007.
- [12] E. O. Sciences en D. G. Gunbi, “Flood Forecasting and Early Warning System for the Upper Awash River Basin , Gora Floodplain of Ethiopia”, 2013.
- [13] A. Thomas, “An introduction to neural networks for beginners”, *Clin. EEG Neurosci.*, vol 26, no 3, bll 180–183, 1995.
- [14] S. Mandal en S. Mondal, *Statistical approaches for landslide susceptibility assessment and prediction*. 2018.
- [15] B. A. Malmgren en U. Nordlund, “Application of artificial neural networks to chemostratigraphy”, *Paleoceanography*, vol 11, no 4, bll 505–512, 1996.
- [16] ASCE, “Task Committee on Application of Artificial Neural Networks in Hydrology, Artificial Neural Networks in Hydrology. II:Hydrologic Application”, *J. Hydrol. Eng.*, vol 5, no 2, bll 124–136, 2000.
- [17] “Artificial Neural Networks in Hydrology”, vol 36, 2000.
- [18] A. Y. Shamseldin, “Artificial neural network model for river flow forecasting in a developing country”, *J. Hydroinformatics*, vol 12, no 1, bll 22–35, 2009.
- [19] C. W. DAWSON en R. WILBY, “An artificial neural network approach to rainfall-runoff modelling”, *Hydrol. Sci. J.*, vol 43, no 1, bll 47–66, 2010.

- [20] K. Thirumalaiah en M. C. Deo, “Real-Time Flood Forecasting Using Neural Networks”, vol 13, bll 101–111, 2017.
- [21] IPCC, *Climate change 2014. Synthesis report. Versión inglés*. 2014.
- [22] M. M. Saab *et al.*, “The effect of adult Early Warning Systems education on nurses’ knowledge, confidence and clinical performance: A systematic review”, *J. Adv. Nurs.*, vol 73, no 11, bll 2506–2521, 2017.
- [23] W. Bewket, “Climate change perceptions and adaptive responses of smallholder farmers in central highlands of Ethiopia”, *Int. J. Environ. Stud.*, vol 69, no 3, bll 507–523, 2012.
- [24] W. Schlenker *et al.*, “Determinants of African farmers’ strategies for adapting to climate change: Multinomial choice analysis”, *Environ. Manage.*, vol 114, no 1, bll 83–104, 2010.
- [25] USAID, “Learning from Experience EVALUATION”, *Administrator*, no January, 2011.
- [26] H. T. Tran, “RENEWABLE ENERGY IN VIETNAM NEED , STATUS QUO AND POTENTIAL FOR NEED , STATUS QUO AND POTENTIAL”, no March, 2018.
- [27] R. H. Moss *et al.*, “The next generation of scenarios for climate change research and assessment”, *Nature*, vol 463, no 7282, bll 747–756, 2010.
- [28] G. P. Wayne, “The Beginner’s guide to Representative Concentration Pathways (RCPs)”, *SkepticalScience*, no August, bll 1–24, 2013.
- [29] K. Riahi *et al.*, “RCP 8.5-A scenario of comparatively high greenhouse gas emissions”, *Clim. Change*, vol 109, no 1, bll 33–57, 2011.
- [30] C. Teutschbein en J. Seibert, “Is bias correction of regional climate model (RCM) simulations possible for non-stationary conditions”, *Hydrol. Earth Syst. Sci.*, vol 17, no 12, bll 5061–5077, 2013.
- [31] “Engineering Hydrology-Subramanya.pdf”. .
- [32] K. K. L. B. Adikaram, M. A. Hussein, M. Effenberger, en T. Becker, “Data Transformation Technique to Improve the Outlier Detection Power of Grubbs’ Test for Data Expected to Follow Linear Relation”, *J. Appl. Math.*, vol 2015, bll 1–9, 2015.
- [33] K. Tsakiri, A. Marsellos, en S. Kapetanakis, “Artificial neural network and multiple linear regression for flood prediction in Mohawk River, New York”, *Water (Switzerland)*, vol 10, no 9, 2018.
- [34] Y.-T. Chang, J. Lin, J.-S. Shieh, en M. F. Abbod, “Optimization the Initial Weights of Artificial Neural Networks via Genetic Algorithm Applied to Hip Bone Fracture Prediction”, *Adv. Fuzzy Syst.*, vol 2012, bll 1–9, 2012.
- [35] A. Lee, Z. Geem, en K.-D. Suh, “Determination of Optimal Initial Weights of an Artificial Neural Network by Using the Harmony Search Algorithm: Application to Breakwater Armor Stones”, *Appl. Sci.*, vol 6, no 6, bl 164, 2016.
- [36] K. S. Cheng, Y. T. Lien, Y. C. Wu, en Y. F. Su, “On the criteria of model performance evaluation for real-time flood forecasting”, *Stoch. Environ. Res. Risk Assess.*, vol 31, no 5, bll 1123–1146, 2017.
- [37] F. Approved en O. M. B. No, “HEC-RAS River Analysis System 2D Modeling User ’ s Manual”, no February, 2016.
- [38] A. Enea *et al.*, “Remote sensing , gis and hec-ras techniques , applied for flood extent validation , based on landsat imagery , lidar and hydrological data . Case study : Baseu river , Romania LANDSAT IMAGERY , LIDAR AND HYDROLOGICAL DATA .”, no November, 2018.

Real-Time Flood Forecasting Using Artificial Neural Networks (ANN) and Flood Inundation Mapping

2019

8. APPENDICES

Appendices A: Rainfall Data used in the study (after quality check)

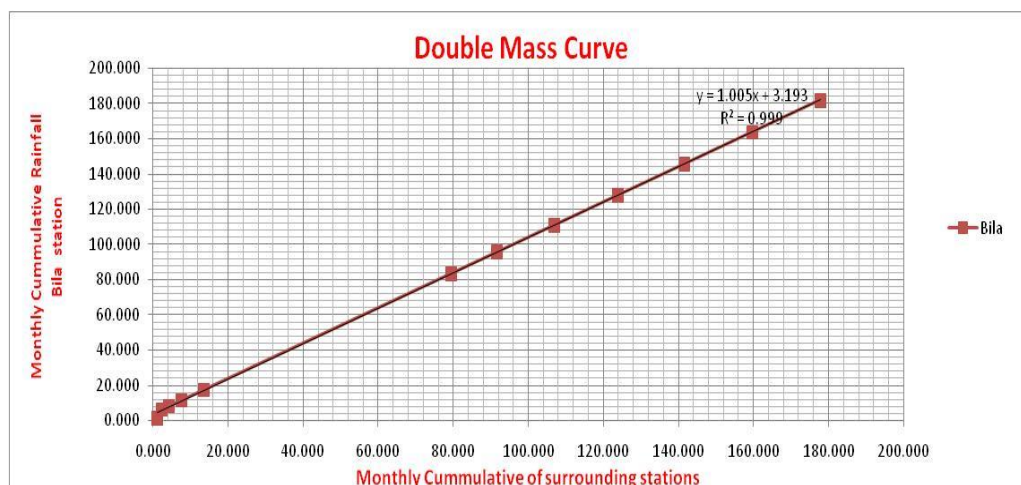
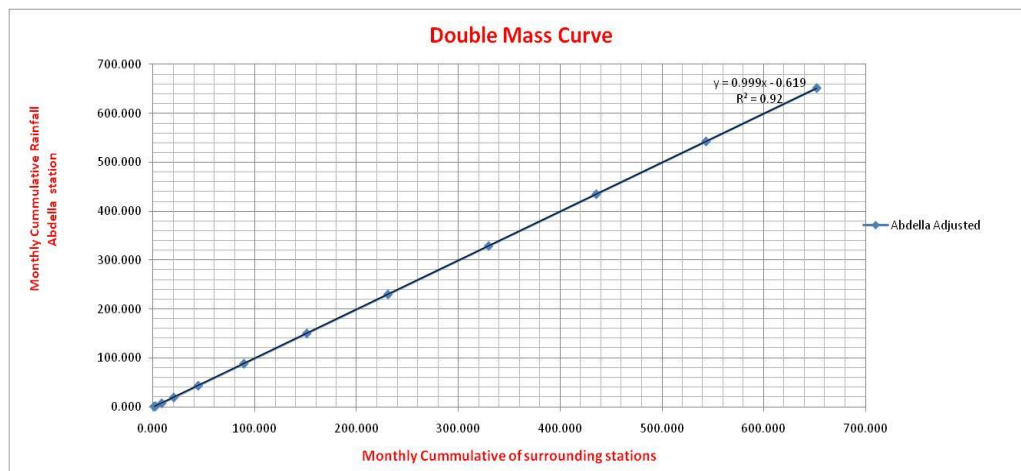
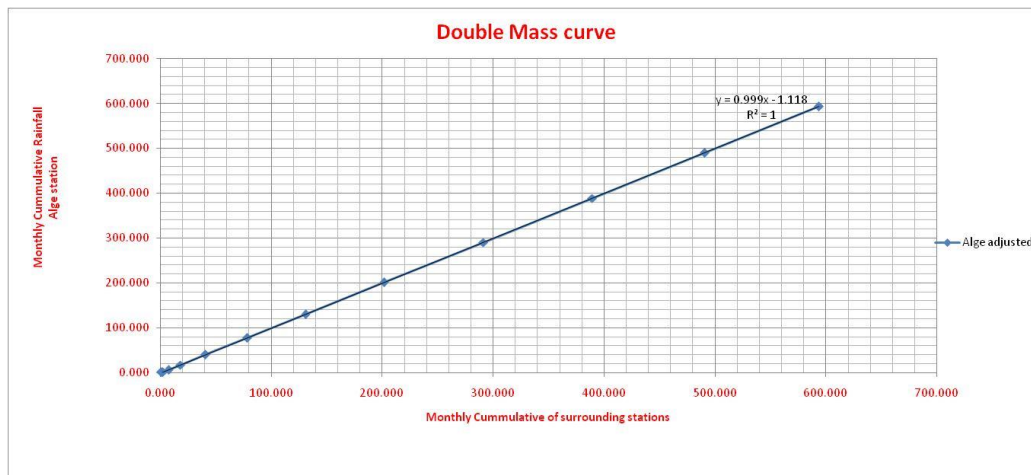
Alge																									
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	
0	0.0	0.0	0.0	8.5	41.0	20.0	24.0	8.0	6.0	2.5	0.1	0.0	0.0	0.0	0.0	0.0	0.0	8.0	14.0	10.0	1.0	4.6	0.0	0.0	
0	0.0	0.0	0.0	3.5	12.2	0.1	3.8	3.9	6.2	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	8.0	0.0	1.2	3.5	5.2	0.0	0.0	
0	0.0	0.0	0.0	0.0	0.0	11.5	1.2	3.5	9.0	16.5	0.0	0.0	0.0	0.0	0.0	0.0	1.5	3.0	6.0	40.3	20.0	0.2	0.0	0.0	
0	0.0	0.0	0.0	0.0	14.0	0.3	3.0	0.3	12.0	3.8	1.5	0.0	0.0	0.0	0.0	0.0	4.5	12.0	23.0	7.5	8.0	11.0	0.1	0.0	
0	0.0	0.0	0.0	0.0	26.0	1.2	8.9	4.1	5.0	12.5	16.0	0.0	0.0	0.0	0.0	2.6	0.0	2.8	2.6	1.0	1.5	32.0	0.0	0.0	
0	0.0	0.0	0.0	0.0	3.7	16.7	3.5	40.0	30.0	16.0	0.0	0.0	0.0	0.0	0.0	1.8	0.0	0.5	9.7	23.5	4.5	23.0	10.0	5.0	0.0
0	0.0	0.0	0.0	0.0	11.0	12.5	0.1	0.4	0.0	4.0	0.0	2.5	0.0	0.0	0.0	0.0	0.0	3.0	17.0	0.4	2.0	3.5	0.0	11.0	0.0
0	0.0	0.0	0.0	0.0	17.0	0.0	0.0	1.3	2.5	5.0	6.0	2.7	0.0	0.0	0.0	0.0	0.0	17.5	5.7	0.0	12.0	5.5	5.0	3.5	0.0
0.6	0.0	0.0	0.9	5.5	0.0	5.0	7.0	0.0	15.5	0.0	1.9	0.0	1.0	0.0	0.0	0.0	2.0	9.0	0.0	14.0	16.4	1.7	0.0	0.0	
0.1	0.0	0.0	0.0	27.0	0.0	18.5	5.5	4.6	16.0	0.0	0.1	0.0	0.0	0.0	0.0	20.0	4.5	8.8	8.0	30.0	1.7	1.2	0.0	0.0	
2	0.0	0.0	2.1	12.5	6.0	6.8	0.9	3.5	0.0	0.0	4.0	0.0	0.0	0.0	0.0	11.5	11.5	0.0	0.0	2.0	30.8	12.8	1.0	0.0	
5.3	0.0	0.0	2.5	1.0	31.7	0.0	0.6	8.0	0.5	0.0	0.4	0.0	0.0	0.0	0.0	2.5	3.5	10.0	5.5	0.0	34.2	30.2	15.0	0.0	
0	0.0	0.0	0.0	5.0	0.7	3.5	20.0	9.5	29.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	14.5	24.6	4.5	18.0	5.5	2.0	1.2	9.0	
0	0.0	0.0	4.5	9.9	6.0	7.0	6.0	10.6	2.0	0.2	0.0	0.0	0.0	0.0	0.0	18.0	11.3	11.7	1.2	8.5	6.0	7.5	0.0	0.0	
0	0.0	0.0	1.8	2.0	6.8	30.0	27.0	6.0	1.6	0.0	0.0	0.0	0.0	0.0	0.0	1.2	5.0	13.6	13.5	30.0	5.2	0.2	1.2	0.0	
0	0.0	0.0	5.7	7.0	19.1	0.2	1.5	0.0	13.0	0.0	0.0	0.0	0.0	0.0	0.0	26.0	0.2	11.0	4.5	4.0	5.4	8.0	16.0	0.0	
0	0.0	0.0	1.6	0.2	14.0	0.3	7.0	4.0	23.8	0.0	0.0	0.0	0.0	0.0	0.0	13.0	6.0	6.9	16.2	1.2	21.6	0.0	0.4	0.0	
0	0.0	0.0	0.0	1.5	1.8	7.1	7.5	22.0	8.0	0.0	1.3	0.0	0.0	0.0	0.0	0.2	12.0	9.0	35.0	12.5	0.0	2.3	0.0	0.0	
10.9	0.0	0.0	8.0	11.0	13.0	6.8	3.5	4.5	2.0	0.2	0.6	0.0	0.0	0.0	0.0	35.0	0.0	1.2	7.2	59.0	2.0	0.3	0.0	0.0	
0	2.2	0.0	0.0	8.5	3.2	0.0	0.0	29.3	3.0	0.0	0.0	0.0	0.0	0.0	0.0	35.5	2.1	0.5	0.0	1.5	14.0	21.0	0.0	0.0	
0	1.2	0.0	0.0	5.2	1.0	4.6	0.6	7.0	7.6	0.0	0.0	0.0	0.0	0.0	0.0	0.1	11.0	13.0	8.9	21.4	3.0	0.5	0.0	0.0	
0	0.0	0.0	3.2	14.5	0.0	0.4	13.4	1.5	0.2	0.0	0.0	0.0	0.0	0.0	0.0	13.5	0.2	10.2	4.0	0.0	0.0	1.3	0.0	0.0	
0	5.0	0.0	0.0	21.0	8.0	1.2	0.6	34.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.5	20.0	1.8	0.0	0.0	8.0	3.5	8.0	0.0	
0	2.8	0.0	19.0	0.0	3.4	1.0	12.5	7.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.2	2.0	8.2	9.0	11.2	8.0	17.0	0.2	0.0	0.0
0	0.0	0.0	8.5	0.1	0.1	8.0	18.5	1.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.2	3.2	4.0	6.5	14.0	3.2	10.3	20.0	0.0	0.0
0	6.5	0.0	24.0	31.0	14.5	5.2	5.7	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	11.2	3.0	27.3	0.2	27.2	0.0	0.0	
0	0.0	0.0	0.0	3.2	10.5	32.0	2.0	15.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	3.5	0.0	3.8	14.0	4.6	4.0	0.0	0.0	0.0	
0	0.0	0.0	0.0	23.6	2.4	0.2	22.6	5.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0	2.0	40.5	20.5	0.3	1.4	34.0	29.4	0.0	0.0	
0	0.0	0.0	1.5	3.5	1.2	3.5	16.2	17.5	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	12.0	8.5	0.0	1.8	5.0	0.4	0.0	0.0	
0	0.0	0.0	14.0	5.0	8.0	25.0	14.0	20.8	11.2	0.2	1.0	0.0	0.0	0.0	0.0	0.0	5.6	1.7	0.0	10.0	1.5	0.0	0.0	0.0	
0	0.0	0.0	0.0	19.7	0.0	0.2	0.0	0.0	2.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	12.5	0.0	1.5	1.5	0.0	0.0	0.0	0.0	
2001	0.0	0.0	0.0	0.0	0.0	3.5	0.0	3.8	1.0	0.3	1.5	0.0	2002	0.0	0.0	16.8	0.3	6.0	16.0	0.0	13.5	7.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	6.8	0.0	20.0	13.0	17.0	0.5	0.0		7.5	0.0	0.0	3.5	6.2	1.0	23.0	7.5	24.0	0.2	2.0	0.0
	0.0	0.0	0.0	2.8	0.0	23.0	15.6	7.0	8.0	0.0	0.0	0.0		17.0	0.0	0.0	0.6	0.0	7.1	2.0	0.5	42.0	0.0	0.2	0.7
	0.0	0.0	0.0	10.5	0.0	12.6	9.7	10.0	4.0	5.5	0.0	0.0		0.0	0.0	0.0	2.7	0.0	21.8	51.0	3.2	1.5	1.2	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	2.0	0.0	3.2	12.0	1.5	0.0	0.0		0.0	0.0	0.0	1.2	0.0	1.2	11.0	44.0	0.2	8.5	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.0	20.2	11.7	0.0	0.0		0.0	0.0	0.0	4.0	0.0	0.2	5.0	1.5	0.0	0.5	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	3.5	0.0	0.8	9.0	0.0	0.0	30.0		0.0	0.0	0.0	0.0	0.0	8.8	7.2	4.2	4.5	38.2	0.0	4.0
	0.0	0.0	0.0	0.0	0.0	8.0	0.5	27.5	8.8	10.0	0.0	20.1		1.0	0.0	0.0	24.0	0.0	23.2	3.5	0.0	1.8	0.0	0.0	2.0
	0.0	0.0	0.0	0.0	5.5	4.0	0.8	9.0	28.0	5.0	8.0	0.0		0.0	0.0	0.0	0.1	1.2	19.3	25.2	0.0	4.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	8.0	4.5	5.0	22.0	0.0	0.0	0.0		0.0	0.0	0.0	0.0	1.5	0.5	1.0	14.5	14.0	0.0	0.0	0.0
	0.0	0.5	0.0	0.0	7.5	5.0	3.8	3.5	25.2	2.5	0.0	0.0		35.0	0.0	0.0	0.0	0.0	1.0	1.5	12.0	16.2	0.0	0.0	0.0
	0.0	1.0	0.0	0.0	7.3	2.5	5.0	3.0	30.2	4.5	0.0	0.0		1.5	1.3	1.0	0.0	0.0	0.3	0.8	0.0	10.5	0.3	0.0	0.0
	0.0	10.0	0.0	0.0	7.8	1.5	25.8	27.2	10.0	6.0	0.0	0.0		11.0	0.0	0.0	0.0	0.0	33.4	3.2	30.0	20.8	1.5	0.0	12.0
	0.0	0.0	0.0	0.0	23.6	0.6	4.5	19.0	9.8	4.0	0.0	0.5		16.3	0.0	15.2	0.0	6.5	3.0	3.7	0.0	11.2	8.6	0.0	0.0
	0.0	0.0	0.0	0.0	32.0	11.0	0.0	1.5	0.0	0.0	0.0	0.0		0.0	0.0	2.0	0.0	10.2	0.0	0.0	8.5	17.0	0.0	0.2	0.0
	0.0	0.0	15.5	0.0	8.0	22.8	0.5	8.0	3.2	16.0	0.0	0.0		0.0	0.0	3.7	0.0	38.0	4.0	0.0	16.2	2.1	0.0	0.2	2.7
	0.0	0.0	6.0	0.0	30.3	14.0	7.4	23.3	5.0	0.0	0.0	0.2		0.0	0.0	0.0	0.0	0.0	36.0	10.7	12.5	13.0	0.0	0.0	0.0
	0.0	0.0	3.5	0.0	20.4	1.7	7.5	4.6	27.8	8.0	0.0	0.0		0.0	0.0	0.0	0.0	0.0	0.0	6.0	1.2	12.1	16.0	0.0	0.0
	0.0	0.0	0.0	5.1	6.5	5.5	5.0	0.0	25.0	6.0	0.0	0.0		0.0	0.0	0.5	16.0	0.0	19.3	2.0	0.2	12.5	7.2	0.0	1.7
	0.0	0.0	1.4	12.5	1.8	30.2	12.0	21.2	32.3	0.0	7.0	0.0		0.0	1.8	0.0	20.1	0.0	18.5	16.0	3.0	10.8	1.5	0.0	2.0
	0.8	0.0	7.5	2.0	0.0	6.0	10.2	41.5	2.5	8.5	13.5	0.0		0.0	0.0	0.0	0.0	0.0	0.0	5.5	27.8	18.0	0.3	0.0	0.0
	0.0	0.0	8.5	0.0	1.0	60.2	2.8	0.6	4.0	3.0	0.0	0.0		0.0	0.0	13.0	0.0	0.0	0.4	10.0	8.5	8.0	2.6	0.0	0.0
	0.0	0.0	0.0	0.0	31.0	24.3	16.0	4.0	7.8	2.5	0.3	0.0		0.0	0.0	7.1	0.0	0.0	1.0	48.0	7.5	5.0	0.0	0.0	0.0
	0.0	0.8	0.0	26.0	11.5	10.2	6.5	3.8	10.5	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.0	6.2	3.5	18.0	11.0	0.0	0.0
0.0	0.0	0.0	0.0	6.7	7.0	27.0	3.2	15.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	12.1	2.5	2.0	1.2	0.0	0.0	0.0		
0.0	0.0	0.0	30.1	18.5	0.0	13.8	0.2	0.0	14.8	0.0	0.0	0.0	0.0	0.0	0.0	3.2	0.3	5.0	12.0	0.8	0.0	0.0	0.0		
0.0	7.0	0.0	9.5	7.8	5.2	6.5	2.5	4.0	0.0	0.0	33.5	0.0	1.5	0.0	16.0	0.0	3.3	3.0	12.5	23.5	36.8	0.0	0.		

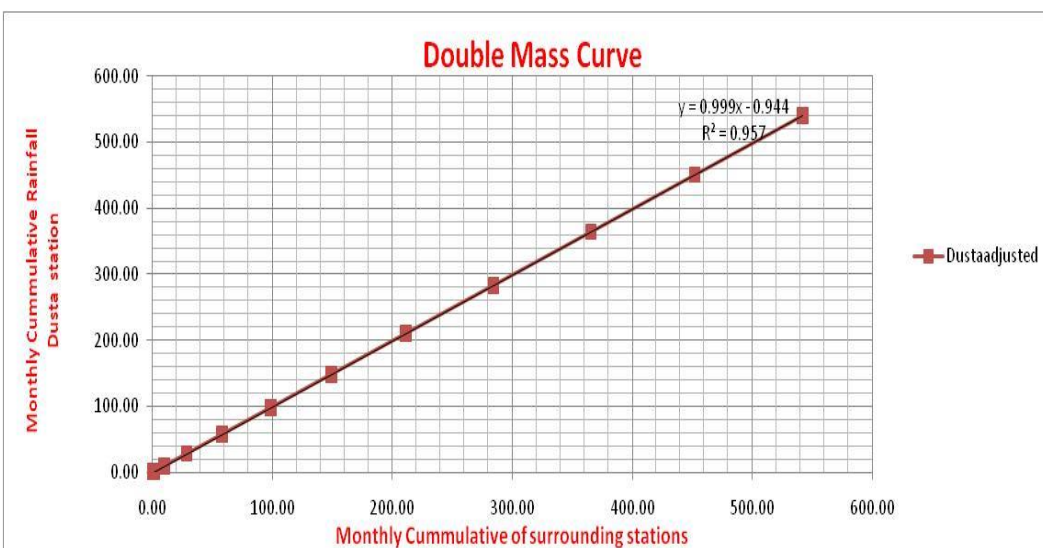
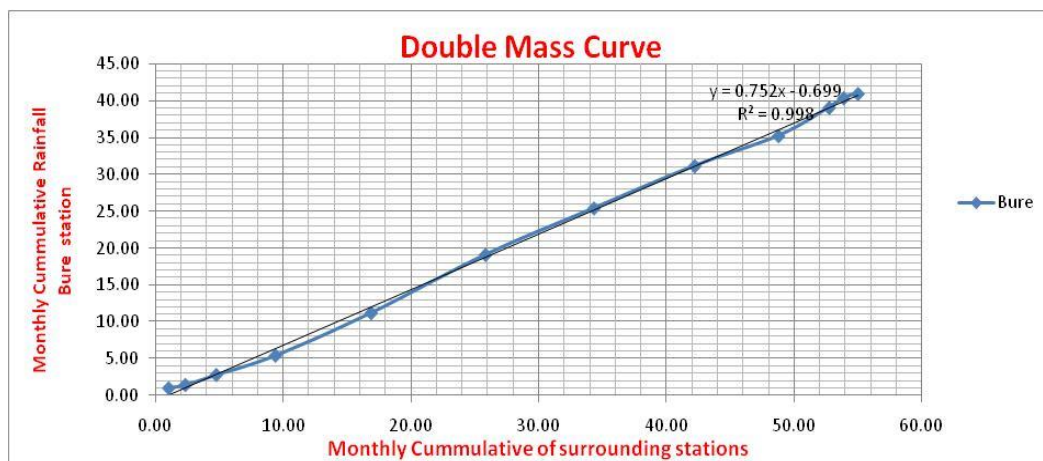
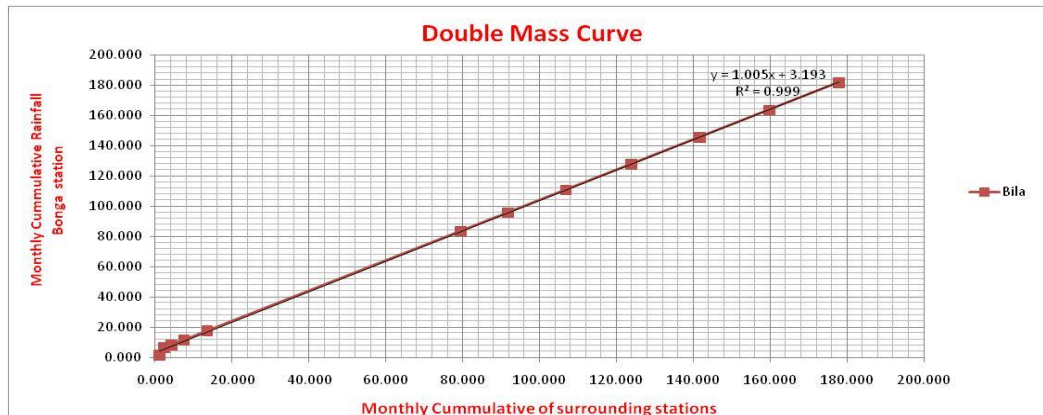
Real-Time Flood Forecasting Using Artificial Neural Networks (ANN) and Flood Inundation Mapping

2019

2003	0.0	0.0	0.1	59.0	0.0	1.6	0.0	0.0	28.2	2.4	0.0	2.0
	0.0	0.0	0.0	8.8	0.0	28.0	9.0	53.0	9.5	3.0	0.0	0.0
	0.0	0.0	9.0	0.0	3.0	0.0	7.0	12.2	14.2	4.2	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	10.8	1.7	4.0	2.0	0.2	0.0	1.5
	0.0	0.0	0.0	0.0	0.0	8.0	0.0	2.8	10.5	0.0	0.0	16.0
	0.0	0.0	0.0	0.0	0.0	3.0	33.0	16.8	0.8	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	2.8	3.2	32.2	5.0	21.0	0.0	0.0
	0.0	0.0	0.0	0.5	0.0	15.0	0.8	5.7	5.5	3.0	0.0	6.0
	0.0	0.0	12.0	0.0	0.0	0.9	18.0	10.0	2.5	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	18.0	8.5	6.8	15.0	0.0	4.5	0.6
	0.0	0.0	0.0	31.5	0.0	8.2	8.0	0.0	8.0	1.0	26.0	0.0
	0.0	0.0	0.0	0.0	0.0	11.5	12.0	3.0	1.5	2.2	0.0	0.0
	0.0	0.0	0.0	0.5	0.0	21.0	67.0	13.5	4.5	10.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	3.0	0.5	2.0	4.0	11.0	0.0	0.0
	0.0	0.0	1.5	0.0	0.8	0.4	7.0	9.5	36.0	0.3	0.0	0.0
	0.0	0.0	2.0	0.0	6.0	0.2	8.5	1.5	2.1	1.0	0.0	0.0
	0.0	0.0	1.5	0.0	10.4	1.5	16.0	5.4	0.0	0.0	0.0	0.0
	0.0	0.5	6.8	0.0	3.8	8.4	2.0	23.0	10.0	0.2	0.0	0.0
	0.0	1.5	10.2	3.5	3.0	10.9	2.1	4.5	2.0	0.2	0.0	0.0
	0.0	0.0	5.0	0.5	2.0	33.6	3.0	1.5	6.5	5.2	0.0	0.0
	0.0	7.0	0.0	0.3	26.0	6.8	2.8	0.7	3.0	0.3	0.0	0.0
	0.0	2.0	0.0	0.2	1.5	0.1	1.5	4.5	27.0	0.0	0.0	0.0
	0.0	15.5	0.0	0.0	2.0	5.8	18.0	47.5	10.5	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	6.0	10.5	32.8	1.5	36.0	0.0	0.0	0.0
	0.0	1.5	2.7	0.0	0.0	1.3	0.0	5.5	24.2	0.0	0.0	0.0
	0.0	2.0	0.0	0.0	0.0	15.7	3.2	2.0	10.5	0.0	0.0	0.0
	0.0	1.2	0.3	0.0	0.0	1.2	1.8	3.2	8.0	0.0	0.0	0.0
	0.0	27.0	0.0	0.0	27.2	5.2	7.5	20.0	28.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	6.0	0.6	2.5	2.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	1.5	0.0	12.0	36.8	0.0	0.5	0.0
	0.0	0.0	0.0	0.0	0.0	3.5	0.0	0.5	0.0	0.0	0.0	0.0
2004	0.0	0.0	0.0	0.0	20.0	14.0	23.0	61.2	0.0	2.5	20.8	0.0
	0.0	0.0	0.0	0.0	0.0	14.5	11.3	0.0	25.2	10.0	1.0	0.0
	0.0	0.0	0.0	0.0	0.0	7.5	9.5	0.0	47.3	2.4	1.5	0.0
	0.0	0.0	0.0	0.0	2.5	0.0	18.0	5.0	2.5	6.0	2.8	3.5
	0.0	0.0	0.0	35.0	0.0	10.0	5.5	4.5	12.0	27.2	0.8	0.0
	0.0	0.0	0.0	1.0	0.0	11.0	10.0	30.0	9.0	5.5	0.0	0.0
	0.0	0.0	0.0	12.0	0.0	0.6	40.2	2.5	27.1	32.0	0.0	0.0
	0.0	4.5	0.0	12.5	0.2	0.0	13.5	0.4	6.5	10.1	0.0	0.3
	0.0	0.0	0.0	0.0	1.5	5.6	6.5	1.0	0.0	1.2	5.3	0.0
	0.0	0.0	0.0	0.0	20.0	13.5	24.0	5.0	29.2	7.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	2.0	4.0	9.0	12.5	1.0	0.0	0.0
	7.0	0.0	0.0	0.0	4.0	4.5	0.2	1.2	2.7	40.0	0.0	0.0
	0.0	0.0	0.0	0.0	25.0	15.0	12.0	46.2	18.0	4.5	0.0	0.0
	0.0	0.0	0.8	0.0	17.5	4.0	25.0	8.0	30.0	20.5	0.0	0.0
	0.0	0.0	0.0	0.0	12.0	5.0	7.5	1.5	5.4	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	7.2	0.0	0.0	25.2	12.2	0.0	5.0	0.0
	0.0	0.0	0.0	0.0	0.0	1.0	0.2	0.0	15.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	8.0	3.0	24.0	12.5	0.0	14.5	0.0
	0.0	0.0	2.5	0.0	0.0	0.5	0.3	40.4	13.0	0.0	0.0	0.0
	0.0	0.0	0.0	15.0	8.5	0.6	5.5	3.5	18.2	0.0	32.0	0.0
	0.0	0.0	0.5	0.0	30.0	2.0	1.5	5.4	21.0	0.0	0.0	0.0
	0.2	0.0	0.0	0.0	20.0	9.0	2.0	6.1	8.5	0.0	0.0	0.0
	0.0	0.0	2.5	20.0	4.4	1.5	0.0	10.0	10.0	0.0	0.0	0.0
	0.0	0.0	14.5	6.4	0.2	27.0	17.5	52.3	42.1	0.0	10.0	0.0
	0.0	0.0	1.4	18.0	21.2	48.0	0.0	29.3	13.8	0.0	50.0	0.0
	0.0	6.0	0.0	1.5	35.2	18.0	18.0	40.0	3.5	0.0	0.0	0.0
	0.0	0.0	3.5	0.0	10.8	5.2	0.0	1.5	1.6	12.5	0.0	0.0
	0.0	0.0	0.0	0.0	18.0	30.0	0.0	10.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	2.0	4.0	9.5	17.0	5.8	2.6	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	16.5	16.0	0.5	10.2	32.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	8.5	0.0	56.0	59.0	0.0	11.0	0.0	0.0
2005	0.0	0.0	0.0	0.0	0.0	0.0	10.0	4.5	15.5	4.0	5.0	0.3
	0.0	0.0	0.0	0.0	0.0	0.0	17.0	1.2	1.6	2.8	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	22.0	7.5	3.3	20.4	1.2	0.0	0.4
	0.0	0.0	0.0	0.0	0.0	0.0	4.5	22.0	2.3	0.0	16.0	5.0
	0.0	0.0	0.0	0.0	0.0	7.5	3.8	20.0	13.0	2.7	18.2	0.2
	0.0	0.0	0.0	0.0	0.0	1.8	29.0	12.0	3.5	1.8	4.6	0.5
	0.0	0.0	0.0	0.0	0.0	0.0	11.5	0.3	1.8	0.0	2.5	0.0
	0.0	0.0	0.0	0.0	0.0	0.0	16.5	12.6	29.0	9.5	0.8	0.0
	0.0	0.0	0.0	0.0	0.0	0.0	1.5	8.7	8.2	23.2	0.0	0.0
	0.0	0.0	10.0	0.0	0.0	0.0	0.3	13.0	0.0	0.5	4.6	0.0
	0.0	0.0	0.0	0.0	0.0	0.0	15.6	0.5	20.0	12.5	2.2	0.0
	0.0	0.0	3.5	0.0	0.0	0.0	21.0	12.0	22.0	1.8	0.6	0.0
	0.0	0.3	20.0	0.0	0.0	0.0	0.0	2.3	0.0	0.0	0.0	0.0
	5.0	0.0	23.0	1.5	0.0	0.0	1.0	5.1	11.0	10.0	0.0	0.0
	0.0	0.0	6.3	0.0	0.0	0.0	28.0	6.0	10.5	0.8	0.2	0.0
	8.5	0.0	5.8	0.0	0.0	0.0	3.0	9.2	3.0	20.2	0.0	0.0
	13.0	0.0	6.0	0.0	0.0	0.0	0.0	8.3	0.0	30.0	0.0	0.0
	0.0	0.0	9.5	0.0	0.0	0.0	1.5	1.6	0.0	0.0	5.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0	2.4	6.2	55.0	0.0	0.0	32.0
	0.0	0.0	24.5	0.0	0.0	0.0	0.0	50.4	0.0	16.7	2.5	7.0
	0.0	0.0	1.0	0.0	0.0	0.0	17.6	1.2	0.0	34.0	1.2	30.0
	0.0	0.0	1.5	10.4	21.0	20.0	6.4	0.5	10.3	0.0	0.0	0.0
	0.0	1.0	23.0	1.2	5.0	0.8	1.6	0.0	18.0	10.0	0.0	0.0
	0.0	0.0	0.0	0.0	4.0	2.5	23.6	7.5	11.0	0.2	0.0	0.0
	0.0	0.0	0.0	0.0	37.2	4.2	0.5	10.2	7.2	0.0	0.0	0.0
	0.0	0.0	1.5	0.0	0.0	2.5	0.0	17.0	20.0	0.0	0.0	0.0
	0.0	0.0	0.0	5.2	16.0	6.0	22.0	0.0	10.0	3.0	0.0	0.0
	0.0	0.0	0.0	1.5	0.0	14.5	0.8	8.2	0.6	5.5	0.0	0.0
	0.0	0.0	0.0	0.0	2.0	0.2	20.0	16.2	0.0	1.5	0.0	0.0
	0.0	0.0	0.0	0.0	2.1	5.0	4.5	8.0	17.3	0.0	6.0	0.0
	0.0	0.0	0.0	0.0	0.0	9.5	0.0	6.5	19.0	2.5	7.2	0.0

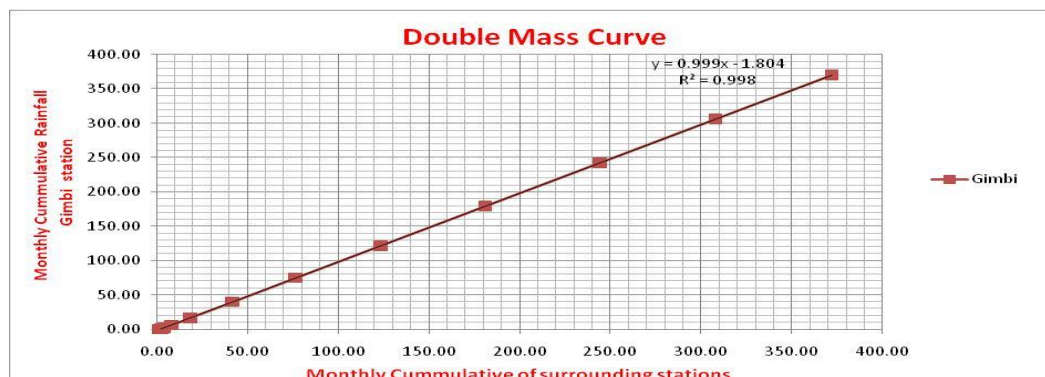
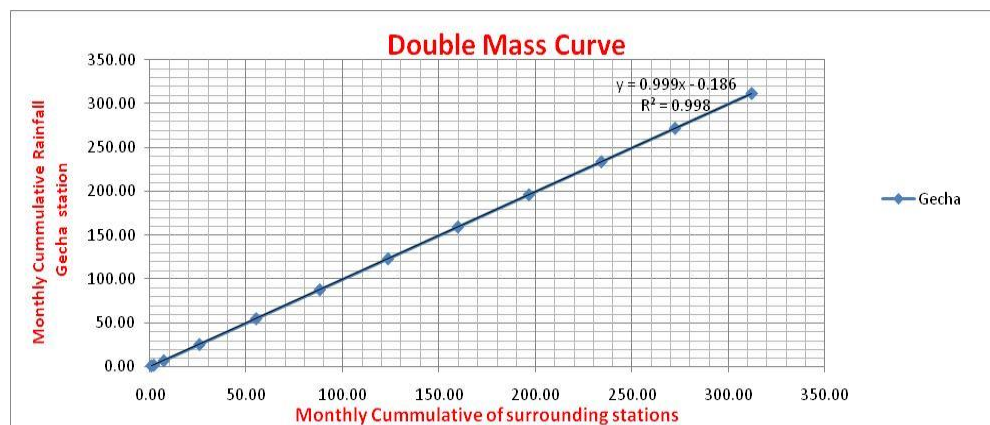
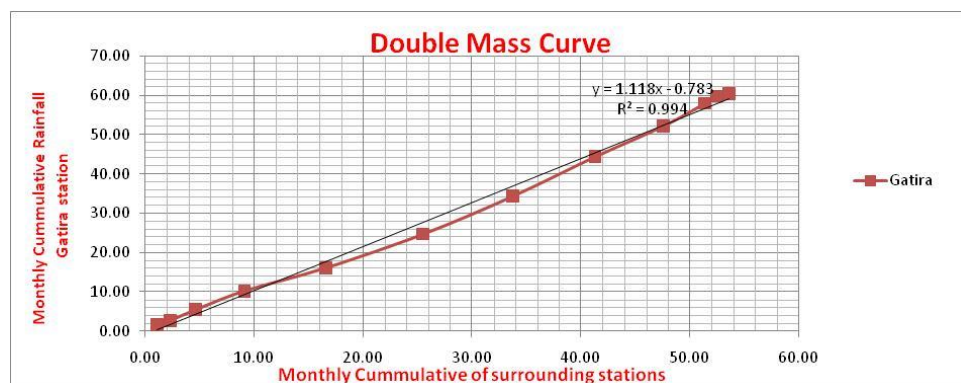
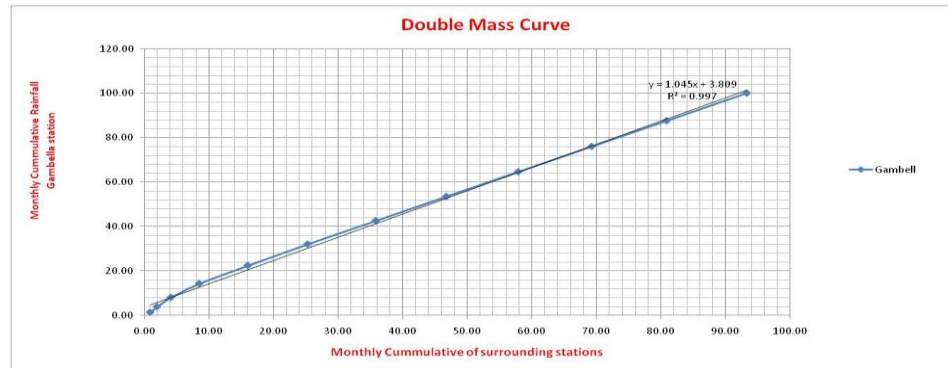
Appendices B: Double Mass Curves for all Rainfall stations

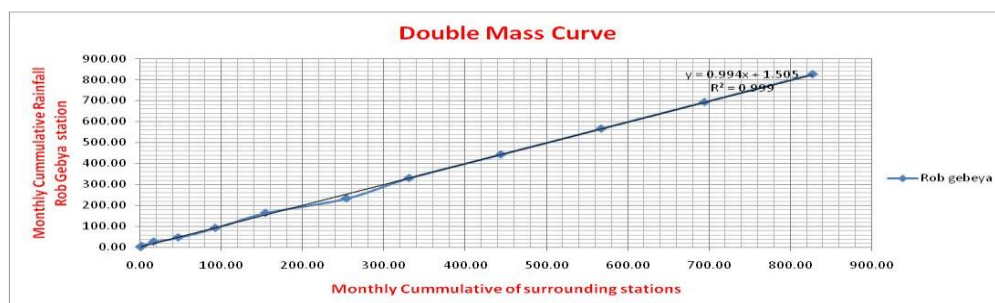
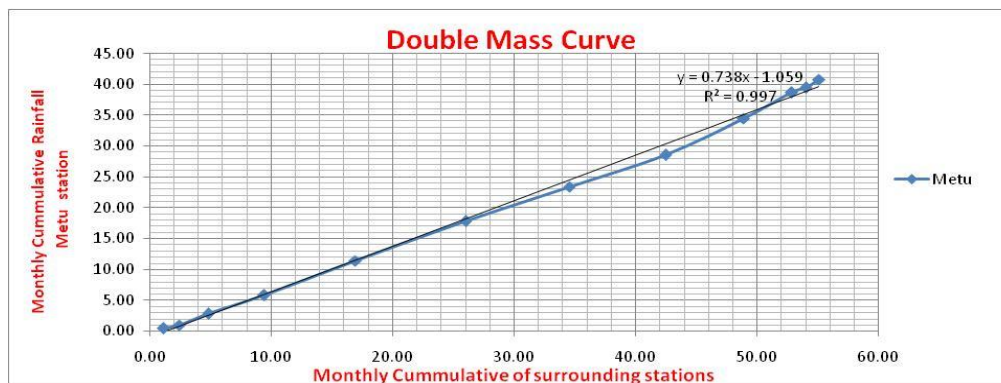
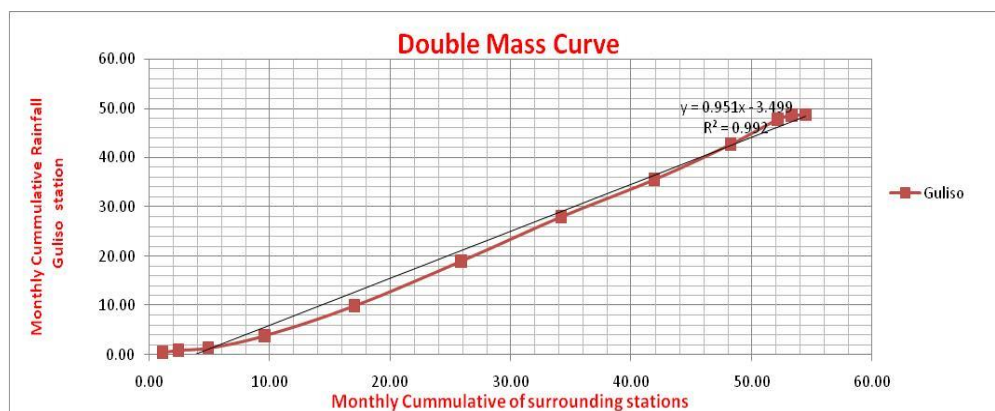
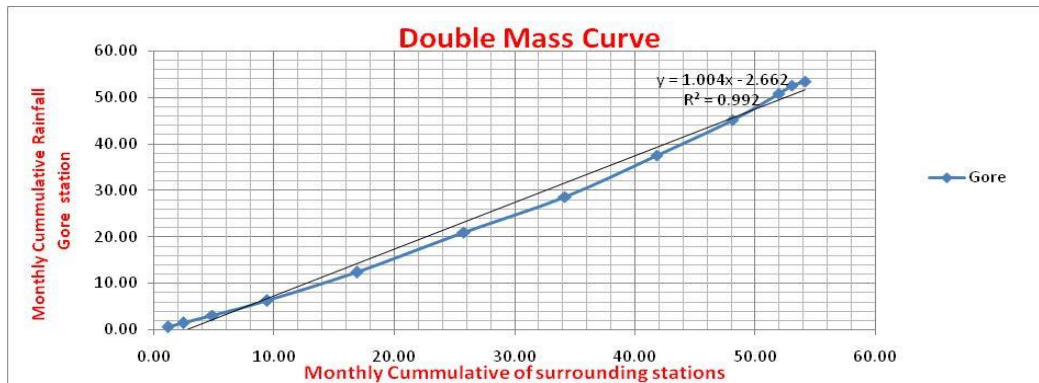




Real-Time Flood Forecasting Using Artificial Neural Networks (ANN) and Flood Inundation Mapping

2019





Real-Time Flood Forecasting Using Artificial Neural Networks (ANN) and Flood Inundation Mapping

2019

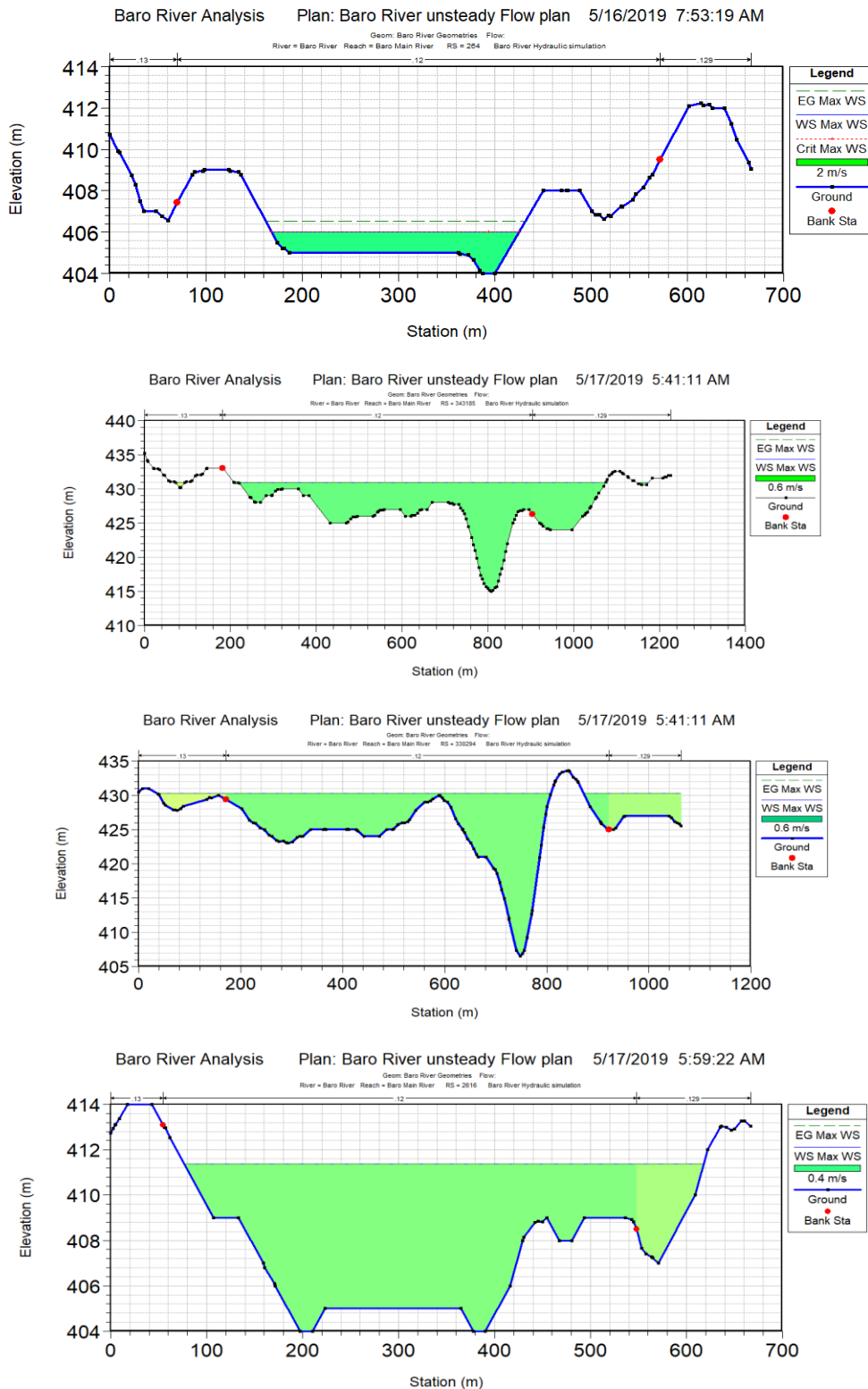
Appendices C: River Geometries Baro River at different stations

	River stations	Length	River	Reach	Length LOB	Length Channel	Length ROB	Left Bank	Right Bank
1	347543	742.20	Baro River	Baro Main River	863.20	891.50	939.80	152.90	604.20
2	343185	677.99	Baro River	Baro Main River	637.80	647.00	742.20	127.50	582.90
3	340622	734.29	Baro River	Baro Main River	1033.60	964.80	857.90	127.90	557.40
4	337680	673.51	Baro River	Baro Main River	494.40	489.50	490.20	111.40	528.90
5	335287	659.09	Baro River	Baro Main River	548.40	525.80	501.90	87.80	507.30
6	332590	639.40	Baro River	Baro Main River	710.70	674.20	638.50	76.70	555.80
7	330294	662.99	Baro River	Baro Main River	605.50	634.20	675.90	119.60	586.20
8	328418	649.75	Baro River	Baro Main River	545.70	505.20	470.60	56.70	531.50
9	326364	524.92	Baro River	Baro Main River	692.70	679.10	704.10	79.50	483.60
10	324474	685.73	Baro River	Baro Main River	489.60	563.10	660.90	212.10	626.40
11	322087	716.34	Baro River	Baro Main River	564.10	583.80	646.60	226.20	624.50
12	320000	559.54	Baro River	Baro Main River	552.10	454.50	355.90	96.50	473.30
13	318777	614.52	Baro River	Baro Main River	370.30	336.50	311.30	104.20	502.60
14	317217	732.36	Baro River	Baro Main River	422.10	403.40	405.50	175.60	558.70
15	315036	823.55	Baro River	Baro Main River	805.00	862.50	946.80	257.90	701.00
16	313409	692.24	Baro River	Baro Main River	684.60	735.40	829.70	187.70	572.50
17	311578	576.35	Baro River	Baro Main River	327.20	306.70	288.80	99.80	462.70
18	307713	662.41	Baro River	Baro Main River	599.90	546.60	515.70	147.30	571.00
19	305513	712.55	Baro River	Baro Main River	682.30	765.00	880.80	210.30	606.40
20	304248	632.35	Baro River	Baro Main River	583.50	608.60	644.40	132.90	455.70
21	302077	711.55	Baro River	Baro Main River	428.40	418.60	402.00	116.00	638.10
22	300678	732.86	Baro River	Baro Main River	329.00	329.70	340.10	138.90	578.20
23	298315	664.17	Baro River	Baro Main River	618.80	540.10	485.90	122.30	543.70
24	296220	680.40	Baro River	Baro Main River	755.00	717.70	761.40	66.10	484.70
25	293723	644.71	Baro River	Baro Main River	585.80	629.20	655.80	87.40	528.30
26	291261	691.14	Baro River	Baro Main River	592.90	574.00	552.80	109.50	499.40
27	288601	592.18	Baro River	Baro Main River	634.80	612.10	586.10	114.20	521.60
28	287540	650.08	Baro River	Baro Main River	621.20	604.70	601.00	130.10	558.80
29	285989	659.49	Baro River	Baro Main River	609.50	613.00	624.60	78.00	537.60
30	284645	706.80	Baro River	Baro Main River	362.40	371.80	391.10	160.40	607.80
31	282912	653.09	Baro River	Baro Main River	421.70	405.50	393.90	97.70	512.50
32	281182	632.49	Baro River	Baro Main River	701.20	625.00	533.20	134.50	541.40
33	279437	689.43	Baro River	Baro Main River	526.80	559.20	670.20	140.90	547.10
34	276465	980.72	Baro River	Baro Main River	1015.00	1102.80	1238.10	220.30	890.00
35	273209	769.80	Baro River	Baro Main River	575.50	593.80	619.20	126.70	614.70
36	270684	646.04	Baro River	Baro Main River	290.50	307.80	348.80	112.50	586.80
37	269192	698.91	Baro River	Baro Main River	553.40	560.30	580.90	70.60	560.90
38	267287	852.10	Baro River	Baro Main River	1358.10	1328.50	1325.00	72.90	691.80
39	265767	1226.24	Baro River	Baro Main River	734.70	781.10	833.80	182.30	904.20
40	263901	794.94	Baro River	Baro Main River	399.80	388.70	402.40	159.00	723.00
41	261697	1090.44	Baro River	Baro Main River	946.00	896.60	892.50	132.30	726.70
42	259458	1175.44	Baro River	Baro Main River	683.20	729.50	757.10	167.10	814.90
43	257492	1226.86	Baro River	Baro Main River	706.70	822.00	864.40	216.40	889.70
44	255829	1009.35	Baro River	Baro Main River	704.50	699.80	725.40	147.60	785.20
45	254698	1063.11	Baro River	Baro Main River	594.30	571.80	574.30	171.10	921.30
46	253764	652.73	Baro River	Baro Main River	427.40	402.10	382.70	47.20	490.00
47	252892	1415.53	Baro River	Baro Main River	547.40	626.20	659.20	243.90	1157.80
48	251074	1406.77	Baro River	Baro Main River	612.80	576.00	583.00	258.50	1172.40
49	248983	1296.45	Baro River	Baro Main River	815.10	727.50	657.90	242.40	1072.90
50	247631	1173.34	Baro River	Baro Main River	632.40	636.10	644.80	229.10	1042.30
51	245877	1259.60	Baro River	Baro Main River	418.50	372.90	325.30	147.20	1029.50
52	243612	1080.93	Baro River	Baro Main River	498.20	475.50	435.00	205.20	878.30
53	241269	950.74	Baro River	Baro Main River	708.40	664.90	598.00	234.80	778.20
54	239978	593.34	Baro River	Baro Main River	409.20	403.90	406.80	57.50	539.30
55	238578	953.74	Baro River	Baro Main River	501.60	495.90	508.60	147.40	691.60
56	236494	1013.89	Baro River	Baro Main River	551.50	558.00	585.20	113.40	716.20
57	234994	1509.21	Baro River	Baro Main River	1093.40	1178.10	1302.30	303.40	1259.60
58	233685	1382.05	Baro River	Baro Main River	659.10	670.50	678.50	316.80	1085.00
59	231510	1460.84	Baro River	Baro Main River	390.30	385.50	387.80	327.70	1054.00
60	230217	1549.10	Baro River	Baro Main River	661.30	661.80	620.50	492.00	1173.90
61	228686	731.71	Baro River	Baro Main River	582.80	583.30	587.40	74.10	608.90
62	227270	1174.38	Baro River	Baro Main River	411.90	426.50	458.80	278.50	928.20

Real-Time Flood Forecasting Using Artificial Neural Networks (ANN) and Flood Inundation Mapping

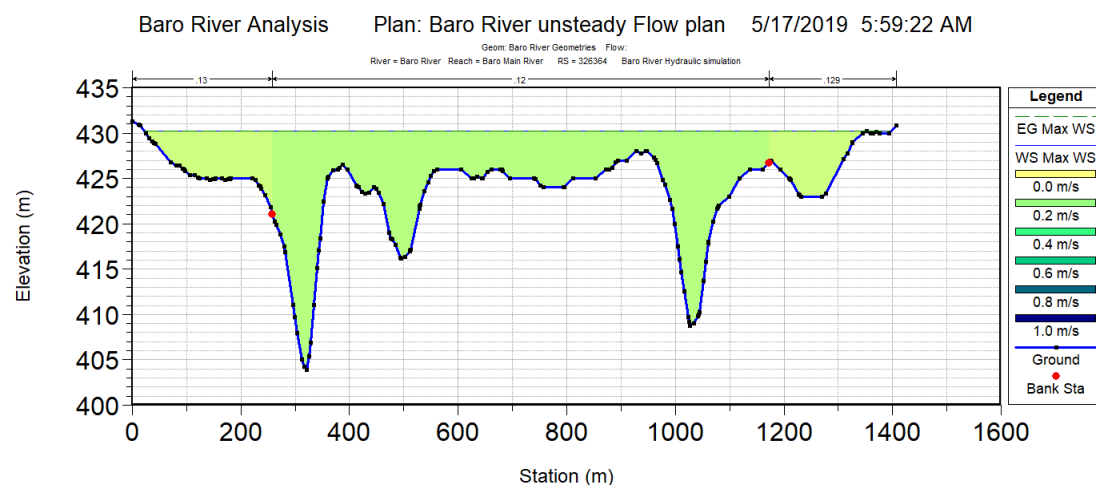
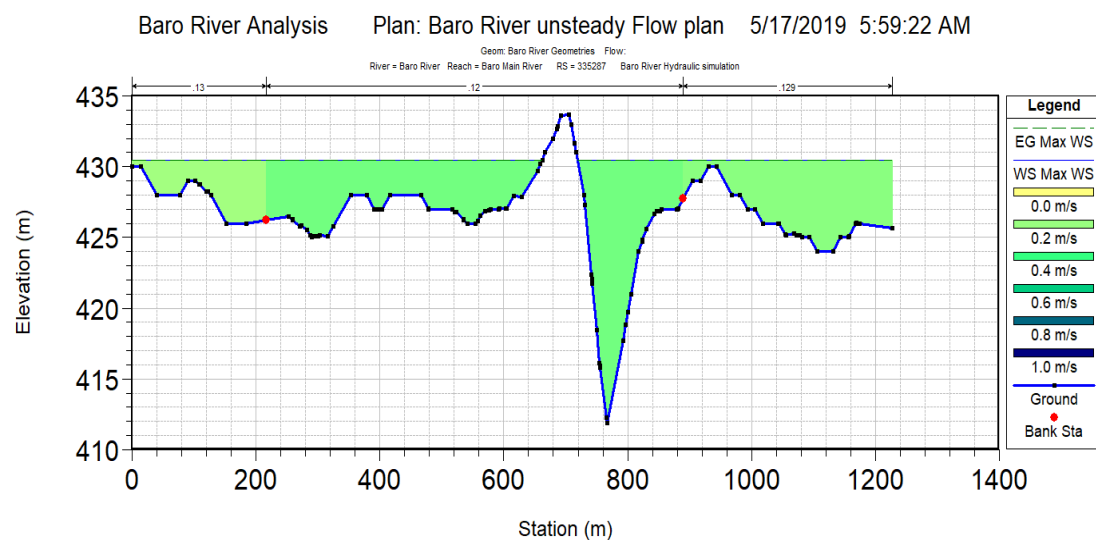
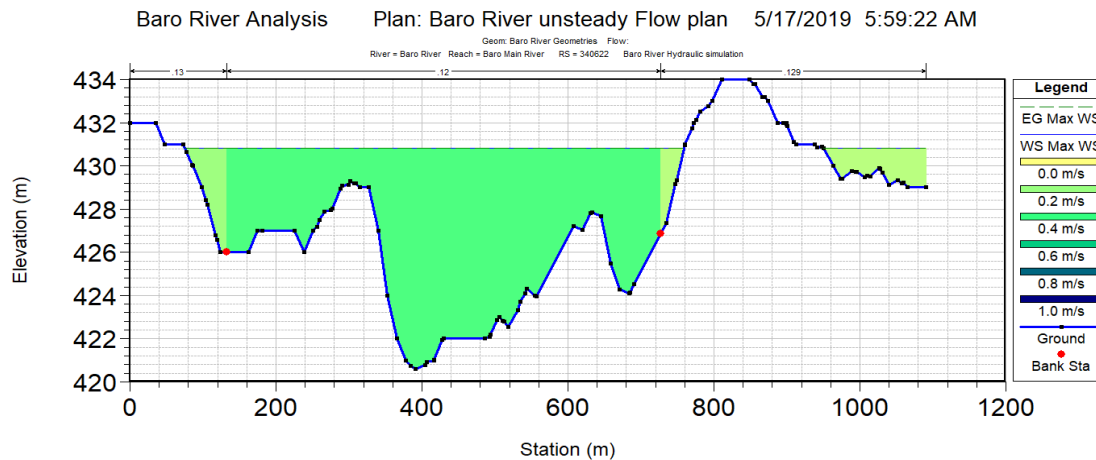
2019

Appendices D: River cross section of Baro River at different stations



Real-Time Flood Forecasting Using Artificial Neural Networks (ANN) and Flood Inundation Mapping

2019



Real-Time Flood Forecasting Using Artificial Neural Networks (ANN) and Flood Inundation Mapping

2019

