SIMULATION OF RAINFALL SURFACE RUNOFF- WATER QUALITY EFFECTS ON SURFACE WATER BODIES IN MID-BLOCK OF YALA

James Odiero

A Thesis submitted in partial fulfillment of the requirements for the award of the degree of Master of Science in Water Resources Engineering of Masinde Muliro University of Science and Technology

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DECLARATION

I hereby declare that this thesis is my original work, and to the best of my knowledge has not been presented in the same or different forms to the Masinde Muliro University of Science and Technology or any other university for the award of a degree.

James Odiero Reg. No. CWR/G/02/15

Signed___________________________ Date: _______________________

CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance of Masinde Muliro University of Science and Technology a thesis entitled **"Simulation of Runoff- Water Quality Effects on Surface Water Bodies in Mid-block of Yala."**

1. Signature: ____________________ Date: ____________________
   Prof. B.T.I Ongor

Masinde Muliro University of Science and Technology
School of Engineering and the Built Environment, Department of Civil and Structural Engineering
P.O. Box 190-50100, Kakamega, Kenya

2. Signature: ____________________ Date: ____________________
   Dr. E. N. Masibayi

Masinde Muliro University of Science and Technology
School of Disaster Management and Humanitarian Assistance, Department of Preparedness and Engineering Management
P.O. Box 190-50100, Kakamega, Kenya

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DEDICATION

To my beloved family: My wife Karen and my sons: Israel, David and Timothy.
They are special and a motivation in my life.

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ABSTRACT

In Kenya and other countries in the world, most water treatment works derive their raw water from rivers that flow in a watershed. Lack of proper management of watershed leads to high runoff generated and subsequent flooding downstream leading to damaged infrastructure, pollution and deterioration of water quality. The main aim of this study was to simulate runoff water quality effects and establish a relationship models in three water sheds in Yala basins. The river watersheds considered were: Edzava River, Zaaba River and Garagoli River which are in Vihiga County, Kenya. ArcGIS software was used to delineate the watersheds and from the DEM Edzava watershed covered an approximate area of 152km^2 with a longest length of 32.344km, Zaaba Water shed covered an approximate area of 79.51km^2 with a longest length of 9.423km and Garagoli Watershed covered an approximate area of 34.04km^2 with a total longest length of 17.118km. Artificial Neural Networks (ANN) model in MATLAB was used for simulation with input data being runoff generated from precipitation and output data was water quality parameters (Turbidity, Color, TDS pH and Iron) which were historical data from the year 2008 to 2017, a period of 10 years. The runoff generated in the three river watersheds had high values in April-May and September- October in each year. The results established that turbidity registered the highest values of 462 NTU and colour 1062 FTU in Edzava. TDS had high values in November to January and had an inverse relationship with runoff. Iron and pH did not have substantive response. ANN simulated model results had physical parameters i.e. turbidity and colour performing well in the three watershed while TDS best fit was in one water shed. The performance of the last two chemical parameter i.e. Iron and PH was very low in all the water sheds and did not respond well to simulated relationship matrix. Garagoli registered high performance for both turbidity and colour with coefficient of correlation, $R > 0.8$. It was only in Zaaba that TDS registered $R > 0.7$ for training, validation and testing. From the results of this study, this model could be used for two parameters that performed well particularly turbidity and colour and provides useful tool for planning of surface water management, water supplies and a general watershed management. The best practices in catchment and watershed management should be adopted.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN:	Artificial Neural Network
ASCE:	American Society for Civil Engineers
AWASCO:	Amatsi Water Services Company Limited
AWWA:	American Water Works Association
DEM:	Digital Elevation Model
DGS:	Directorate of Graduate Studies
Fe:	Iron
GIS:	Geographic Information System
GOK:	Government of Kenya
LVNWSB:	Lake Victoria North Water Services Board
LVNWWDA:	Lake Victoria North Water Works Development Agency
MAE	Mean Absolute Error
MATLAB:	Matrix Laboratory
NBI:	Nile Basin Initiative
NEMA	National Environment Management Authority
NTU:	Nephelometric Turbidity Units
NH_3	Ammonia
NH_4	Ammonium
NO_3	Nitrates
N-S:	Nash Sutcliffe
NSE	Nash-Sutcliffe Efficiency
PBIAS	Percent Bias
SEBE:	School of Engineering & Built Environment
TDS:	Total dissolved solids
R	Correlation Coefficient
R^2	Coefficient of Determination
RGS	River Gauging Station
RMSE	Root Mean Square Error

USGS:	United States Geological Survey
VCG:	Vihiga County Government
UNEP:	United Nations Environmental Program
WRMA:	Water Resources Management Authority
WASREB:	Water Services Regulatory Board
WSP:	Water Service Providers
WHO:	World Health Organization
WQ	Water Quality

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of the Study

Water is becoming a major constraining resource for sustainable development in the world. Water quality is one of the main characteristics of a river, studies show that water quality has become continuously a concern and a problem particularly for human water supply. This is brought about by deterioration of Surface water quality (Kazi, Arain, Jamali, & Jalbani, 2009). Human activities are the major factor in determining the quality of our water bodies through municipal and industrial wastewater discharge, eroded soils and land use, atmospheric pollution (Zali, Retnam, Hafizan, & Sharifuddin, 2011) which flows to the rivers as runoff. Studies done in Western Africa explained that runoff from rainfall can significantly contribute to variation in the quality of surface waters. The effects of rainfall intensity on surface water quality is increasingly becoming a cause for concern because of its indirect impact on the cost of water treatment, and consequently on the quantity of water available for public water supply (Olaoye, Oladeji, & Olaji, 2013).

Rainfall-runoff process is closely related to many factors, such as rainfall intensity, terrain slope, land use, vegetation and soil properties. On the one hand, increased rainfall intensity may lead to increased runoff, due to the fact that increased rainfall intensity may bring about the formation of the soil crust, and the development of such soil crusts would reduce infiltration (Richard H. Hawkins, 1981), thus increased runoff from lands increases flows carrying sediments that increases turbidity and affecting the water quality. The quality of water determines the water treatment process which has a bearing on the cost. Research by (Dearmont, 1998), did calculations of Partial derivatives of cost with respect to turbidity, total amounts treated, the contamination proxy, and annual rainfall. The elasticity of cost associated with turbidity and total gallons treated were as well calculated. The derivative of cost with respect to turbidity implied that the chemical treatment costs increase at a decreasing rate as the level of turbidity increases. The elasticity of chemical cost with respect to turbidity implied that a 1% reduction in turbidity will reduce the cost of treating water by 0.27 percent (Dearmont, 1998). Recent hydrological reports in Nigeria indicated that the water quality indicator parameters i.e. turbidity, sedimentation, and color showed consistent and significantly high correlation with the temporal rainfall intensity during comparatively low rainfall periods and this suggests occurrence of significant influence of the varying rainfall amount on the water quality (Olaoye et al., 2013). A study carried out to project streamflow in the Huaihe river basin using artificial neural network, concluded that neural network modelling is an exact instrument in estimating the lowering quality degree in this river (Gao et al., 2010).

In Kenya, most of the surface water sources like rivers and streams are key in supplying raw water to the treatment plants. With increasing human activities and pressure on water resources, runoff from the catchments have polluted rivers resulting to challenges of flooding, loss of lives, damage to infrastructure and high cost of treating water for domestic use and drinking. Hydrologists have developed models to help understand and derive solution to these challenges. Hydrological modelling is simplified description of hydrological cycle to imitate the natural system. Rainfall-runoff model is the standard tool routinely designed for hydrological investigations and it is used for many purposes such as for detecting catchment response towards climatic events, calculations of design floods, management of water resources, estimation of the impact of land-use change, forecast flood and of course for stream flow prediction (Bloschl, 2005). Simulating requires use of rainfall-runoff model involving various interacting processes by the transformation of rainfall into runoff which sometimes maybe complex. Various methods have been developed to simulate the rainfall runoff process in the catchment. They can be classified as conceptual model and data driven model. The conceptual models are based on the several assumptions so as to simplify the model as there may be many variables which might be difficult to consider all and also to have acceptability along with their assumption (Sharma & Mohandatta, 2017). On the other hand data driven models are developed and validated completely based only on the length of the data series, for example ANN and regression model (Sharma & Mohandatta, 2017). In recent years, ANN has been successfully used as a rainfall-runoff model (Vos & Rientjes, 2005), and in this paper, they state that ANN had advantages over many other techniques, since it was able to simulate nonlinearity in a system and also effectively distinguish relevant from irrelevant data characteristics. Moreover, ANN is nonparametric technique, which means that the model does not require the assumption or enforcement of constraints.

In this research therefore, ANN model was used to simulate runoff in the catchment areas of Edzava, Zaaba and Garagoli rivers Sub-Basins that are sources for major water supply schemes in Vihiga County in the Mid-Block of Yala Catchment.

1.2 Problem Statement

The Lake Victoria Basin in western Kenya is the most flood-prone region in the country (Ong'or, Shu, & Jinning, 2009) & (GOK., 2007) which is caused by runoff generated from the catchment. Western Kenya is characteristically wet throughout the year with no distinctive dry season but with two high rainfall seasons experienced during the year (ICPAC., 2007). The mean annual rainfall in western Kenya is above 1600 mm (Institute, 2007). High runoff generated in Yala river basin are caused by intense storms upstream than the catchment can store or the main Yala river and its tributaries can carry within their normal channel (Kiluva, Mutua, Makhanu, & Ong'or, 2010), that leads to floods. Floods related fatalities constitute a whopping 60% of disaster victims in Kenya (UNEP., 2009). Catchment generated high runoff occurrence trends increasingly becomes a major concern to the country's socio-economic development due to the substantial economic and financial losses incurred to respond to frequent flood disasters. (Institute, 2007), indicate that rainfall seasons can be extremely wet and erratic resulting to damages include physical destruction to public and private assets such infrastructure, houses, buildings, crops and vehicles resultant from contact of the assets with flood water (Institute, 2007). High runoff that leads to floods seriously damaged water supply infrastructure and transport networks, dams, water pans, and some pipelines (Mogaka, Gichere, Davis, & Hirji, 2006) across the country. The high levels of runoff also damaged irrigation infrastructure such as intake structures, weirs, canals, drains and the main cause for erosion. The top soil picked up by the water as it flows towards a river is deposited into the river and causes serious water quality problems affecting both the clarity and purity of water. Contaminants carried by the runoff water flows across paved and unpaved streets and through fields carrying chemicals compounds leading to accumulation of these materials in the water bodies in the watershed and can have deleterious effects when used for drinking if not treated. The above challenges affects the treatment of water in our water supply treatment works and increase of water quality challenges increases the cost of treating water.

There are few studies done on effects of runoff to receiving water to water supply works and therefore limited information in this watersheds that could inform the water supply and watershed managers for informed decision making. This limited information makes it difficult to handle in a planned and coordinated manner in the catchment.

1.3. Research Objectives

1.3.1: Main Objective

To simulate runoff- water quality effects in surface water supply treatment works by use of Artificial Neural Network (ANN).

1.3.2: Specific Objectives

i) To evaluate watershed rainfall surface runoff volume for River Edzava, Zaaba and Garagoli

ii) To determine the raw quality abstracted from River Edzava, Zaaba and Garagoli

iii) To use the ANN model to simulate run off and water quality for each watershed

iv) To establish relationship and effects associated with the runoff and water quality in water treatment works

1.4. Research Questions

i) What is the extent of runoff in the three river watersheds?

ii) What are the parametric quality and quantity levels of the raw water from the rivers?

iii) How suitable is the ANN Model in simulation of Runoff and Water Quality?

iv) What are the effects associated with runoff and water quality in water treatment?

1.5. Justification and significance of the study

This study is geared towards enhancing proper catchment management practices from complex catchment phenomenon, both natural and human activities. It has scientifically analysed and provide useful information that will help in mitigating future catchment challenges like runoff, erosion, poor river water quality floods and risks involved.

Catchment runoff and emanating flood risks when managed well has the potential of reducing flood damages and losses resulting to huge economic savings. The government, private agencies and the general public stands to spend less on responding to emergency catchment runoff disasters and they can invest in other income generating activities. Major challenges to management of resulting risks in the specific catchments is lack of technical resources, data and information from which strategic decisions could be based on. This study therefore provides information for water resources development and management in a watershed which could be used for planning. Correlation of run-off and the quality of water in the watershed provides a reliable information in management of technical activities and processes in water treatment across the seasons. The ANN model was used in this study because other researchers had found it to be a popular forecasting tool in water and other hydrological studies (Kanda, Kipkorir, & Kosgei, 2016). These research results are vital in the development of catchment management plans and policies. It augers well with Kenyan Vision 2030 on Economic and Social pillars, Constitution of Kenya 2010; on the bill of rights chapter four, article 43(d) that provides the right to clean and safe water in adequate quantities to all citizens. The sustainable development goals number 6 also envisages improving access to water of good quality.

CHAPTER TWO

2.0. LITERATURE REVIEW

This chapter discusses literature related to run off and water quality in the study area including the three rivers namely Idzava, Zaaba and Garagoli. The chapter gives the general scope of the research. It further provides a brief of other models for runoff and water quality then narrowing to ANN model which was be used in this research.

2.1 Hydrology of the catchment

The hydrologic response of catchment to rainfall, estimates of catchment yield, and runoff data are of importance to hydrological analysis for the purpose of water resources planning, flood forecasting, pollution control and many other applications (Shamsudin & Hashim, 2002).

Yala basin is divided into three zones; the upper, middle and lower catchment zones. The upper catchment falls in Nandi County, middle catchment falls in Kakamega and Vihiga counties of Western region and the lower catchment is found in Siaya County in Nyanza region (Wanyonyi, Wakhungu, & Kiluva, 2015).

The Yala Basin is important environmentally and economically as it acts as a buffer to Lake Victoria in terms of sediment loading into the lake. The extent of floods in the area results in the deteriorating health status of the basin in terms of water management (Wanyonyi et al., 2015)

2.2 Surface Runoff and its Characteristics

Surface runoff is water from rain, snowmelt, or other sources that flows over the land surface, and is a major component of the water cycle. When runoff flows along the ground, it can pick up soil contaminants such as petroleum, pesticides, or fertilizers that become discharge or overland flow. Urbanization increases the surface runoff by creating more impervious surfaces on pavement and buildings which do not allow percolation of the water down through the soil to the aquifer (Needhidasan, 2013). Runoff from non-urban areas carries eroded sediments, nutrients from natural and/or agricultural sources, bacteria from animal droppings, and pesticides and herbicides from agricultural practices. After urbanization, runoff carries solids particles from automobile wear and tear, dust and dirt, and winter sand, nutrients from residential fertilizers, metals such zinc, copper, and lead, hydrocarbons leaching from asphalt pavement materials, spilled oils and chemicals, and bacteria from domestic animals. This change of runoff quality causes a general degradation of water quality in the receiving waters (Needhidasan, 2013). Runoff can also be described as the part of the water cycle that flows over land as surface water instead of being absorbed into groundwater or evaporating after a storm event.

2.3 Water quality

Water quality encompasses the physical, chemical and biological characteristics of water. Both natural water quality and man induced changes in quality are important consideration in river watershed management. Water quality management plays an important role in water pollution control and river basin planning. The possibility of a pollutant being discharged to the river as municipal and industrial waste is a constant concern to those diverting and using water from rivers (Sarkar & Pandey, 2015). According to Hasan, Khan, Nesha, and Masuma (2014), pollution control issues were relatively recent in Bangladesh. With few exceptions whereby the industries were not equipped with pollution control systems. Once the ground water is polluted, it is virtually impossible to purify even for a highly technologically advanced industrial country and thereby endangering human health, aquatic lives and crop production. The effluents may contain heavy metal like Ni, Pb, Cr, Cu, Hg, Mn, Zn or Fe (Hasan et al., 2014). The concentration of the chemical parameters of River water in rainy season is less than that of winter season except Sodium and Calcium with a significant positive correlation found between Sodium and Chloride while significant negative correlation was found between Sodium and Iron, Zinc and Copper (Hasan et al., 2014). Turbidity is a measurement of the decrease in transparency of stream water as light is scattered by suspended particulate matter (Ziegler, Giambelluca, & Sutherland, 2002). Results from above studies show that turbidity measurements may correlate closely with sediment concentrations in streams. In Kenya there are institutional framework that deals with quality as stipulated in Water Act 2016, this could help in ensuring that the set standards are realized at the grass root level as the local government is able to closely supervise the service. Furthermore, it is important for legislative clarity on the relationship among the institutions created by the Water Act 2016 and the roles of the institutions in the water and sanitation sector such as the WWDA, the County Government, WASREB and the WSP for sustainable interventions (Kanda, Odiero, Lutta, & Ong'or, 2018). Though Kanda et al 2018 observed this legal challenges, they didn't provide ways in which water quality guidelines can be clarified and field based solutions arrived at.

2.4 Hydrologic modelling

It is becoming increasingly critical to plan, design and manage water resources systems carefully and intelligently. For many years, hydrologists have attempted to understand the transformation of precipitation to runoff in order to forecast runoff for purposes such as water supply, flood control, irrigation, drainage, water quality, power generation, recreation, fish and wildlife propagation. The rainfall-runoff relationship is one of the most complex hydrologic phenomena to comprehend due to the tremendous spatial and temporal variability of watershed characteristics and precipitation patterns and the number of variables involved in the modeling of the physical processes (Shrivastav, Haresh, Ramanuj, Chudasama, & Joshi, 2014). Hydrologic models especially simple rainfall-runoff models are widely used in understanding and quantifying the impacts of land use changes and to provide information that can be used in land-use decision making. Many hydrologic models are available; varying in nature, complexity and purpose (Chouhan, Tiwari, & Galkate, 2016). One such hydrologic model is Artificial Neural Network model (ANN). In recent years, ANNs has been used intensively for prediction and forecasting in a number of engineering and water-related areas, including water resource study (Liong, Lim, & Paudyal, 1999) and environmental science (Grubert, 2003). The use of data-driven techniques for modeling the quality of both freshwater (Chen & Mynett, 2003) and seawater (Lee, Huang, Dickmen, & Jayawardena, 2003) has met with success in the past decade (Reckhow, 1999).

2.4.1 Hydrologic Models

Rainfall-runoff models play an important role in water resource management planning and therefore, different types of models with various degrees of complexity have been developed for this purpose. These models, regardless of their structural diversity generally fall into three broad categories namely; black box or system theoretical models, conceptual models and physically-based models. Black box models normally contain no physically-based input and output transfer functions and therefore are considered to be purely empirical models. Conceptual rainfall-runoff models usually incorporate interconnected physical elements with simplified forms and each element is used to represent a significant or dominant constituent hydrologic process of the rainfall-runoff transformation. Conceptual rainfall-runoff models have been widely employed in hydrological modeling (Jain & Chalisgaonkar, 2000).

2.4.2 Empirical versus physically based

Hydrologic models can also be distinguished on a conceptual basis as being empirical or physically-based. Along the spectrum of techniques used in hydrological modeling there lies at one extreme, the empirical, black-box techniques and at the other extreme, the physically-based techniques. The black box models do not take into account the internal structure and response of the catchment, rather they only match the input and output of the catchment system. Thus, they do not simulate the hydrologic processes that are involved in the input-output relationship (Githui, Gitau, Mutua, & Bauwens, 2009)

2.4.3 Model Choice

Model choice is based on its performance in the prevailing conditions and relevancy in the study**.** Model performance, i.e. the ability to reproduce field observations, and calibration/validation are most often evaluated through both qualitative and quantitative measures, involving both graphical comparisons and statistical tests (Donigian, 2002). ANNs have been used by researchers for rainfall-runoff modeling, stream flow prediction, ground-water modeling, water quality, water management, precipitation forecasting, time series, reservoir operations, and other hydrologic applications. These studies indicated that ANNs can perform as well as existing models (ASCE. & Task, 2000, April).

The ANNs have also been successfully used in many hydrological studies and proved suitable for simulation. The performance of ANN was tested and It was found to be efficient approach for water quality modelling (Sarkar & Pandey, 2015). Besides the above explanations from authors, I considered the following for the choice of ANN as my preferred model for this research:

- The model has been proved to be effective in hydrological modelling
- Ability to implicitly detect complex nonlinear relationships between dependent and independent variables,
- ability to detect all possible interactions between predictor variables
- Ability to produce similar results even with few data sets
- Other researchers used different models in Yala catchment

2.5 Artificial Neural Networks (ANN)

2.5.1 The ANN theory

Neural networks are powerful data driven modelling tools that has the ability to capture and represent complex input/output relationships. The three-layer back propagation network has been proved to be universal function approximations in the field of environmental prediction (Poggio & Girosi, 1990). Neural networks has also been applied to simulate, solve and predict engineering hydrologic problems estimating optimum alum doses in water treatment (Maier, Jain, Dandy, & Sudheer, 2010) and long term tidal waves (Lee et al., 2003). The input layer consists of a set of neurons, each representing an input parameter and propagates the raw information to the neuron in the hidden layer, which in turn transmits them to the neurons in the output layer. Each layer consists of several neurons and the layers are connected by the connection weights (W). The most commonly used transfer function is the sigmoid function as described by: $F(x)= 1/ (1-e^{-x})$. This produces output in the range of 0−1 and introduces non-linearity into the network, which gives the power to capture nonlinear relationships. The back propagation network is the most prevalent supervised.

ANN learning model uses the gradient descent algorithm to correct the weights between interconnected neurons (Maier et al., 2010). During the learning process of the network, the algorithm computes the error between the predicted and specified target values at the output layer.

2.5.2 ANN Architecture and training

Determination of appropriate network architecture is one of the most important but also one of the most difficult tasks in the model building process (Sarda & Sadgir, 2015). The basic and the most commonly used ANN architecture consists of an input layer, a series of hidden layers and an output layer, where each of the layers consists of a number of interconnected neurons (Antanasijević, Pocajt, Perić-Grujić, & Ristić, 2014; Chau, 2006). There are a number of ANN model but the most widely used are the feed forward neural network, multi-layer perceptron (MLP) or Back-Propagation network. The MLP is organized as layers of computing elements, known as neurons, which are connected between layers via weights. Apart from an input layer receiving inputs from the environment and an output layer generating the network's response, one or more intermediate hidden layers also exist. Multilayer Perceptron's (MLPs) which is the most common form of feed-forward back-propagation model architecture (Maier et al., 2010) was used in this study.

2.5.3 Application of ANN in water resources management

Applications of ANNs in the areas of water engineering, ecological sciences, and environmental sciences have been reported since the beginning of the 1990s. In recent years, ANN is a popular model used as a forecasting tool in water quality studies (Kanda et al., 2016) to simulate runoff and water quality. ANNs have been used by researchers for rainfall-runoff modeling, stream flow prediction, ground-water modeling, water quality, water management, precipitation forecasting, time series, reservoir operations, and other hydrologic applications. ANNs can be trained on input-output data pairs with the hope that they are able to mimic the underlying hydrologic process (ASCE. & Task, 2000, April).

2.5.4 Advantages and disadvantages of ANN

Artificial neural networks are algorithms that can be used to perform nonlinear statistical modeling and provide a new alternative to logistic regression, the most commonly used method for developing predictive models for dichotomous outcomes in medicine. Neural networks offer a number of advantages including requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms. Disadvantages include its “black box” nature, greater computational burden, and proneness to over fitting, and the empirical nature of model development (Tu, 1996).

2.5.5 Review of previous studies

Some specific applications of ANN to hydrology include modeling daily rainfall-runoff process, assessment of stream's hydrologic and ecological response to climate change, rainfall prediction, sediment transport prediction, and groundwater remediation. According to L.C. Nkemdirim (1979) the availability and use of water are vital concerns in developing countries. As these countries face a rapidly growing population, an unprecedented level of rural-urban migration, and an apparent rise in living standards, the demand for safe and reliable supplies of water, especially in the major population centers, has never been as intense as it is now. A persistent problem in water- resource planning in these countries is the dearth of information on the amount of available water and on its spatial and seasonal distributions. Nkemdirim, concluded that areas of high runoff and large runoff coefficients correspond to areas of heavy rainfall (Lawrence C. Nkemdirim, 1979) According to Jun, Chang-xing, and ZHANG (2013) a correlation analysis indicates that runoff and sediment yield is positively correlated with the precipitation indices, while negatively correlated with the vegetation indices. The results do not point out the prediction of future scenarios of the same basin. ANN as a model was recommended after it was been compared with existing methods and found to be perform better (Shrivastav et al., 2014).

2.5.6 Previous studies done within or near the catchment of this research

Artificial Neural Network (ANN) has been applied in water quality forecasting. A study by Kanda et al. (2016), aimed at assessing the ability of ANN to predict dissolved oxygen using four inputs variables of temperature, turbidity, pH and electrical conductivity. Feed-forward back propagation network algorithm was used in the study. The results obtained during training, validation and testing were satisfactory with R^2 varying from 0.79 to 0.94 which imply that ANN can be used as a monitoring and prediction tool. The study by Kanda et al. (2016) majored on dissolved oxygen in a river but did not go further to cause effect relationship in a perspective of water treatment for domestic water supply. This proposed research will bridge the gap and consider, runoff, quality aspect and their relationship with effect to water treatment outlined. Where this study will be undertaken, Cunge (M-C) model by Kiluva et al. (2010), was used to model the hydrologic processes of the Yala river network and the conclusion was that the Geo-SFM and M-C models were useful tools for flood mitigation by issuing flood early warning messages defined by peak stream flow and flood wave travel time but this study did not focus on effects of runoff on water supply in the particular area. Therefore as well this study bridged the gap.

2.6. Conceptual Framework

The study involved delineation of the three water catchment to get the characteristics of the water sheds for the purpose of calculating runoff from rainfall with the watersheds. The rainfall data was collected from meteorological department in Vihiga, Water quality was LVNWSB and AWASCO. Generation of runoff was done by use of mathematical model i.e. rational method. Runoff was taken as in depended variable while water quality parameters i.e. Colour, Turbidity, pH, TDS and Iron were dependent variable. Simulation was done using ANN model inbuilt in MATLAB. The input data was Runoff and Water quality parameters as output. The results were observed, discussed and recorded including the established effects of runoff-water quality effects. The conceptual framework employed in this study is illustrated in Figure 2.1

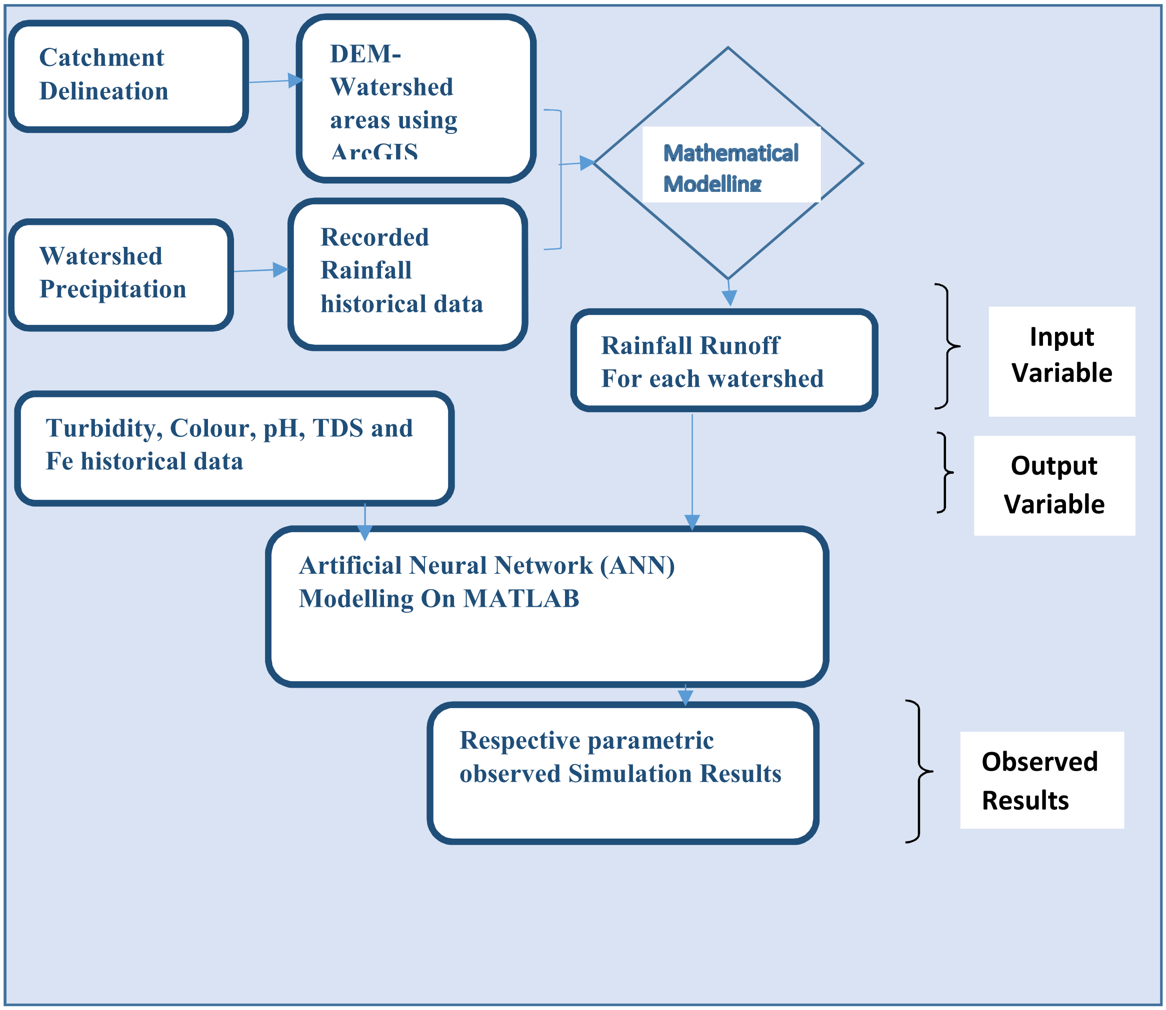


Figure 2. 1: Conceptual Framework

CHAPTER THREE

3.0 MATERIALS AND METHODS

The research utilized data for both runoff and water quality. ANN model was used for simulation.

3.1 Study Area

The study area is located within River Yala basin that crosses three counties in Kenya namely Vihiga, Kakamega and Busia in the Western Region of Kenya. The Yala River Basin covers an area of 3,351 km^2 and it is one of the main Kenyan rivers draining into Lake Victoria. Average monthly discharge is 27.4 m^3/s (Boye, Verchot, & Zomer, 2008). Yala basin is located within Lake Victoria North Catchment in Kenya. The catchment is centered about 35° E, 0.1° N (Githui et al., 2009). The basin is divided into three zones; the upper, middle and lower based on regular gauging stations at the outlet of each sub-catchment. The upper catchment falls in Nandi County, middle catchment falls in Kakamega and Vihiga counties of Western region and the lower catchment is found in Siaya County in Nyanza region (Wanyonyi et al., 2015). Vihiga County has some of the feeder streams which are Zaaba, Edzava, and Garagoli that serve the Water Supply treatment plants namely Kaimosi, Mable and Maseno. These study therefore focuses on three river watersheds. Garagoli River flows in the upstream side and serves Kaimosi treatment works. Edzava is the middle tributary of Yala and serves Mbale water treatment works and finally Zaaba River is in the downstream serving Maseno water treatment works. The river basin locations and characteristics are presented in Figure 3.1, 3.2, 3.3 and Table 1. The river basins differ in size and natural conditions.

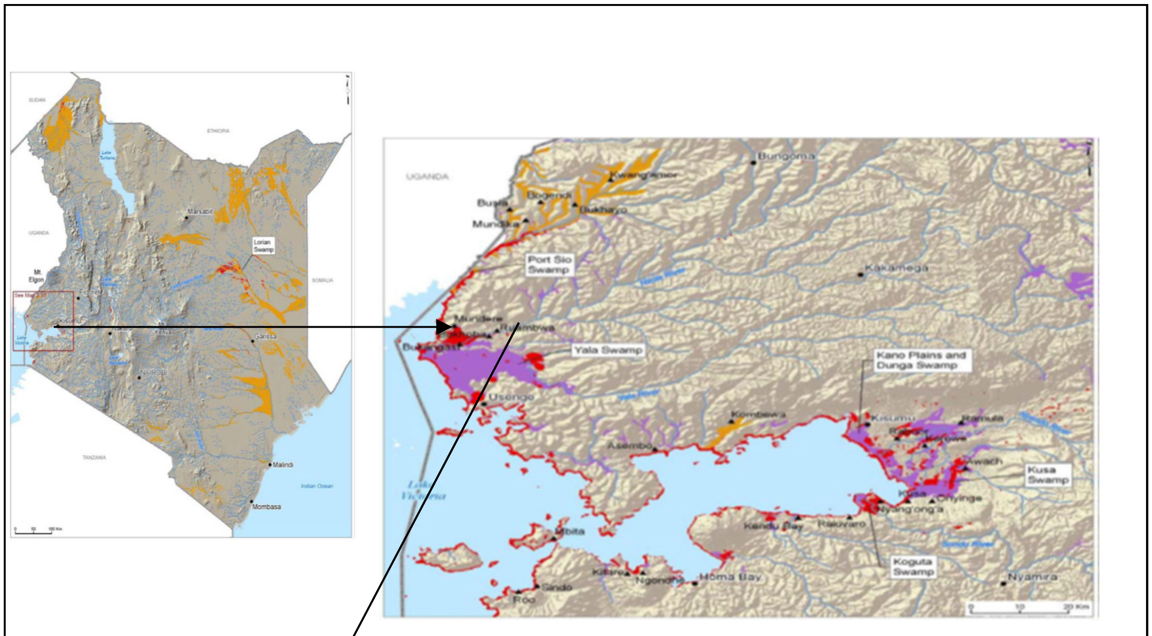


Figure 3. 1: Map of Kenya and Lake Victoria Basin (Source World Resource Institute, 2006)

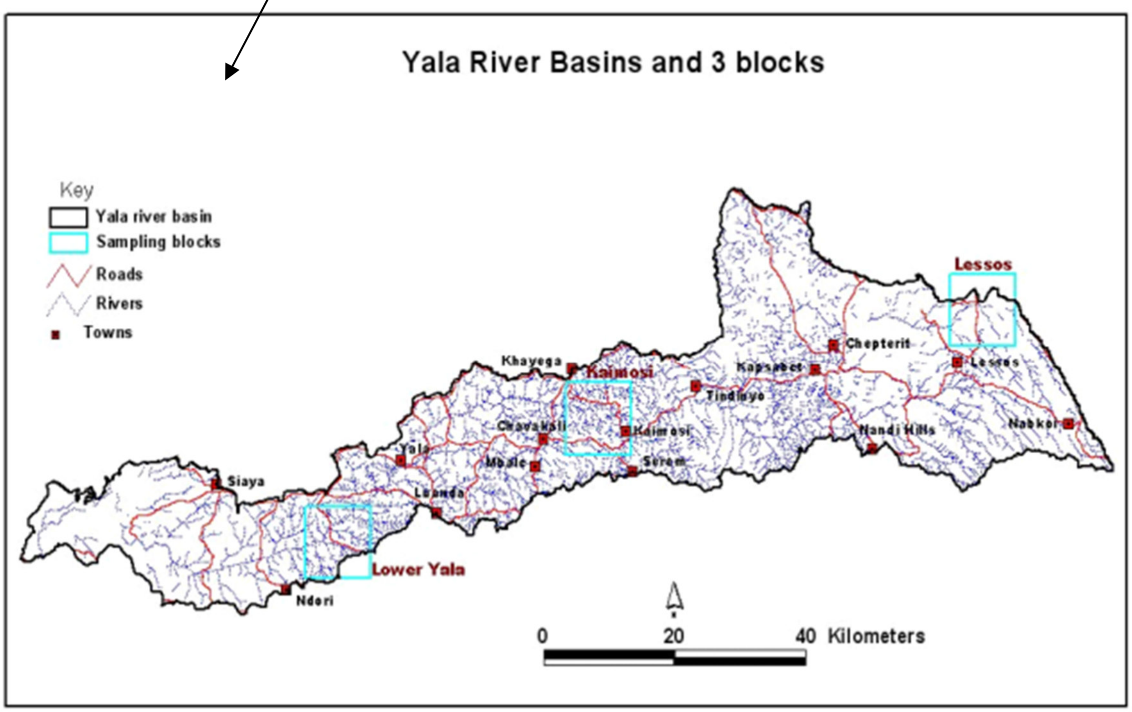


Figure 3. 2: Map of the Yala River Basin,(From Yala & Nzoia river basin report, 2008)

Figure 3. 3: The specific Water treatment plants in Vihiga (From Google earth July 2017)

3.2 Topography

The study area lies within the larger Yala basin, Vihiga County in Kenya, between longitudes 34^0 30' and 35^0 0' East and between latitudes 0^0 and 0^{0}15' North. The equator cuts across the southern tip of the county. The county covers a total area of 531.0 Km^2 (GOK., 2013). The area is located in the Western Region of Kenya. Its altitude ranges between 1,300 m and 1,800 m above sea level and slopes gently from west to east. Generally the area has undulating hills and valleys with streams flowing from northeast to southwest and draining into Lake Victoria. The area has equatorial climate with fairly well distributed rainfall throughout the year with an average annual precipitation of 1900mm. Temperatures range between 14ºC and 32ºC, with a mean of 23ºC (GOK., 2013).

3.2.1 Soils

The Yala catchment has a variety of soil types of volcanic origin some of which are young, fertile and rich in nutrients. In the mid zone, in Vihiga and southern Kakamega counties, the soils are developed from the older basement rocks, and consist mainly of coarser-textured, granite-derived, well developed and well drained ferralsols, moderately deep to very deep on gentle slopes, reddish brown to yellow brown, friable sandy loams with moderate to low fertility with most soils being unable to produce without the use of either organic, inorganic or in most cases both type of fertilizers. The soils in this area is mainly sedimentary in nature. The soils support various farming activities which include cash crops like tea and coffee. The abundant rain in the area enables rearing of livestock, crop farming, fruits and other horticultural crops vital for sustainability of agro based industries. The types of soils and climate favour two planting seasons in the year; County, First County Integrated Development Plan (GOK., 2013).

3.2.2 Land Use

The natural vegetation cover of the upper Yala Catchment consists of high altitude forest and high altitude moist savannas. Forests in the Mid Yala catchment are represented by the Kakamega and Kaimosi forests, which are the only remnants of the equatorial Congolese/Guinean forest which is represented in Kenya, with indigenous species, and to a lesser extent Vihiga forests. These forests have also lost much of their original area to cultivation in the past 50 years (NBI, 2011).

In the Mid Yala and Lower Yala catchment agriculture is also the predominant land use. Here, it is characterized by small-scale mixed farming, which includes a wide range of traditional subsistence food crops and cash crops. The main crops grown are maize, beans, sorghum, bananas, sweet potatoes, and horticultural crops such as onions and tomatoes and other vegetables. The farming also includes livestock keeping (NBI, 2011).

3.3 Climatic Conditions

The research area experiences high equatorial climate with well distributed rainfall throughout the year with an average annual precipitation of 1900 mm. The rainfall ranges from 1800 – 2000mm. Temperatures range between 14ºC - 32ºC, with a mean of 23ºC. Long rains are experienced in the months of March, April and May which are wettest while short rains are experienced in the months of September, October and November. The driest and hottest months are December, January and February with an average humidity of 41.75 %. This climate supports a variety of crop farming such as coffee, tea, and horticultural crops and rearing of livestock (GOK., 2013).

3.3.1 Climate change and its effect in the area

Climate change has been felt in the county as high temperatures are experienced with heavy and erratic rainfall. More dry spell that interfere with the soil and crop productivity and natural disasters like hailstorms have become a common feature during rain period and they do interfere with crop production. Wetlands are fast diminishing in size due to deforestation, siltation as a result of soil erosion and human livelihood activities including increased settlements. Sources of water such as rivers, springs and wells suffer reduced sizes and low water volumes with obvious pollution from car wash, refuse, raw sewage and garbage from homes, roads and plants. This has led to crop failure and increase in malaria cases (GOK., 2013).

3.3.2 Water resources pollution

According to the report by Nile Basin initiative (Boye et al. (2008), the Yala River with a catchment area of 3,357 km^2 discharges into Lake Victoria directly from its Yala catchment basin. Its trans-boundary importance lies on its volume of water contribution into Lake Victoria and as a carrier of pollutants into Lake Victoria. Nationally, the Yala River system supports major activities which include domestic water supplies to the towns within its catchments, minor industrial concerns and agricultural activities. The river system is prone to both non-point and point sources of pollution. The non-point sources of pollution encompass:

- Environmental degradation through catchment and wetlands destruction
- Release of high nitrate and phosphate quantities and other chemicals into the environment as a result to poor application on land.
- Soil erosion due to poor agricultural practices, soil cover destruction and overgrazing (Boye et al., 2008)

3.3.3 Water sources

Majorly, the water sources for domestic water supply in the area are; water springs, hand dug & dilled wells, rain water harvesting, streams and rivers. These sources according to Impact report by Water Regulatory board 2015, the WSP covers only 16% of the population in the area. The challenges of less coverage is attributed to the challenges of treatment and supply. Most households have challenges with the quality of the water (GOK., 2015).

3.4 Delineation of the water sheds

A watershed consists of all points enclosed within an area from which rain falling at these points will contribute water to outlet

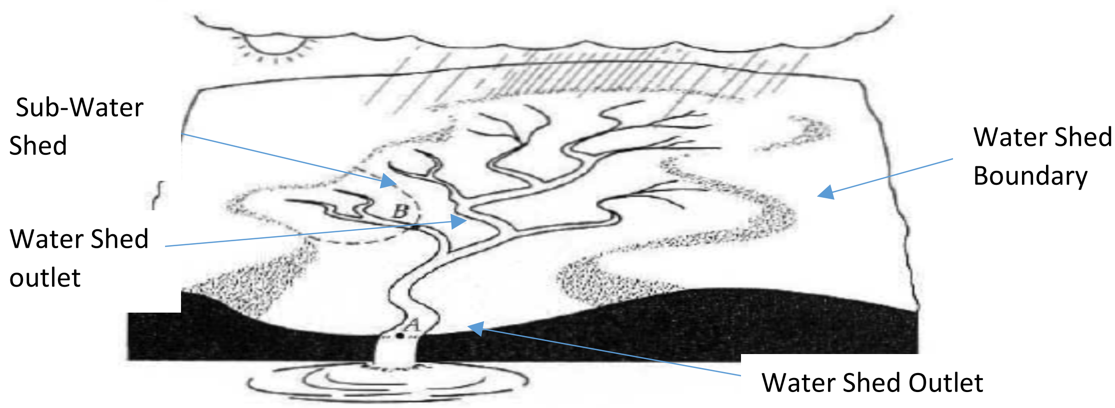


Figure 3. 4: Water shed (University of Utah 2015)

The last years have seen the recognition of a catchment, drainage basin or water shed as the most significant surface unit for hydrological studies. Traditionally catchment boundaries have been manually derived from topographical maps and labour intensive activities. This limitation changed by the introduction of the Digital Elevation Models (DEM) (Bertolo, 2000).

For this study, the watershed boundary, the length of the river and the areas of the watershed was generated from the Yala River catchment shape file maps. The soil map was overlaid in ArcGiS. It was given spatial reference which was the same as the study area (WGS 1984 UTM Zone 37N) and a Digital Elevation Model of 30m resolution—reference data set from Vihiga County Survey office (GIS Department) developed for the three river water sheds. The study area was then clipped from the rest of the soil map feature and attribute table of the study area embedded before it was changed to raster file and computation of areas and length of the river done.

3.4.1 Mid-block of Yala-Three Water Sheds

The three river water sheds in this study are Edzava, Garagoli and Zaaba where Mbale, Maseno, Kaimosi towns respectively were located as shown in the DEM map below.

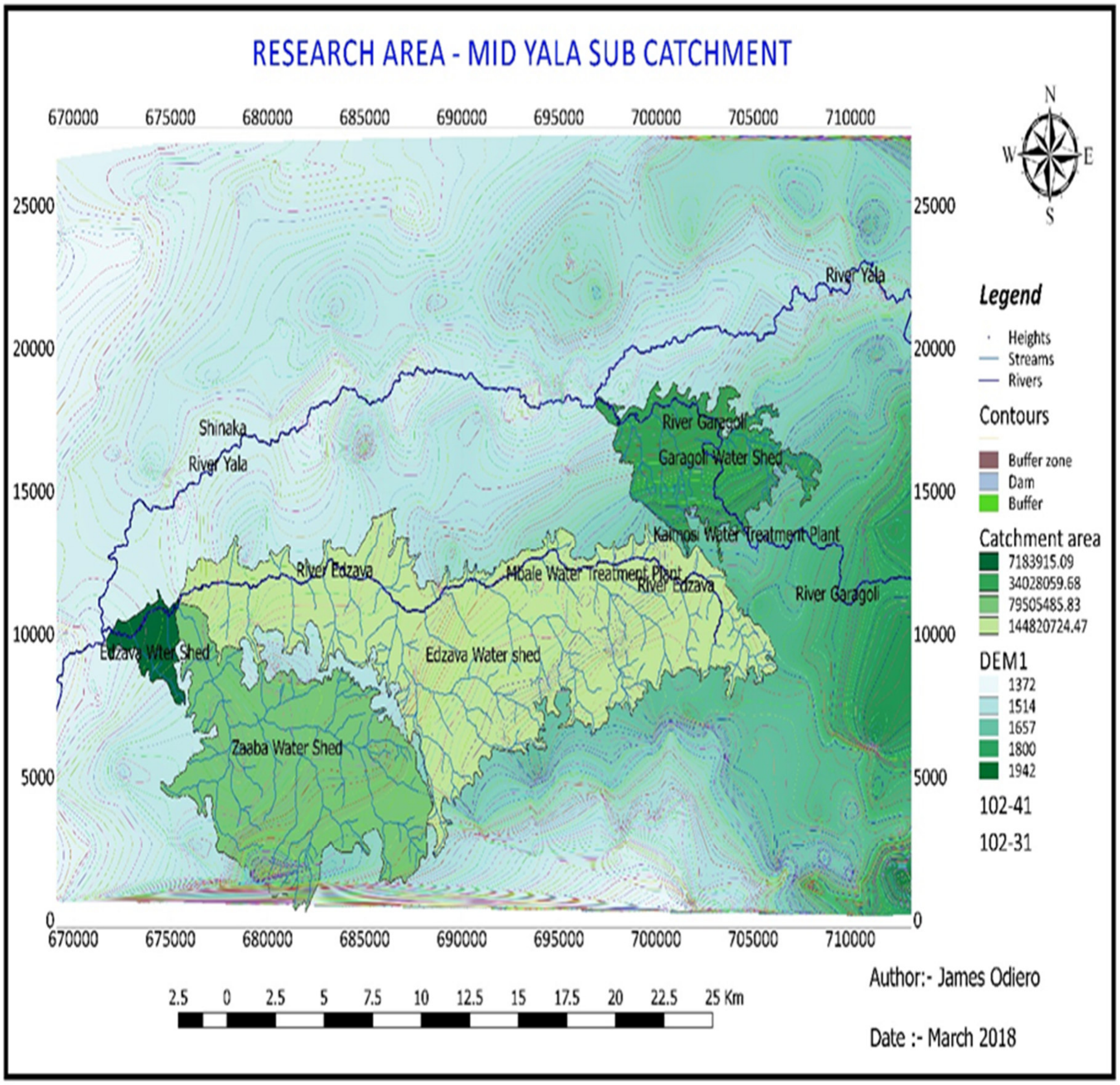


Figure 3. 5: Delineated DEM for Yala midblock (source- field data 2019)

3.4.2 Edzava River Water Shed.

The Edzava watershed area is in the middle between Garagoli and Zaaba. It has two urban centers i.e. Mbale and Chavakali. Mbale is the headquarters of Vihiga County and has many Government institutions like the County general Hospital and High schools which have high demand of water. The two centers are separated and drained by river Edzava which also is a source of raw water for Mbale Water supply treatment plant. The river flows south west and drains to Yala River. It emerges from the areas of Senende, Kalwani and Mago with small tributaries i.e. Digoi and other small streams that feeds Edzava river. From the DEM of Edzava, the watershed covers an approximate area of 152km^2 and draining two Sub-Counties in Vihiga County namely Hamisi and Sabatia (GOK., 2013). The water quality in the watershed is among the highest priorities as it is a source of water particularly for drinking. Runoff from the agriculture activities, largely tea and maize farming and urban areas of Mudete, Chavakali and Mbale increasingly affects the water quality. During the period of this study, the area lacked proper sewerage facilities to cater for high organic loading from the urban and peri-urban areas (GOK., 2013).

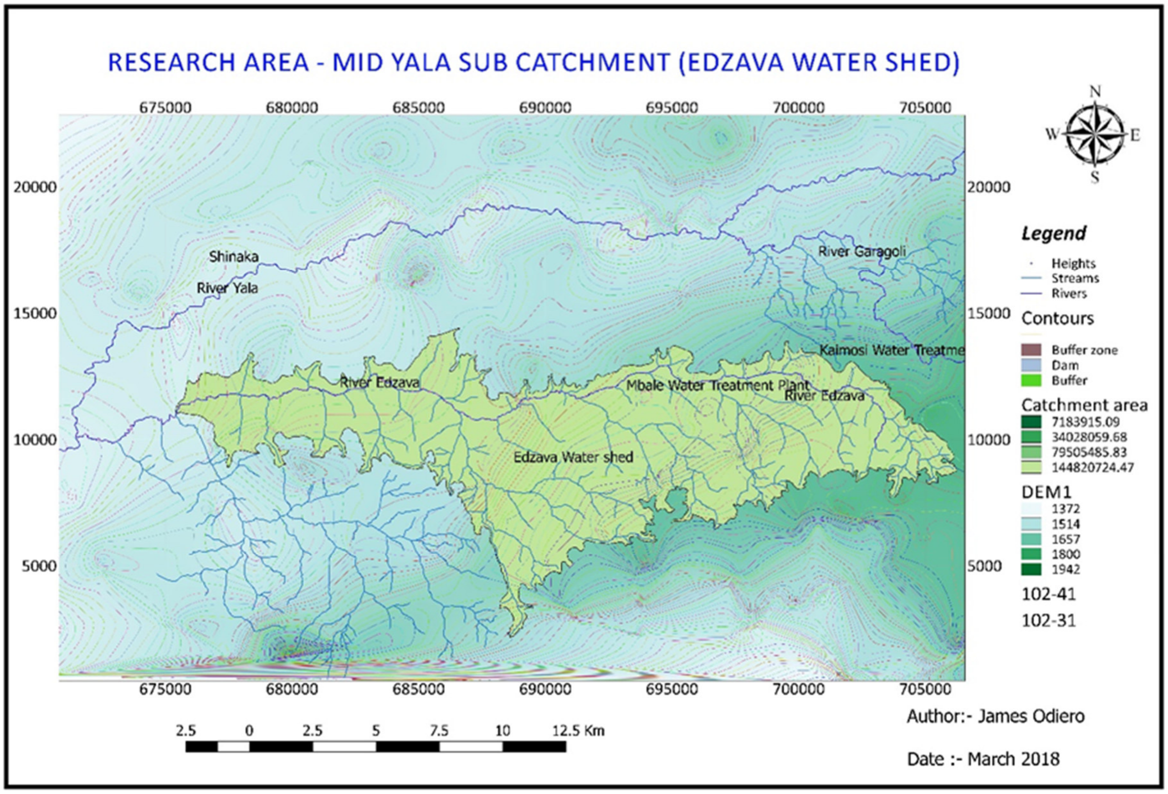


Figure 3. 6: Delineated DEM for Edzava river watershed (Source- field data 2019)

From the DEM of Edzava, the watershed covers an approximate area of $152km^2$ and draining two Sub-Counties in Vihiga County namely Hamisi and Sabatia. The river also covers a longest length of 32.344km.

3.4.3. Zaaba River Water shed

Zaaba water shed lay in the lower side towards the end of the Yala mid-block in Vihiga County. The Major urban set up in the area are Kima center, Emuhaya Sub-County offices and Luanda market. The river that drains this area is Zaaba River which as well joins Edzava just before draining to River Yala. The River also is a source of raw water for Maseno treatment plant. The water supply serves the areas of Emuhaya, Luanda and Maseno University.

From the DEM of Zaaba water shed, it covers an approximate area of 79.51km^2 and draining three Sub-Counties in Vihiga County namely Vihiga, Emuhaya and Luanda. Because of its position in the lower region, its turbidity is normally high during rainfall periods.

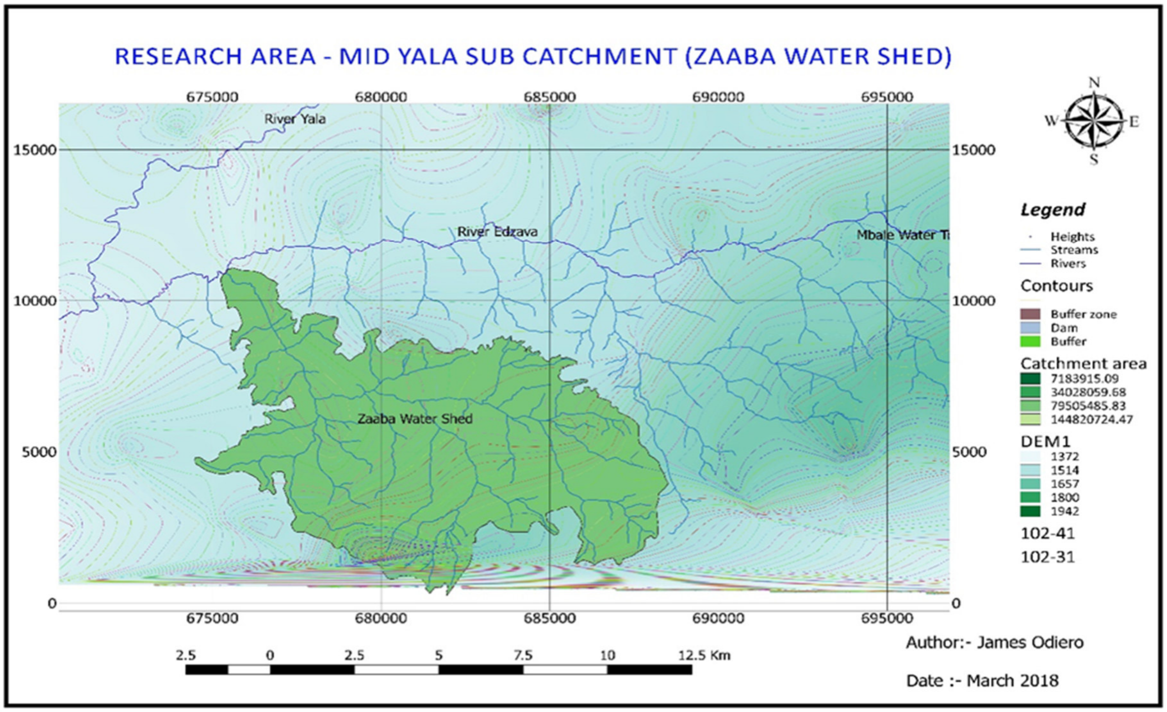


Figure 3. 7: Delineated DEM for Zaaba river watershed (Source- field data 2019)

Zaaba Water shed covers an approximate area of 79.51km^2 and draining three Sub-Counties in Vihiga County namely Vihiga, Emuhaya and Luanda and covering a total longest length of 9.423km (refer to section 3.4)

3.4.4. Garagoli River Water Shed

Garagoli watershed lays in the upstream of the study area. It is being drained by river Garagoli which flows into a Kaimosi reservoir. The water supply treatment plant derives its water from the reservoir and serves on one side, Kaimosi complex which has major institutions among them a University, Teachers College, and Polytechnic, High school, Jumuia Hospital and a number of primary schools. On the other side it serves the areas of Shamakhokho urban center and the surrounding. There are institutions and schools besides the individual residential customers. From the DEM of Zaaba water shed, it covers an approximate area of $34.04km^2$ and draining the Nandi forest and through to Yala river.

The watershed is characterized by high population and increased urbanization which is exerting pressure on the water resources. In addition, urbanization, deforestation and farming on riparian areas increase volume of runoff to rivers and thus affects the quality and quantity of water. In addition during the period of study, the reservoir was silted and colonized by marine plants i.e. the reed and other water plants. This phenomenon has reduced the capacity of the reservoir and increased the organic load.

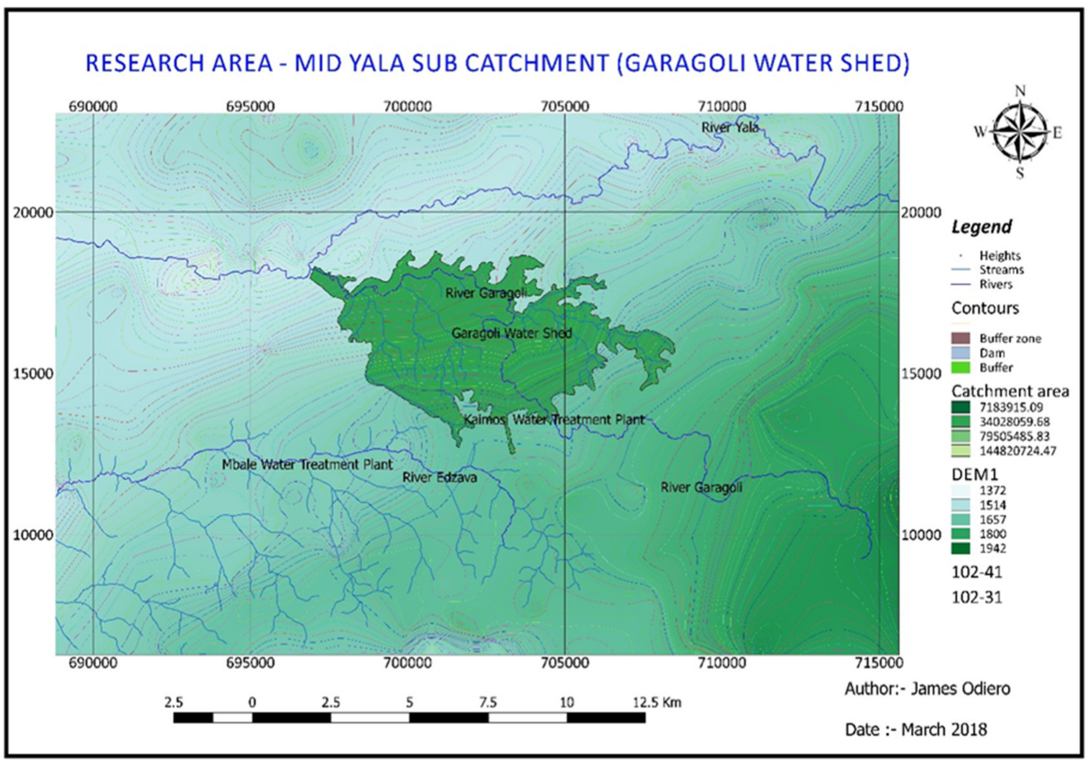


Figure 3. 8: Delineated DEM for Garagoli river watershed (source- field data)

Garagoli Water Shed covers an approximate area of 34.04km^2 and draining the Nandi forest through Hamisi Sub-County to Yala River and cover a total length of 17.118km.

3.5 Research Design

The study involved data collection both primary and secondary from Water Resources Management Authority, Meteorological department and the Amatsi Water Services Company Ltd, the WSP mandated in the area. ANN was used to simulate runoff and water quality and historical data was used in simulation and as well as Real time scenarios considered. In this study, the parameters considered were Color, Turbidity, PH, TDS and Iron. This parameters were historical data recorded as from 2008 to 2017, a 10 year period sourced from LVNWSB.

3.5.1 Input Data

The basic meteorological data requirement was majorly precipitation. On this basis, the model produces a catchment runoff, water quality effects of the hydrological system.
The reliable rainfall data was sourced from the following meteorological station i.e. Shamakhokho station ID-8934200 which is in River Garagoli sub-catchment of Yala, Sabatia station ID-8934150 which helped to cover Edzava river sub catchment and Vihiga D.C's Office station ID-8934213 for the period of 10 years i.e. from 2008 to 2017 was used for modelling.

3.5.2 Secondary data

Secondary information was collected from secondary sources i.e. the demographic reports from Kenya National Bureau of Statics, rainfall from the meteorological department, River discharges from the Water Resources Management Authority, and data of water quality parameters from the Water Services Board; LVNWSB and the Department of Water, in the republic of Kenya.

3.5.3 Methods for Estimation of Missing Rainfall Data

This study utilized the normal ration method for estimation of the missing data. According to Suhaila, Sayang, and Jemain (2008), normal ratio method provides missing precipitation as expressed in the following equation:

$$P_x = \frac{1}{n}\sum_{i=1}^{i=n}\frac{N_x}{N_i}P_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textit{Equation 3.1}$$

Where Px is the missing precipitation for any storm at the interpolation station 'x', Pi is the precipitation for the same period for the same storm at the "ith" station of a group of index stations, Nx the normal annual precipitation value for the 'x' station and Ni the normal annual precipitation value for 'ith' station.

3.6.0 Data analysis

The daily and monthly rainfall data of four rain-gauge stations Kaimosi, Sabatia, Mbale and Kima/Luanda was used. The river discharges was used to compute the runoff using rational methods. The Runoff generated was used as input in ANN model and Water quality parameters as output. ANN analysis was performed using MATLAB Neural Network Toolbox.

3.6.1 Run-off generated in the water sheds

In general, runoff is defined as “the water flow that occurs when soil is infiltrated to full capacity and excess water from rain, melt-water, or other sources flows over the land” Runoff quantities were generated using rational method as follows:

$$Q_p = CiA \quad \text{...} \textit{Equation 3.2}$$

Where, • Q_p = peak flow (m^3/s)

• C = runoff coefficient (for *Garagoli water shed C=0.1, Edzava and Zaaba C=0.16*)

• i = rainfall intensity (in/hr.), • A = catchment area (ac)

The Rational Equation relates peak discharge to the runoff coefficient, rainfall intensity, and drainage area, based on watershed slope, land use, and hydrologic soil type. The coefficient of runoff for the area of study was taken to range from 0.1 to 0.16 considering the soil properties and catchment characteristics. *See Table Appendix I-(Soil Group Coefficient Of runoff*).

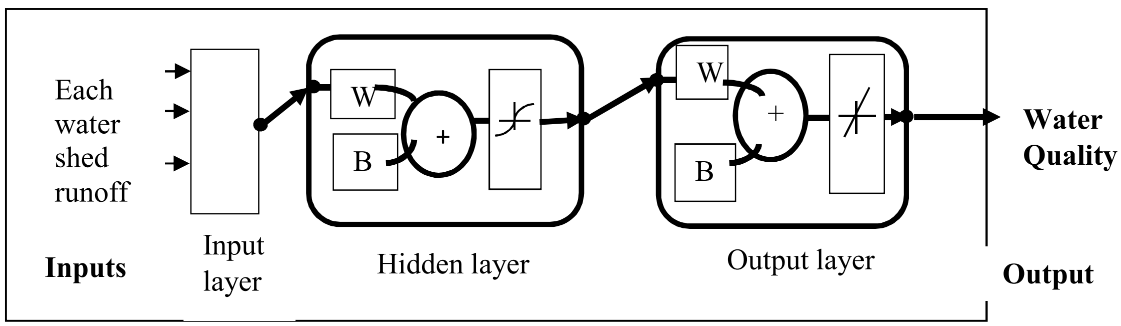
3.6.2 Water quality in river Edzava, Zaaba and Garagoli

Historical data from LVNWSB was utilized for analysis. The following parameters was considered; Color, Turbidity, pH, TDS, Ferrous (Iron). In this study, the research considered both the physical and chemical water quality parameters. The historical water quality data from Lake Victoria North water Services Board was used to assess the evolution of water quality in the three sub-basins collected during 2008–2017 from each river. The water quality indicators used were Color, Turbidity, pH, TDS and Ferrous (Iron). The results were benchmarked with water quality acceptable standards. On average there were a total of 480 tests for each parameter considered for the period of ten years i.e. as from 2008 to 2017. This tests helped in training and testing of the model.

3.6.3 Simulation using ANN model

3.6.3.1 Artificial Neural Network

The ANN model for runoff –water quality simulation was done using MATLAB environment, Levenberg–Marquardt back propagation algorithm which was also used to train the network. The network structure adopted in this study is illustrated in Figure 3.9.



Key: W = weights, B = bias

Figure 3. 9: ANN structure adopted for the study (Adopted from Kanda et al 2016)

A total of 480 data for each water quality parameter and runoff covering a weekly data for the period of 10 years as from 2008 to 2017 was considered for the three river water sheds. These run off generated was taken for model development as input variables and each water quality parameter (Colour, Turbidity, pH, TDS and Iron) as output. The behaviour of model during training, testing and validating is represented in Figure 5 which shows its capability to predict the process input output relation. Performance evaluation of the model was done using the correlation coefficient value (R) and when R was tending towards 1, then the better the model.

3.6.3.2 Input and Output variables

In ANN, one of main tasks is to determine the model input variables that significantly affect the output variable(s). In this study, the input variable was runoff and the output variables were the water quality parameters (Turbidity, Color, TDS pH and Iron). The records for the past 10 years as from 2008 to 2017 were used.

3.6.3.3 Training and Validation:

The input data was divided into two categories, namely training (calibration) and validation periods. In order to gain the most optimum and efficient ANN networks for runoff forecasting, the parameters were adjusted during the training process. The parameters were: 1) input data, 2) algorithm, 3) number of hidden neurons in hidden layer, and 4) learning rate value. Levenberg-Marquardt back propagation in trainlm is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. Trainlm is often the fastest back propagation algorithm in the toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. The training process of ANN was terminated when the overall error on the testing dataset was minimal (Integrated Hydrological Modelling System, 2008). The main function for training process is to reach an optimal solution based on some performance measurement such as overall error, coefficient of determination known as R value. The validation sets are usually used to select the best performing network model. In this paper, the ANN was the optimal at over 1 million iterations and ranged between 7-15 epochs with 10 hidden nodes. It was found that R ranged between 0.7 to 0.99 for training, validation and testing phases giving a good agreement with coefficient of determination. Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error. Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship (Integrated Hydrological Modelling System, 2008).

3.6.3.4 ANN parameter selection

A rule of thumb for selecting the number of hidden nodes relied on the fact that the number of samples in the training set should at least be greater than the number of synaptic weights. A one-hidden-layer network is commonly adopted by most ANN modelers; the number of hidden nodes M in this model was determined by trial and error. Networks with fewer hidden nodes are generally preferable, because they usually have better generalization capabilities and fewer over fitting problems (Integrated Hydrological Modelling System, 2008).

3.6.3.5 Data partition

The data in neural networks are categorized into three sets: training or learning sets, test or over fitting test sets, and production sets. The learning set is used to determine the adjusted weights and biases of a network. The test set is used for calibration, which prevents overtraining networks. The general approach for selecting a good training set from available data series involves including all of the extreme events (i.e. all possible minimum and maximum values in the training set). The over fitting test set should consist of a representative data set. For development of ANN model, the observed data were used as 70 percent for training, 15 percent for testing and 15 percent for validation.

3.6.3.6 Model performance evaluation

The performance evaluation of the model is assessed using standard statistical performance evaluation criteria including the coefficient of correlation (R), root mean squared error (RMSE), mean absolute error (MAE), relative root mean squared error (RRMSE), and Nash-Sutcliffe (NS) efficiency coefficient (Yaseen, El-shafie, Jaafar, Afan, & Sayl, 2015).In this study the above evaluation criterion was used and majorly the Correlation, R represented. The methodology of those criteria calculation and the simulation models also references (Chang, Wang, & Mao, 2015). The statistical criterion R^2, mean values and a graphical representation is used in the analysis of the model calibration results. The efficiency criterion R measures the proportion of the total variance of the observed data as explained by the predicted data. Nash–Sutcliffe efficiencies can range from $-\infty$ to 1. The perfect model results in R^2 equal to 1. However, normally R^2 is in the range between 0.8 and 0.95. Naturally, this is only the case when input data are of good quality (Integrated Hydrological Modelling System, 2008). The correlation of runoff and water quality parameters (Colour, Turbidity, TDS, pH & Iron) are obtained by performing a linear regression between the ANN-predicted values and the targets.

CHAPTER FOUR

4.0. RESULTS AND DISCUSSION

4.1 Rainfall trends in the three water sheds

The names of the River Water Shed, and the mean annual rainfall, are given in the following table.

Table 4. 1: Watershed characteristics

Station ID	Station Name	Name	Area (KM^2)	Mean Annual Rainfall (mm)	Value at 95% Conf. Level
8934150	Sabatia Div. Office	Edzava	152	1,870	270
8934200	Shamakhokho	Garagoli	34.04	2,168	260
8934213	Vihiga D.C. Office	Zaaba	79.51	1,889	280

From the records in the three stations, the rainfall recorded is higher in Garagoli with a mean annual rainfall averaged over 10 years to be 2,168mm. Edzava and Zaaba seems to have similar rainfall patterns. As shown in the graph below, the highest precipitation values registered were in April and October having over 550mm and 350mm respectively of each year. The three water sheds being in the same and adjacent area in Yala catchment, the trends seem to be the same with Garagoli registering the highest rainfall. This may be attributed to the fact that it is in the proximity of the Kakamega and Nandi forests.

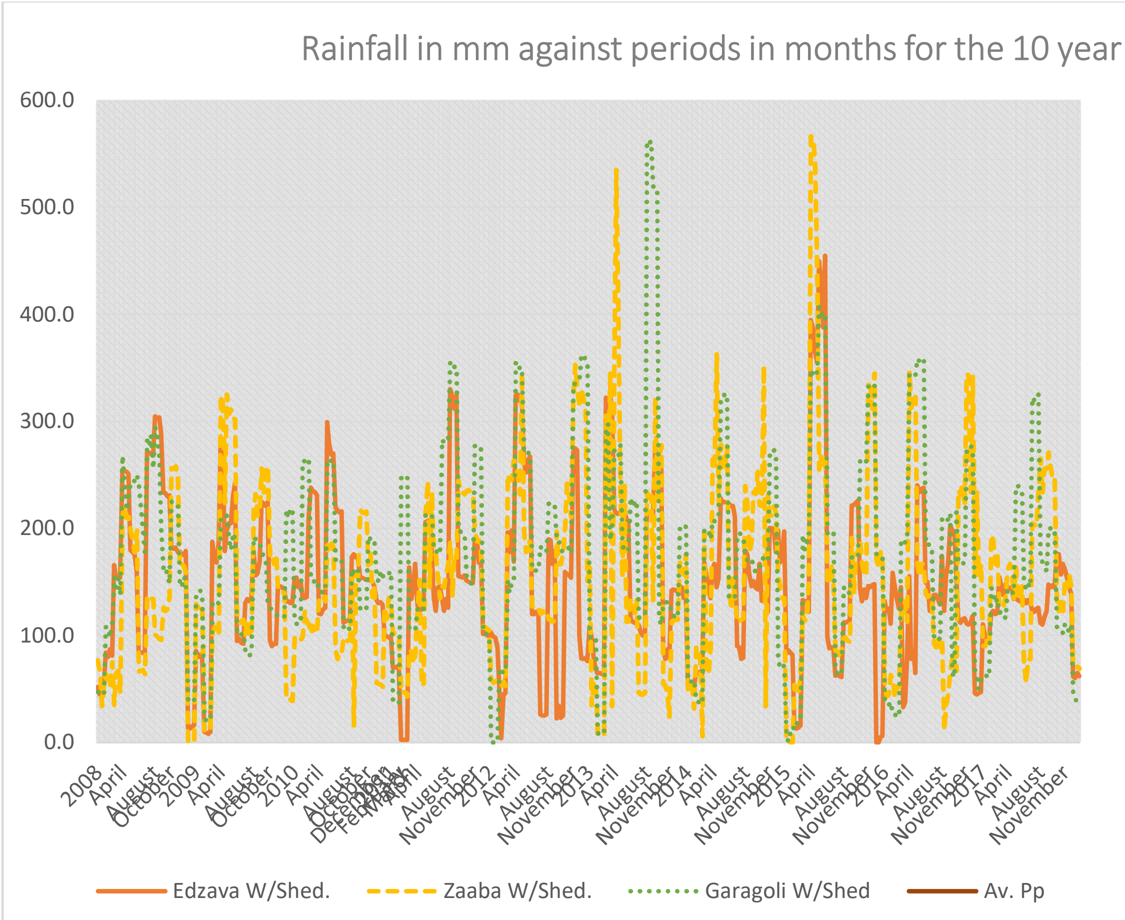


Figure 4. 1: Rainfall trends in three watersheds (Field data 2019)

Test of precipitation values

The probabilities and level of confidence of the precipitation values was done using the ANN embedded *ntool* and the following results were arrived at.

Below is a plot of the each water shed cumulative probability at 95% confidence level

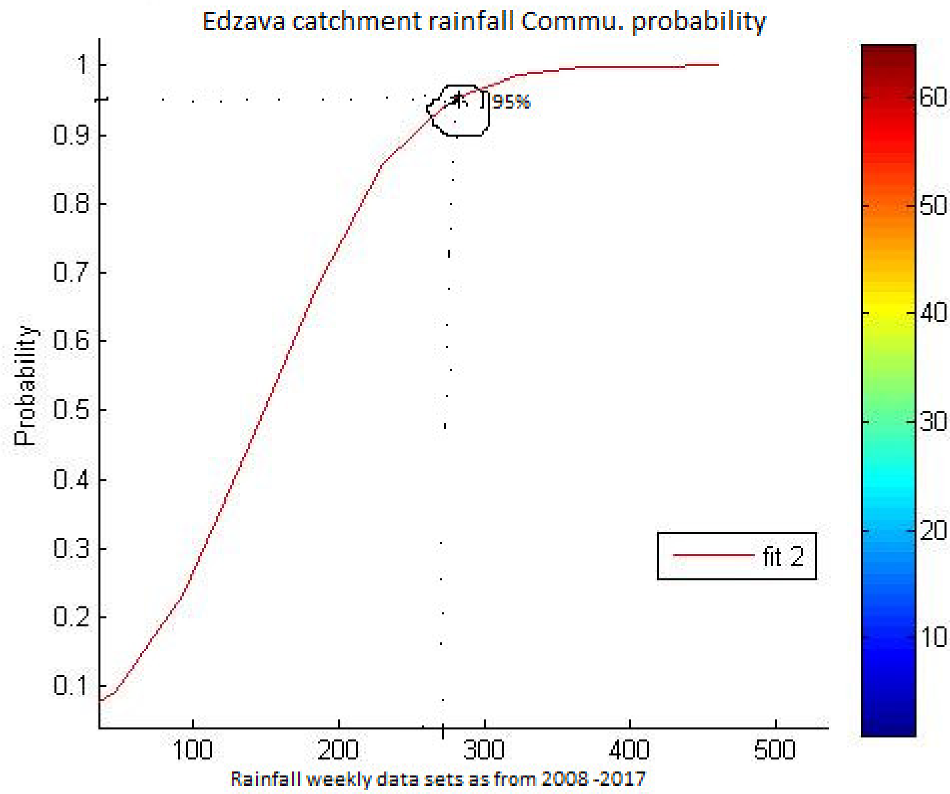


Figure 4. 2: Edzava watershed at 95% confidence level the value was approximately 270

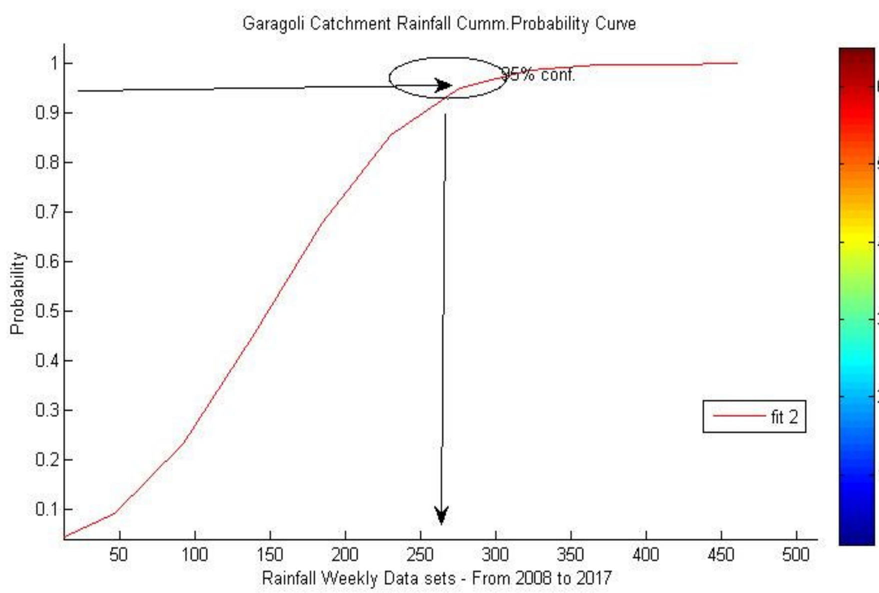


Figure 4. 3: Garagoli watershed at 95% confidence level the value was approximately 260

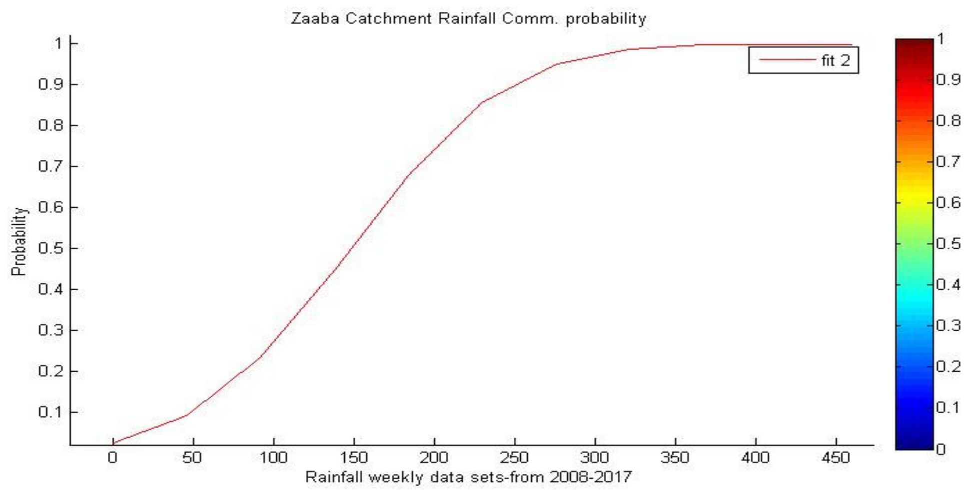


Figure 4. 4: Zaaba watershed at 95% confidence level. The value was approximately 280

4.2. Runoff generated

The runoff values generated were used tabulated and used as input in the ANN model.

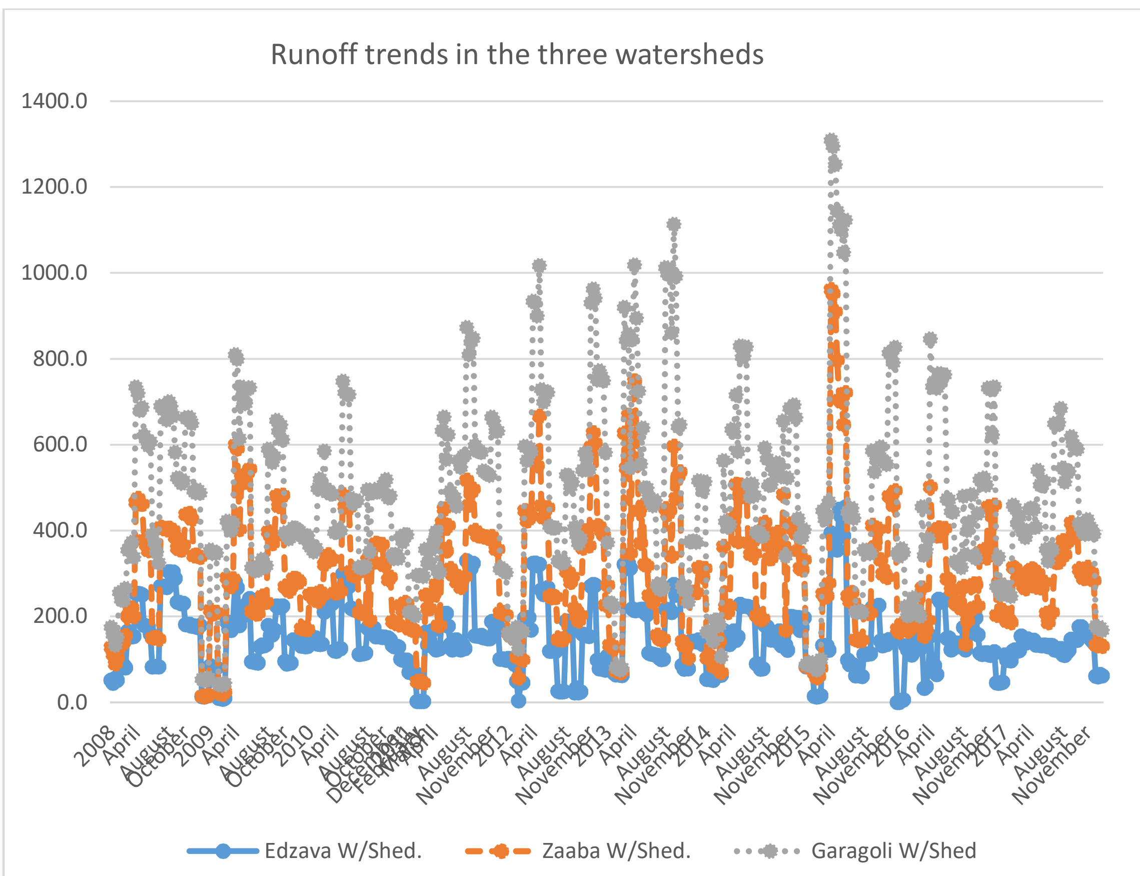


Figure 4. 5: Runoff trends in the three watersheds (Field data 2019)

The runoff in the three-river water shed was generated and analysed. All the three water shed had high values in April-May and September- October the period which coincided with the peak rainfall values.

The rainfall and runoff peak and low values are as tabulated below

Table 4. 2: Rainfall and Runoff peak values

River water shed	**Rainfall (mm)**		**Runoff (m^3/hr)**	
	Peak	Month /Year	Peak	Month /Year
Edzava	455	May 2015	374	March 2013
Zaaba	566	April 2015	358	March 2013
Garagoli	562	August 2015	128	August 2015

The highest peak values were registered in all the Water shed in the month of March - April and August – September which are the peak rainfall periods. The sub peak values in each month alternated between the short and the long rainfall periods in each year. High runoff events takes place in the month of March which is normally a planting season in the catchment and fields were normally prepared (GOK., 2013). This trends will guide the water supply managers to understand the maximum values expected in the water shed and more so in their water supplies. The runoff values reduced amounts of rainfall which may be attributed to either global warming or climate change.

4.3 Rainfall - runoff relationship in the three water shed.

The research considered rainfall measurements for a period of 10 years and the average duration. The information collected shows that rainfall has a direct relationship with runoff. The higher the rainfall that higher the runoff when all other factors (Land use/cover, soil) are kept constant.

This research observed that there was a direct relationship of rainfall and runoff in the three watersheds. The more the rainfall increased, the higher the values of runoff generated. The runoff peaks coincided with the rainfall peak months or periods.

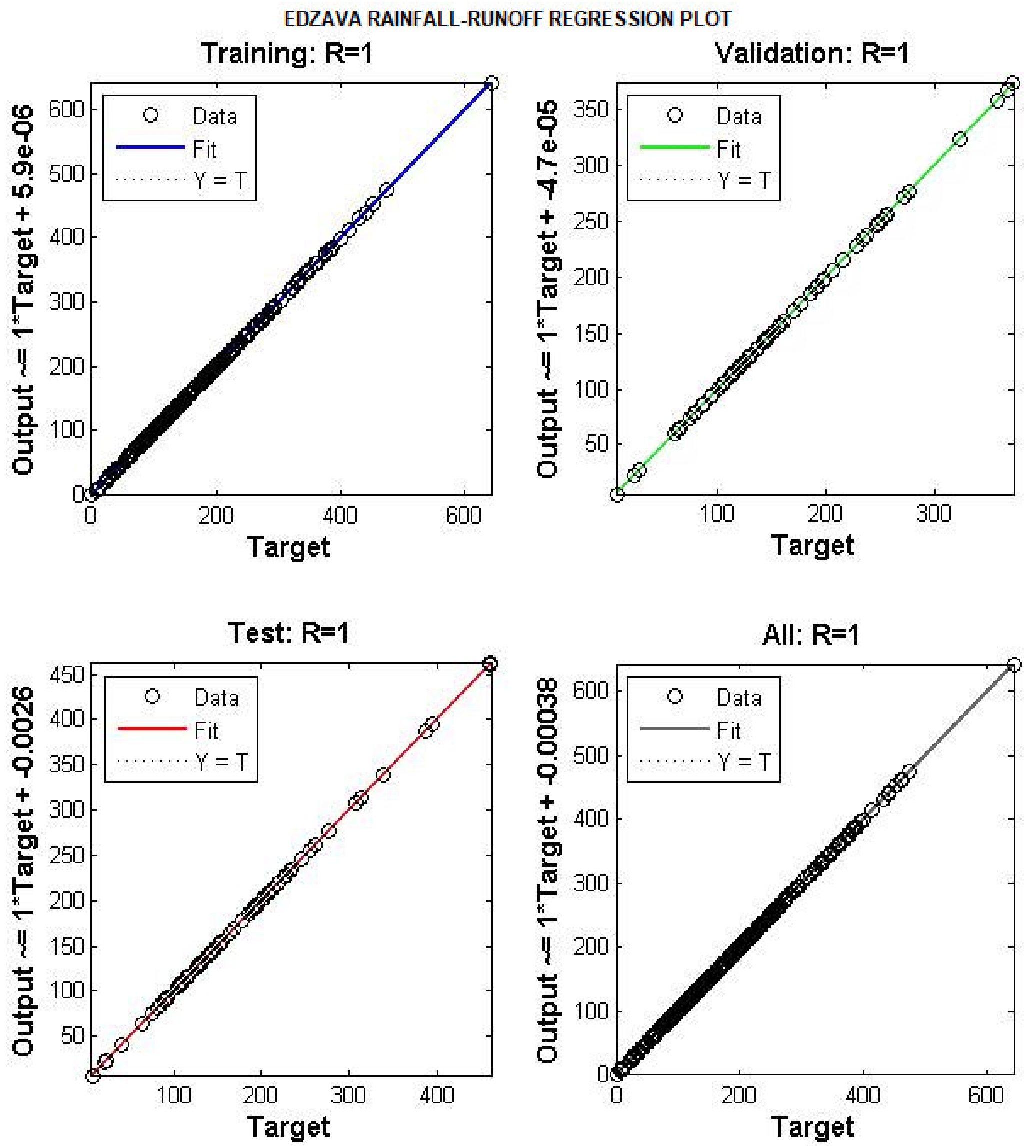


Figure 4. 6: Edzava rainfall – Runoff regression plot.

Rainfall - runoff regression plot with correlation coefficient (R) tending towards 1

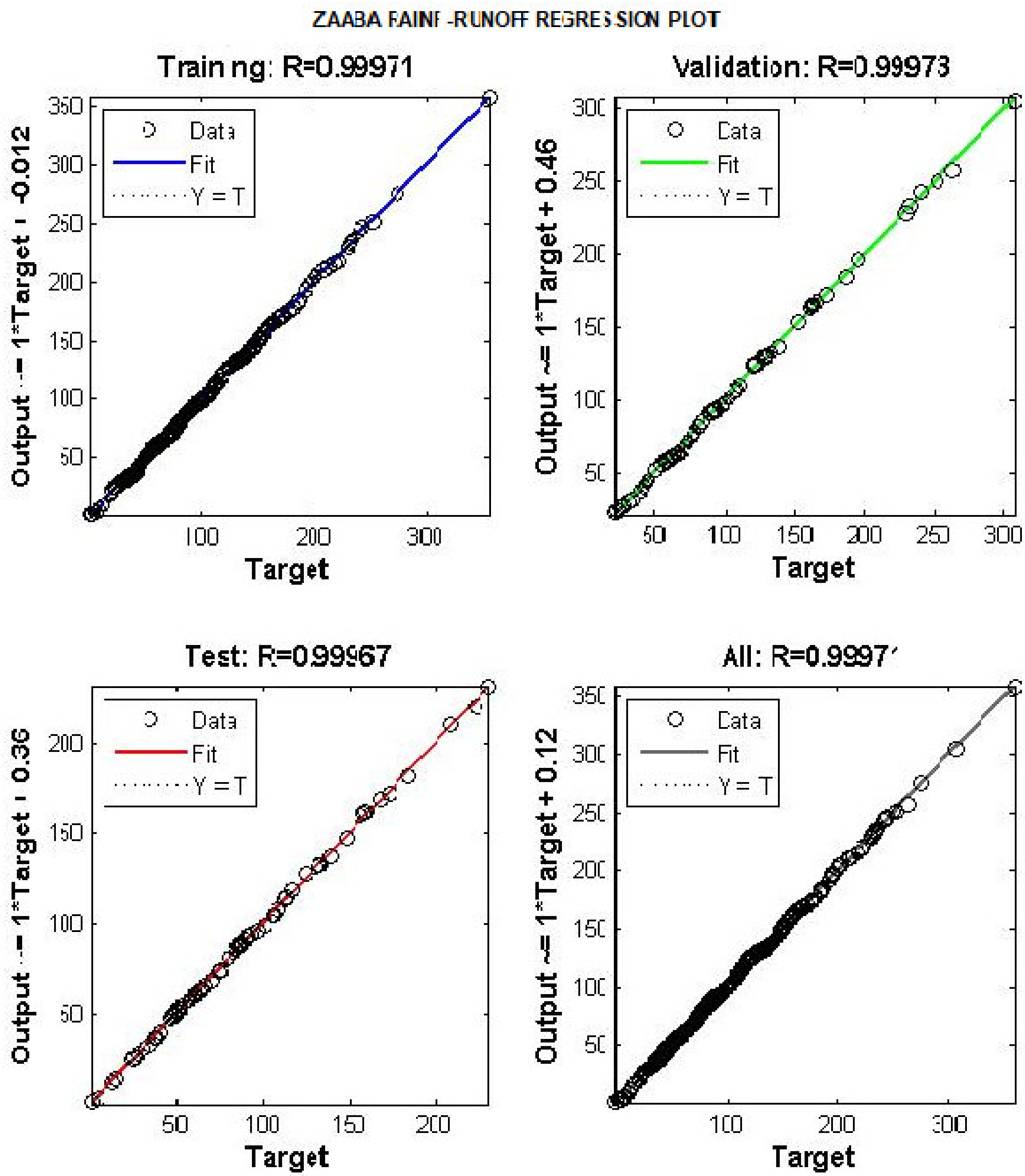


Figure 4. 7: Zaaba rainfall – Runoff regression plot.

Zaaba Rainfall Runoff regression plot after simulation gave a best fir of R=0.999.

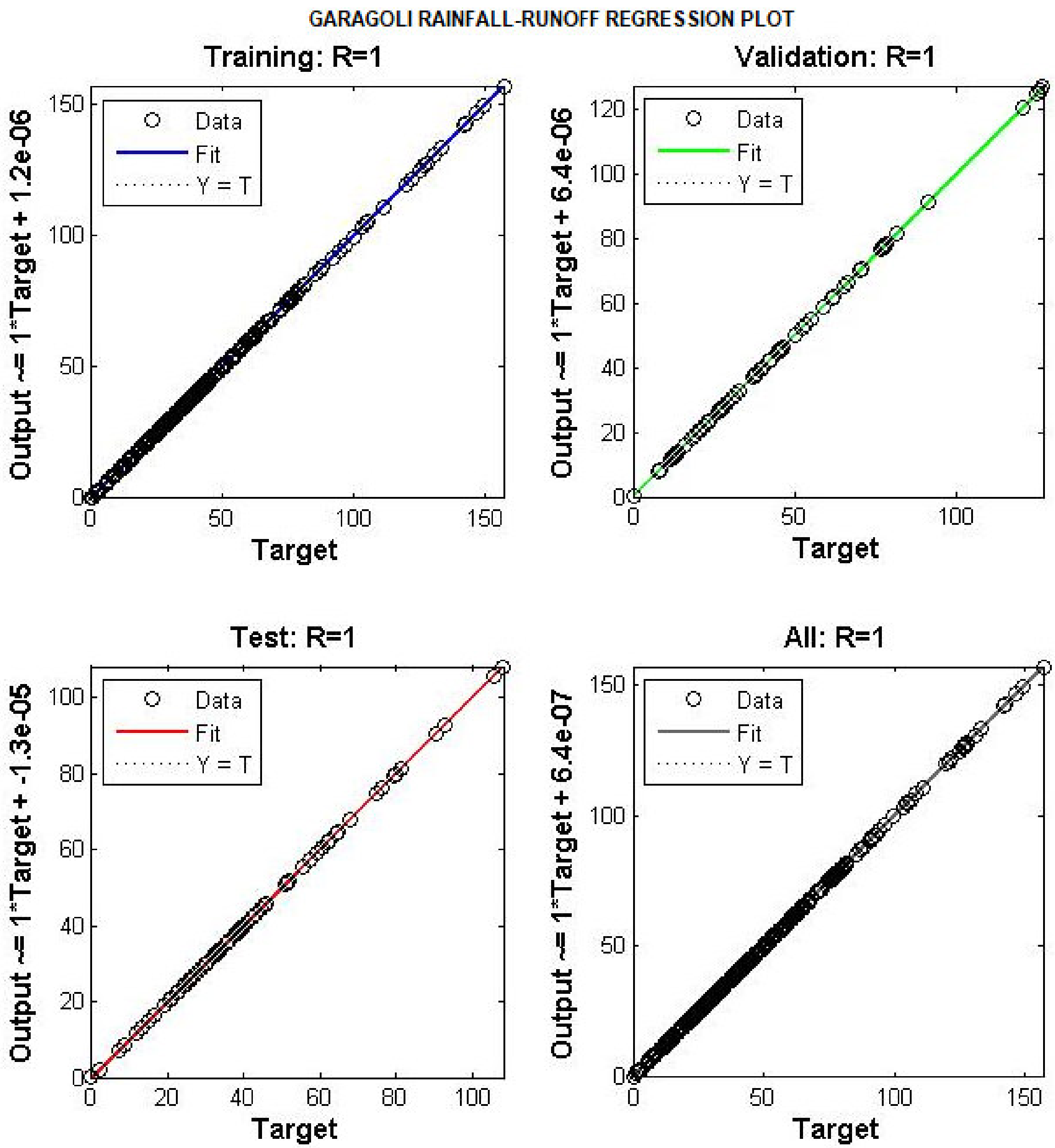


Figure 4. 8: Garagoli rainfall – Runoff regression plot.

The regression plot for Garagoli with rainfall - runoff regression plot with correlation coefficient (R) tending towards 1

4.3.1 Correlated results of rainfall and runoff

Rainfall- Runoff regression plot gave coefficient of correlation of R=0.9 for the three water sheds.

The following Rainfall runoff relationship were established from the regression results:

Edzava- $R_e = P_e - 0.00038$ …………………………………………………*Equation 4.1*

Zaaba - $R_z = P_z - 0.12$………………………………………………………*Equation 4.2*

Garagoli - $Rg = P_g - 6.4^{-0.07}$ ……………………………………………………*Equation 4.3*

Where,

$P_{e,z,g}$ = Precipitation (Rainfall in mm),

$R_{e,z,g}$ =Runoff (in m^3/h).

The additional value C, are the relationship constants.

4.4 Water quality

After plotting the values from the information collected from the field, the graphs were done to help analyze each parameter. The flowing were the water quality analysis for each parameter:

4.4.1 Colour

The graph of values of color against monthly observations.

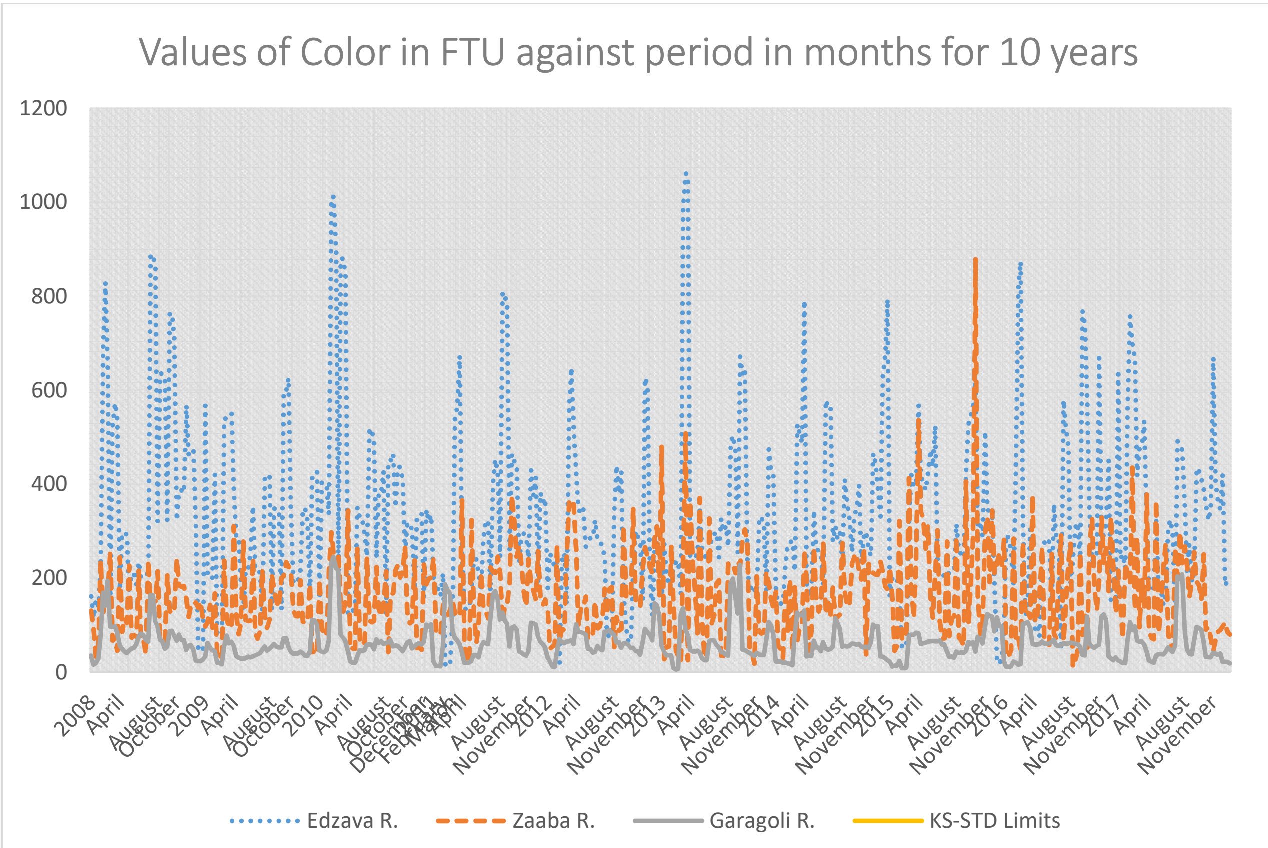


Figure 4. 9: Colour trends in the three watersheds (Field data 2019)

As observed in the graph above, levels of color in the three rivers for the last 10 years has beein increasing against the maximum drinking water standards which caps it at 15 FTU. The highest spikes have been registered in Edzava ain April 2014 with a highest value of 800, October 2015 registered value of 620 and october 2016 and 2017 a value of over 700.

In Zaaba, the highest registered values were in 2013 February with a value of 500 , 2015 a value of 2015 and April 2016 and 2017 a value of 400. Garagoli river, 2015 october was 800 and 2017 a value of 1150 (refer to water quality standards Appendix I).

All the three rivers registered high values above the acceptable values. This might be attributed to increased poor farming activities, soil erosion, defforestation and incresed surface runoff. This all activities carry soil, debris, solid and waste waters from the farms and biuld up areas to the rivers.

4.4.2. Turbidity

The graph below shows the monthly sampled turbidity values ranging from January 2008 to December 2017 for the three water supply intakes in the three rivers.

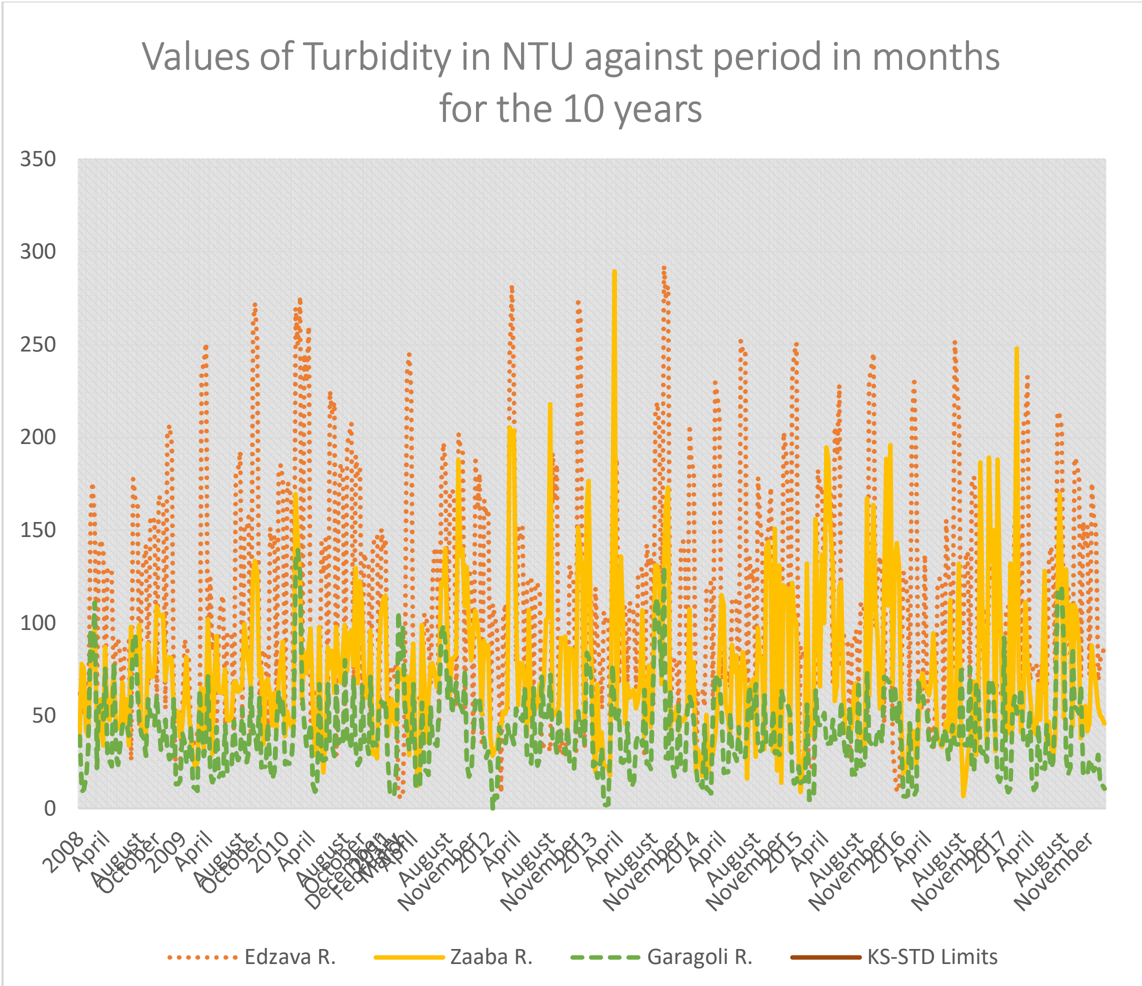


Figure 4. 10: Turbidity trends in the three watersheds (Field data 2019)

Turbidity is often undesirable in drinking water, plant effluent waters, water for food and beverage processing, and for a large number of other water-dependent manufacturing processes. Turbidity removal is often accomplished by coagulation, sedimentation, and various levels of filtration. According to drinking water standards, the turbidity value should be less than 5NTU (refer to Appendix II). The turbidity levels in the three rivers in the period of study flactuated with the high values recorded in April and September of each year. The highest values of over 150 were recorded in the year 2015 in Zaaba river. The highest values might be attributed to the position of the watershed which is on the lower side of mid block of Yala catchment that drains to L.Victoria as well as the land use and cover aspects in the area. These high values gives pressure to the treatment processes which has to reduce them to the acceptable values.

4.4.3 pH

The graph below shows the monthly sampled pH values ranging from January 2008 to December 2017 for the three water supply intakes in the three rivers.

The pH levels for surface water is supposed to range from 6.5-8.5 (Refer to appendix II). The trend from the recorded as depicted in the graph above clearly shows that the pH values trended within the limits.

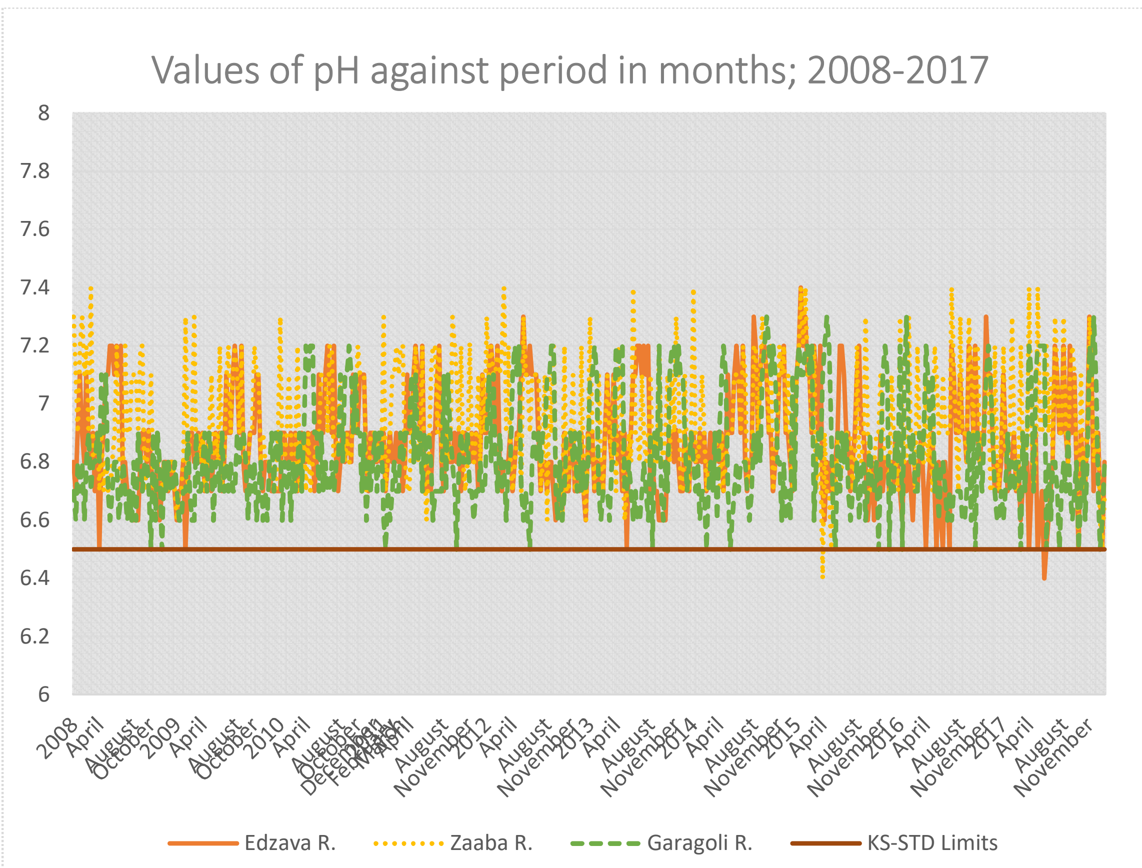


Figure 4. 11: pH trends in the three watersheds (Field data 2019)

4.4.4. Total Dissolved solids

The graph below shows the trends as recorded in the three rivers. The standards dictates that TDS should range below 1500mg/l (refer to Appendix II). From the records in the three rivers, there was no recorded value that is above the standards. The highest values of TDS were recorded during the wet months. This is due to surface runoff that either causes solubility of the minerals in the soils.

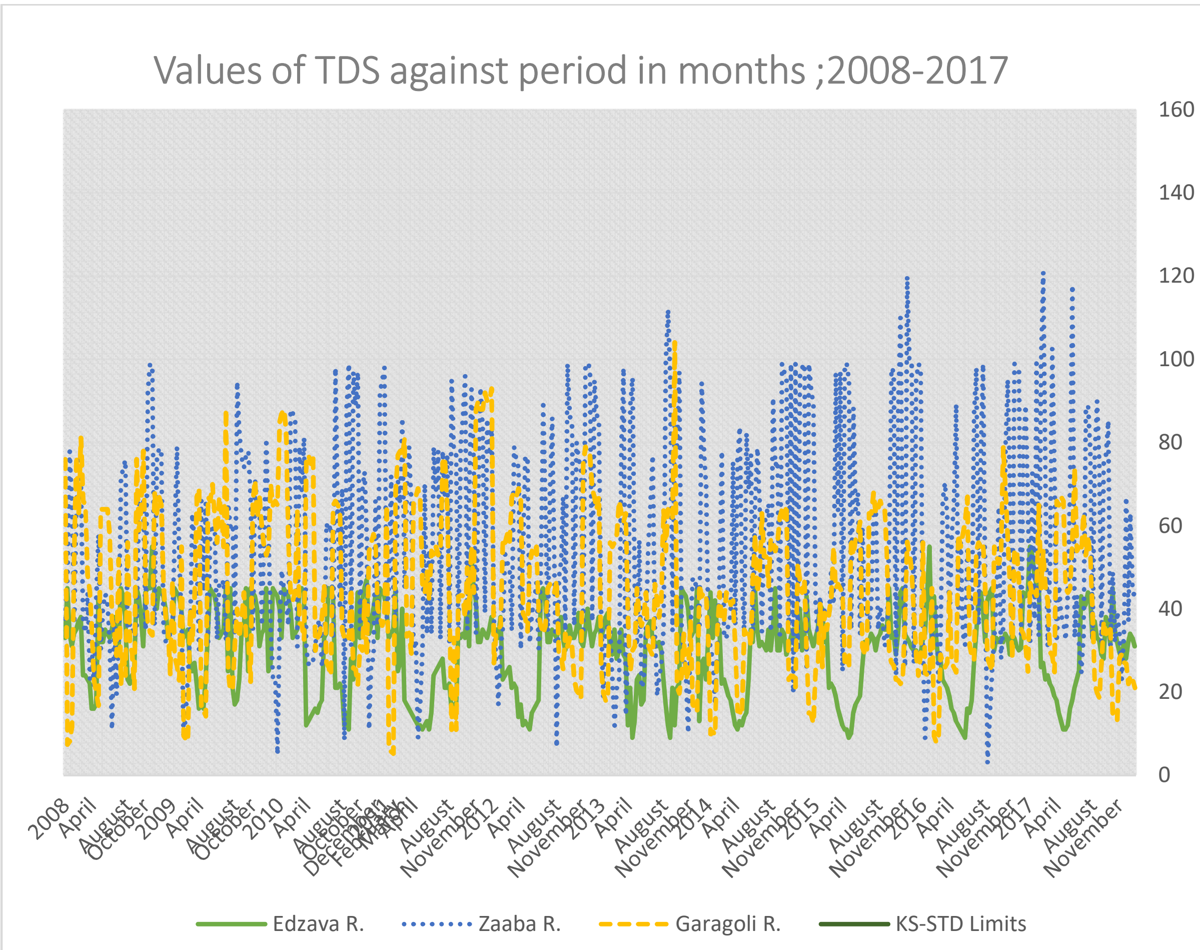


Figure 4. 12: TDS trends in the three watersheds (Field data 2019)

4.4.5. Iron

The graph below shows the trends of iron traces in the three river water sheds as collected on monthly basis from January 2008 to December 2017.

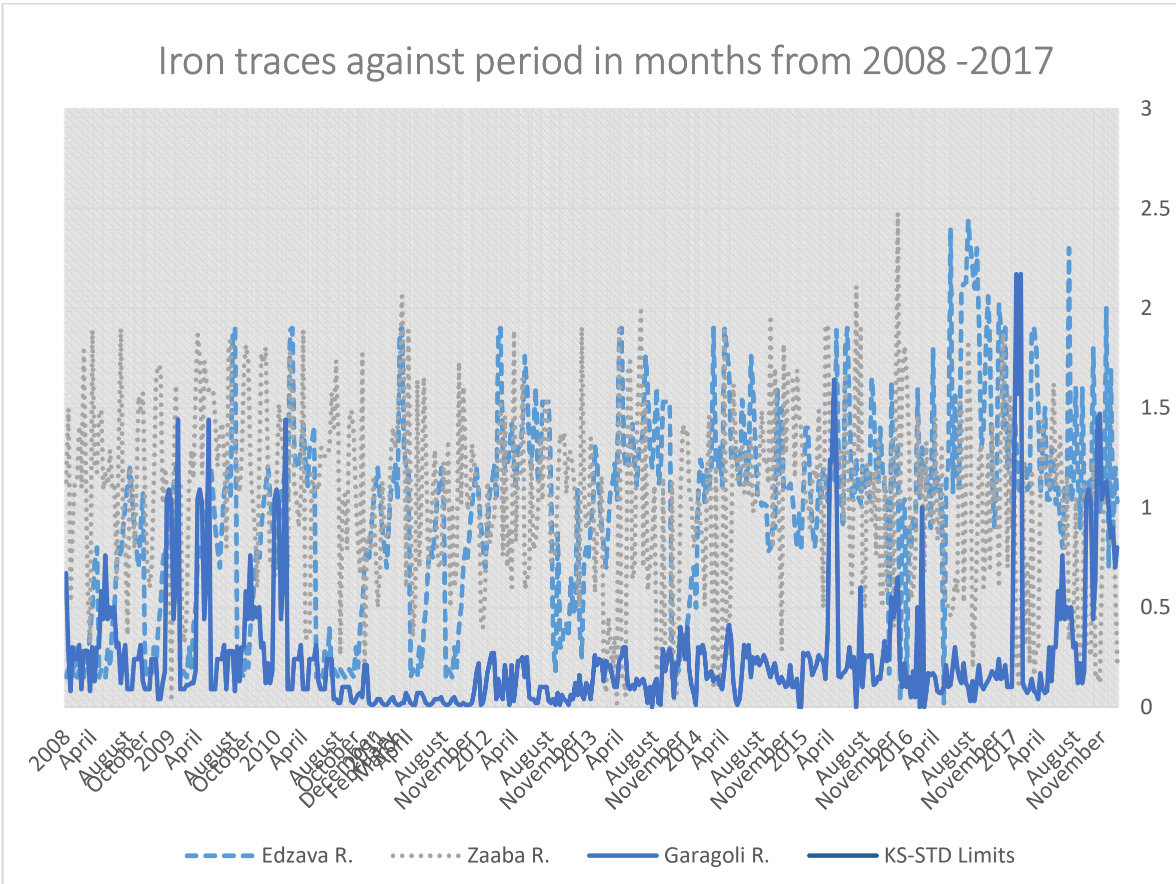


Figure 4. 13: Iron trends in the three watersheds (Field data 2019)

Browning of inland waters has been noted over large parts of the world and is a phenomenon with both ecological and societal consequences. The increase in water colour is generally ascribed to increasing concentrations of dissolved organic matter of terrestrial origin. Water colour is known to be affected also by the quality of organic matter and the prevalence of iron (Kritzberg et al., 2012). Iron in drinking water increases colour and makes the water un-sighty and unfit for consumption. Iron as well reacts with the metal materials used for water treatment i.e. the pipes, fittings and steel basins and filters. The higher values were reported in the earlier years as from 2015. Edzava River recorded high values than other river with a high value of 5mg/l in May 2016 and May 2017.

Water quality particularly to the treatment plants in the three watershed was an issue of concern. The results shows that turbidity, colour and TDS increased in the water. The results also shows that for turbidity the highest values of 248 NTU was recorded in the February 2017 in Zaaba river watershed, 462 NTU was recorded in Edzava watershed in January 2017 and 140 NTU recorded in February 2010 in Garagoli watershed. The lowest values of turbidity were recorded in December and January of each year in the period of study. For colour the highest values of 509 NTU was recorded in March 2013 in Zaaba river watershed, 1062 NTU was recorded in Edzava watershed in March 2013 and 245 NTU recorded in February 2010 in Garagoli watershed. The lowest turbidity values apart from Edzava water sheds were recorded also in December and January of each year in the period of study. For TDS, the Highest was in dry months of November, December and January of each year while lowest in the wet months of February March and April in each year. This observation then points out that two parameters i.e. turbidity and colour values are inversely proportional to the amount of runoff while TDS is inversely proportional to the amount runoff in all the three watersheds. Iron and pH had no did not show any relationship.

4.5 Simulation results from ANN model

4.5.1 Regression charts for simulation of runoff and colour

Edzava Watershed gave a best fit model for colour with R for training, Validation and Testing as 0.734, 0.729 and 0.777 respectively as shown below.

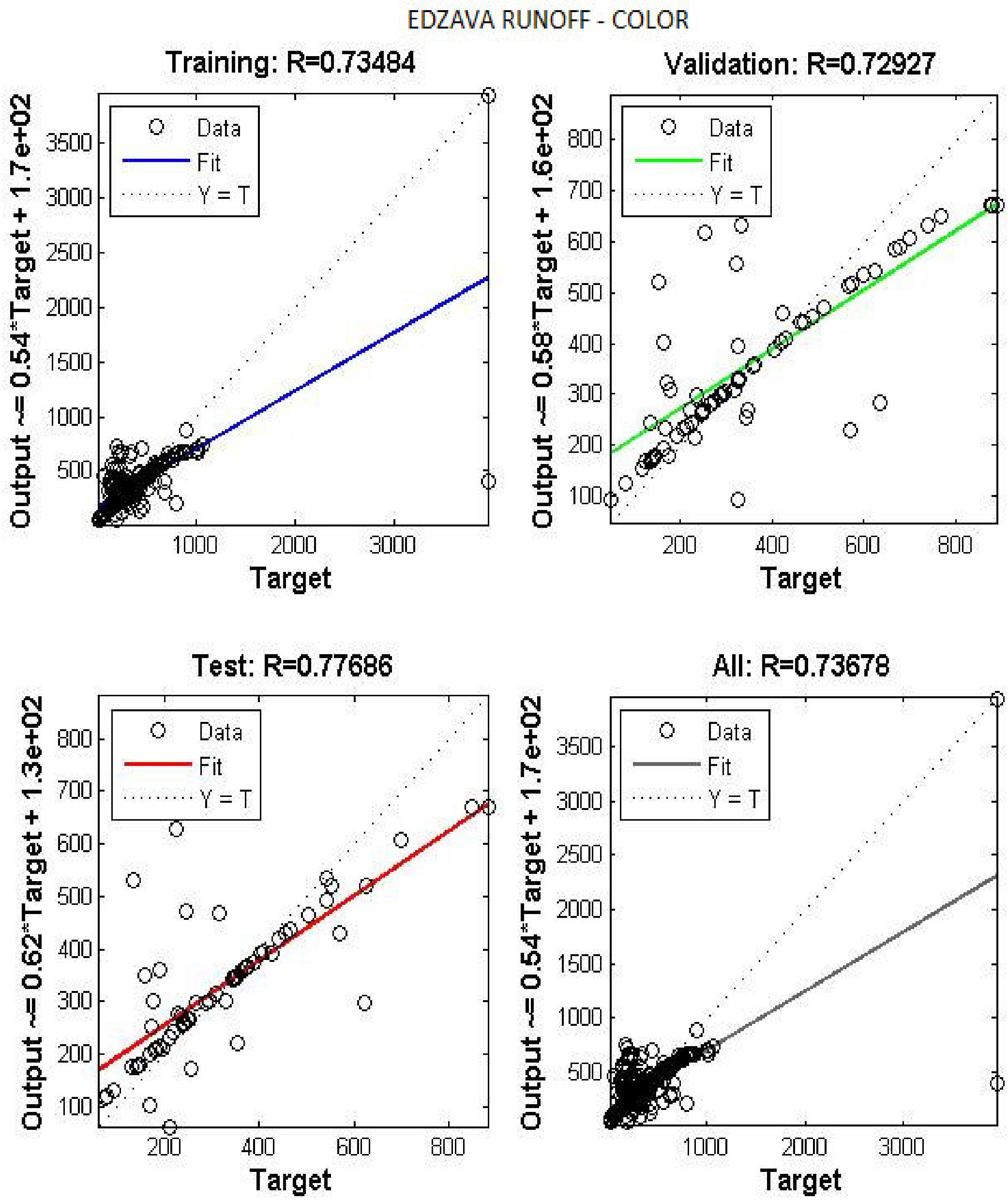


Figure 4. 14: Edzava Runoff –Color regression plot.

Garagoli watershed gave a best fit model for colour with R for training, Validation and Testing as 0.902, 0.878 and 0.841 respectively as shown below.

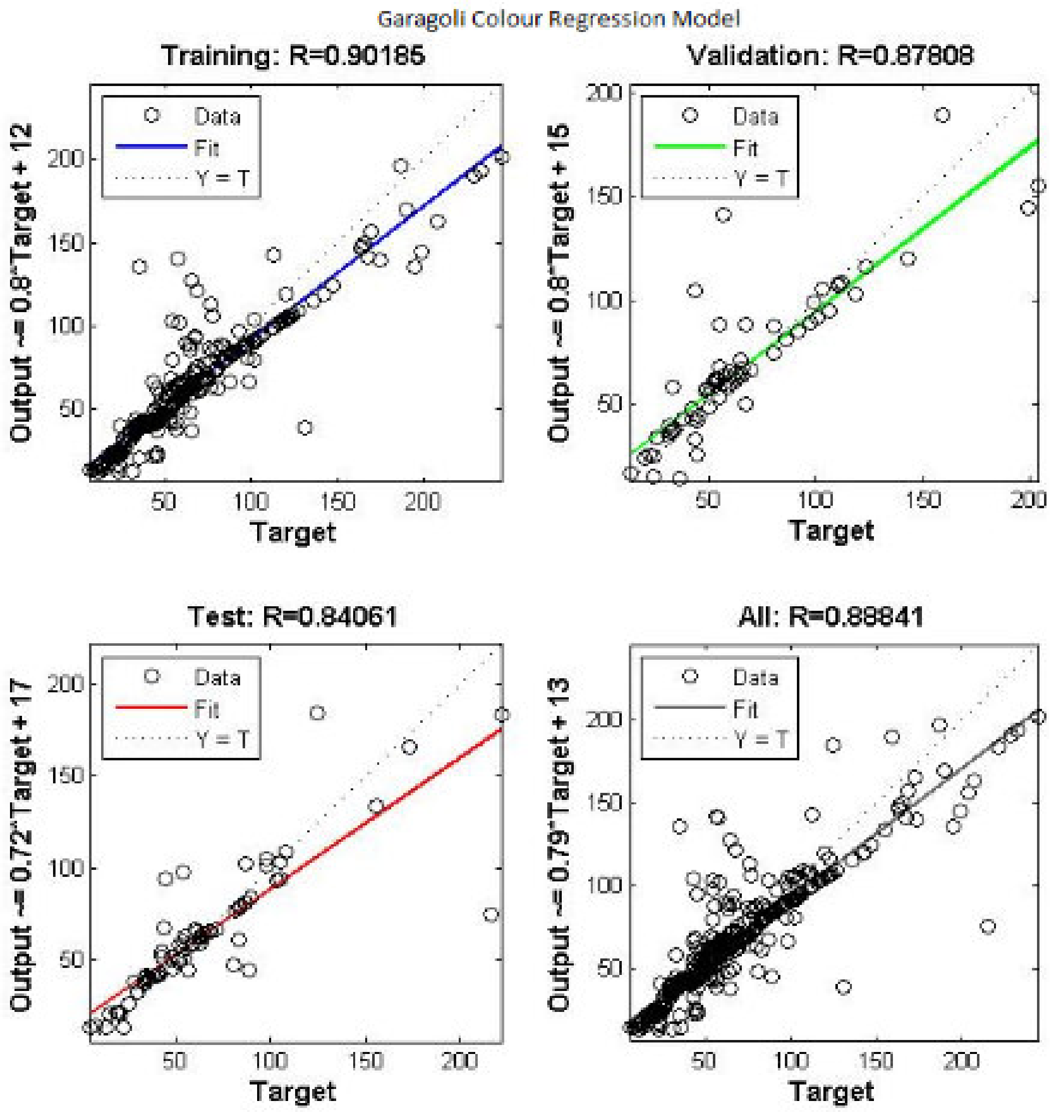


Figure 4. 15: Garagoli Runoff –Color regression plot.

Zaaba watershed gave a best fit model for colour with R for training, Validation and Testing as 0.811, 0.857 and 0.790 respectively as shown below.

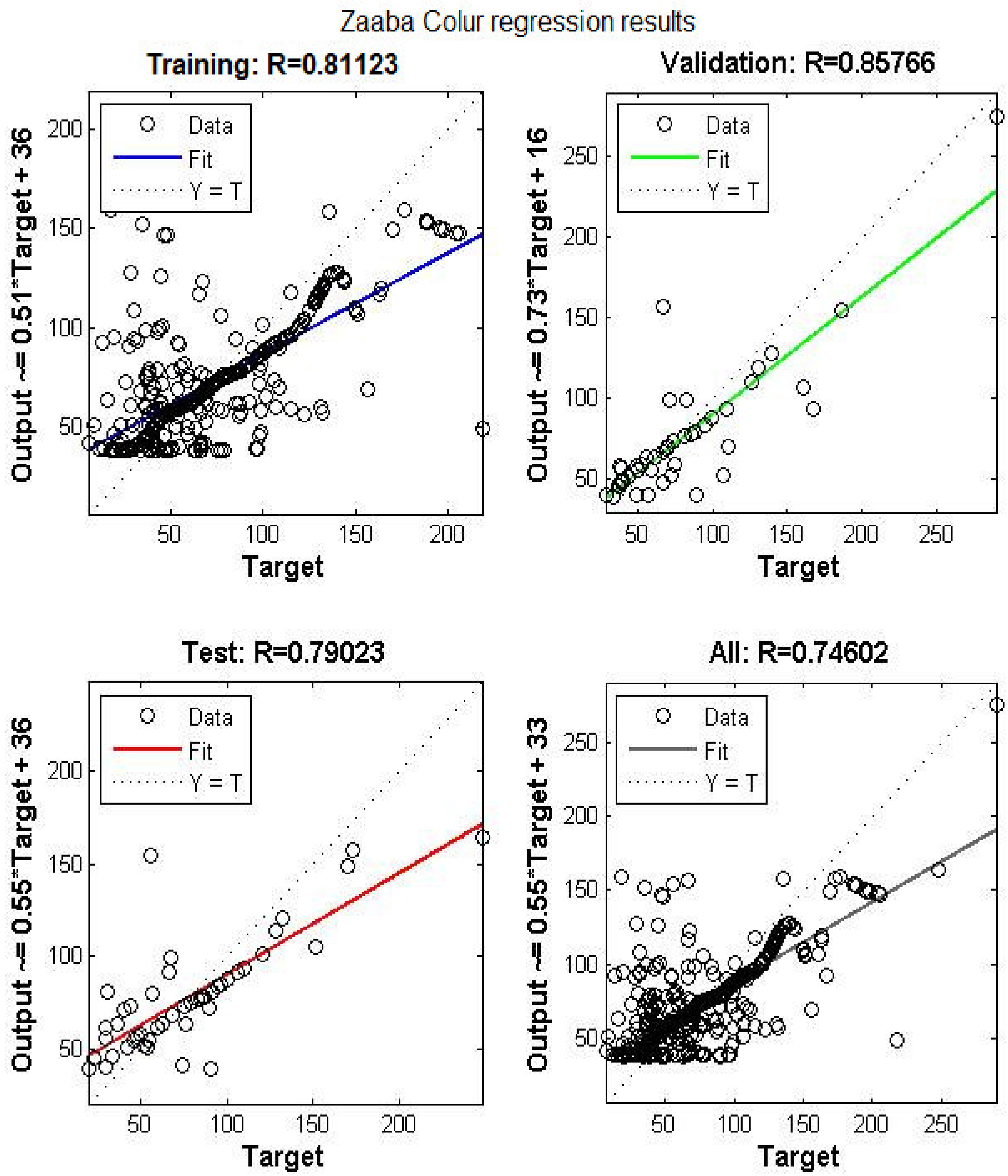


Figure 4. 16: Zaaba Runoff –Color regression plot.

4.5.2 Regression charts for simulation of runoff and Turbidity

Edzava Watershed gave a best fit model for turbidity with R for training, Validation and Testing as 0.714, 0.867 and 0.857 respectively as shown below.

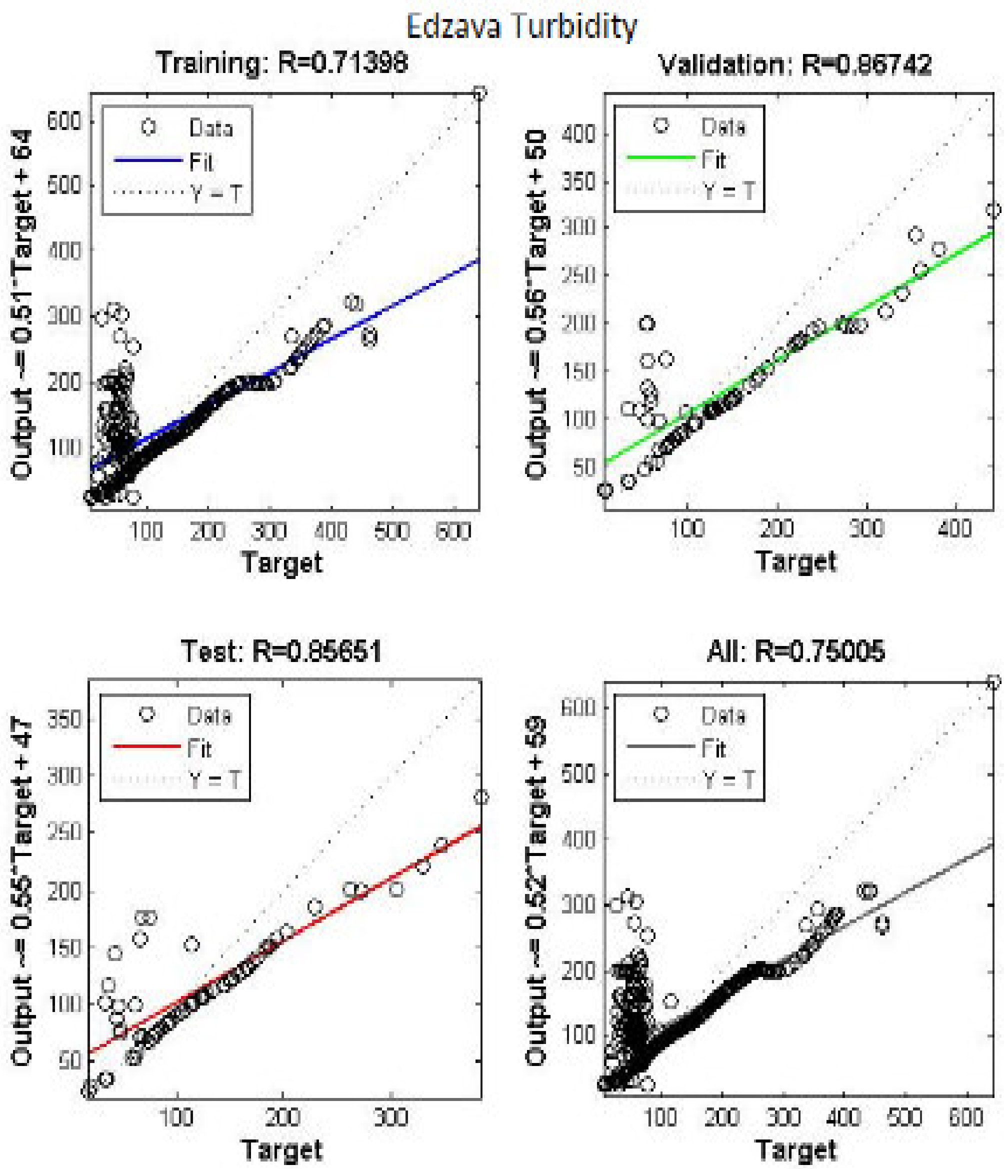


Figure 4. 17: Edzava Runoff –Turbidity regression plot.

Zaaba Watershed gave a best fit model for turbidity with R for training, Validation and Testing as 0.717, 0.858 and 0.79 respectively as shown below.

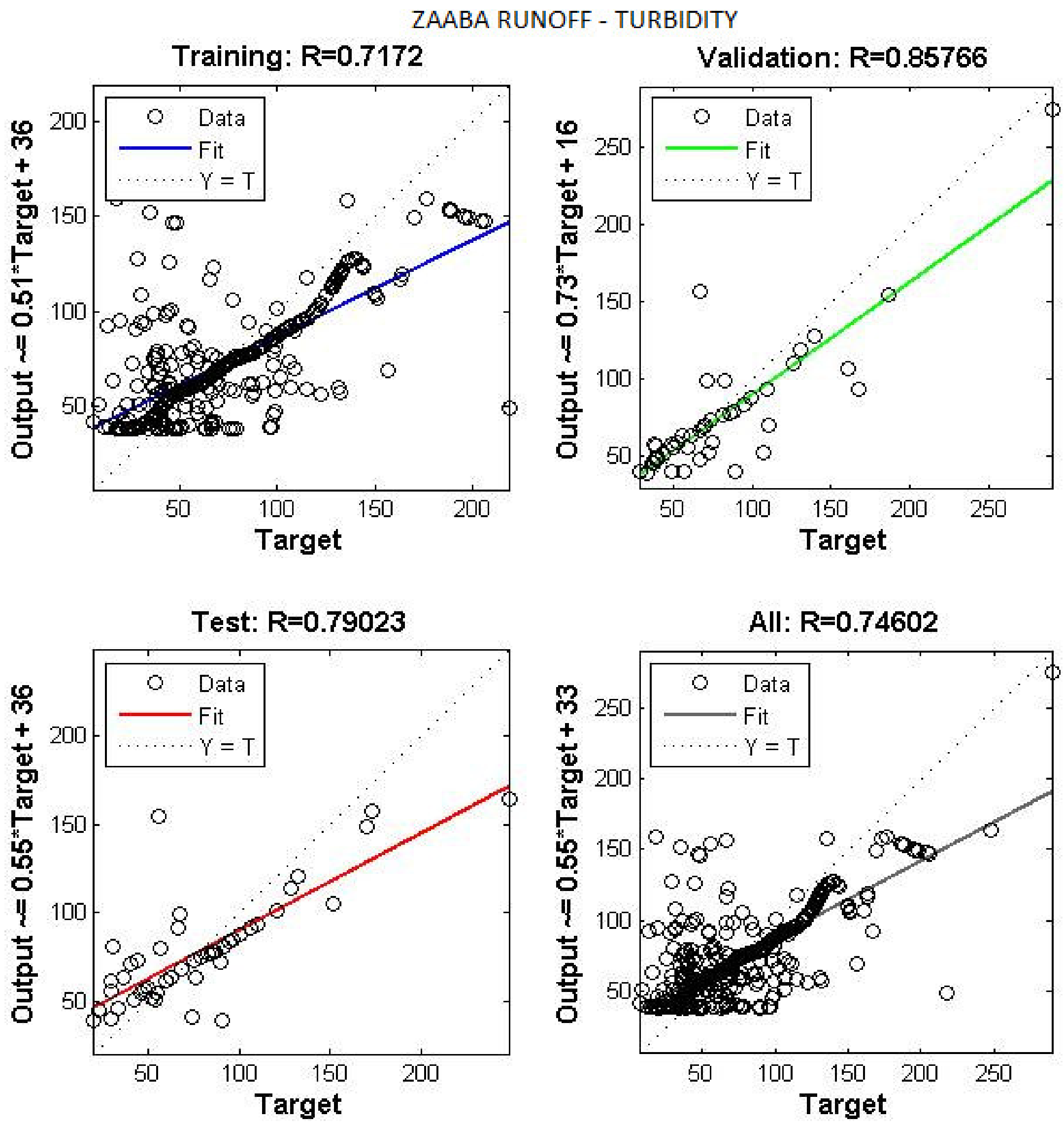


Figure 4. 18: Zaaba Runoff –Turbidity regression plot.

Garagoli Watershed gave a best fit model for turbidity with R for training, Validation and Testing as 0.869, 0.899 and 0.928 respectively as shown below.

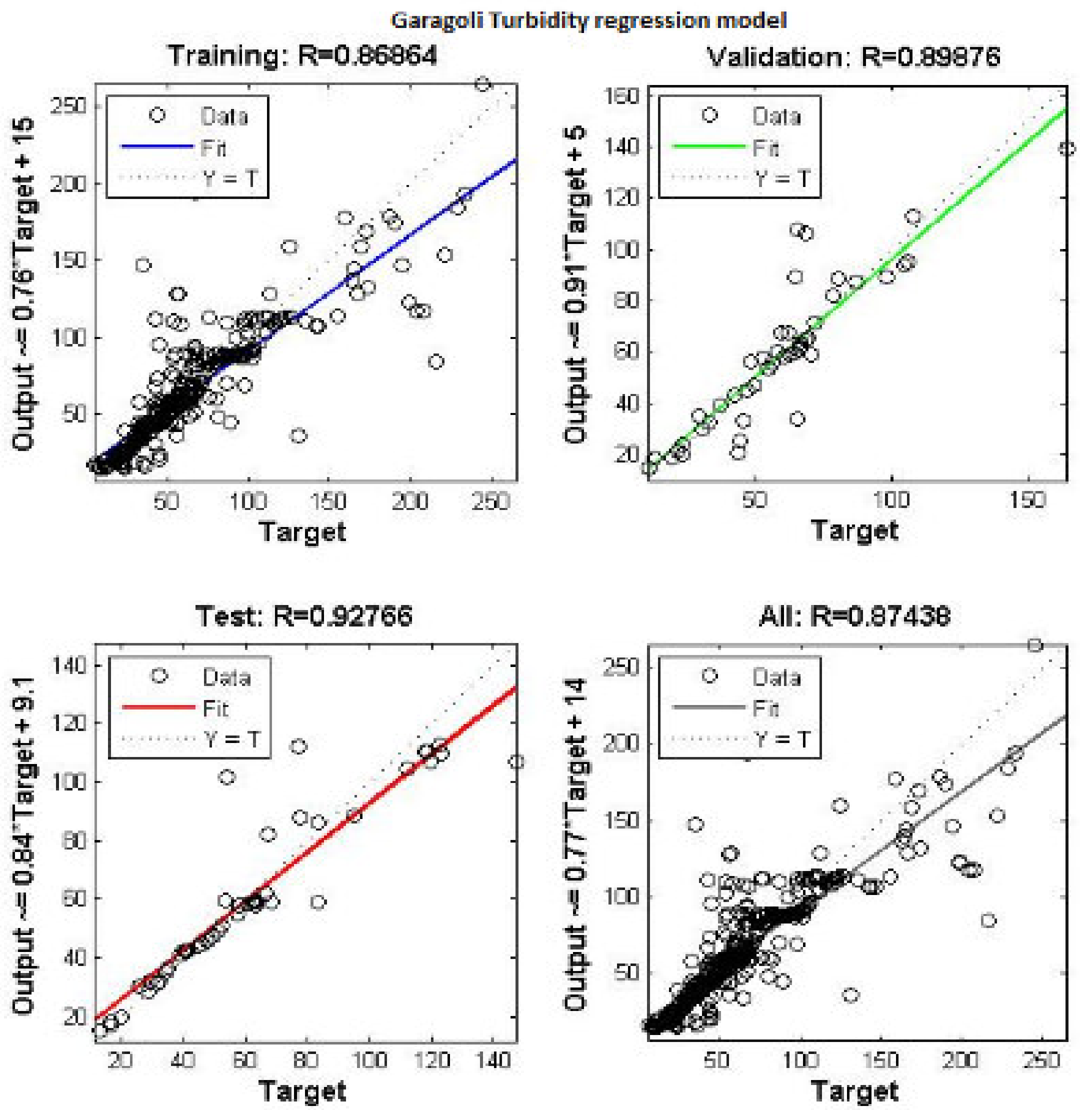


Figure 4. 19: Garagoli Runoff –Turbidity regression plot.

4.5.3 Regression charts for simulation of runoff and TDS

Edzava Watershed gave a best fit model for TDS with R for training, Validation and Testing as 0.124, 0.200 and 0.150 respectively as shown below.

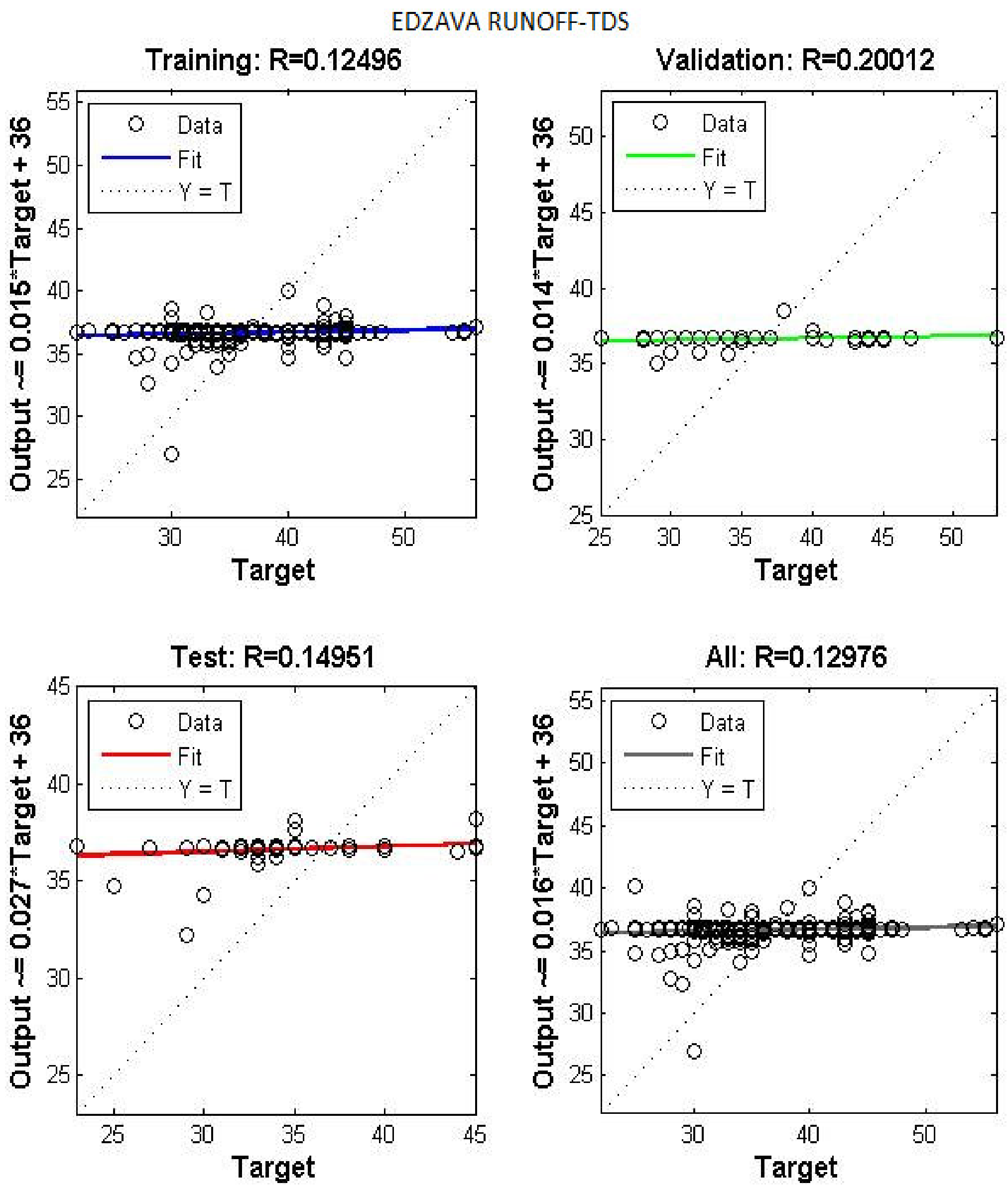


Figure 4. 20: Edzava Runoff –TDS regression plot.

Zaaba Watershed gave a best fit model for TDS with R for training, Validation and Testing as 0.804, 0.734 and 0.812 respectively as shown below.

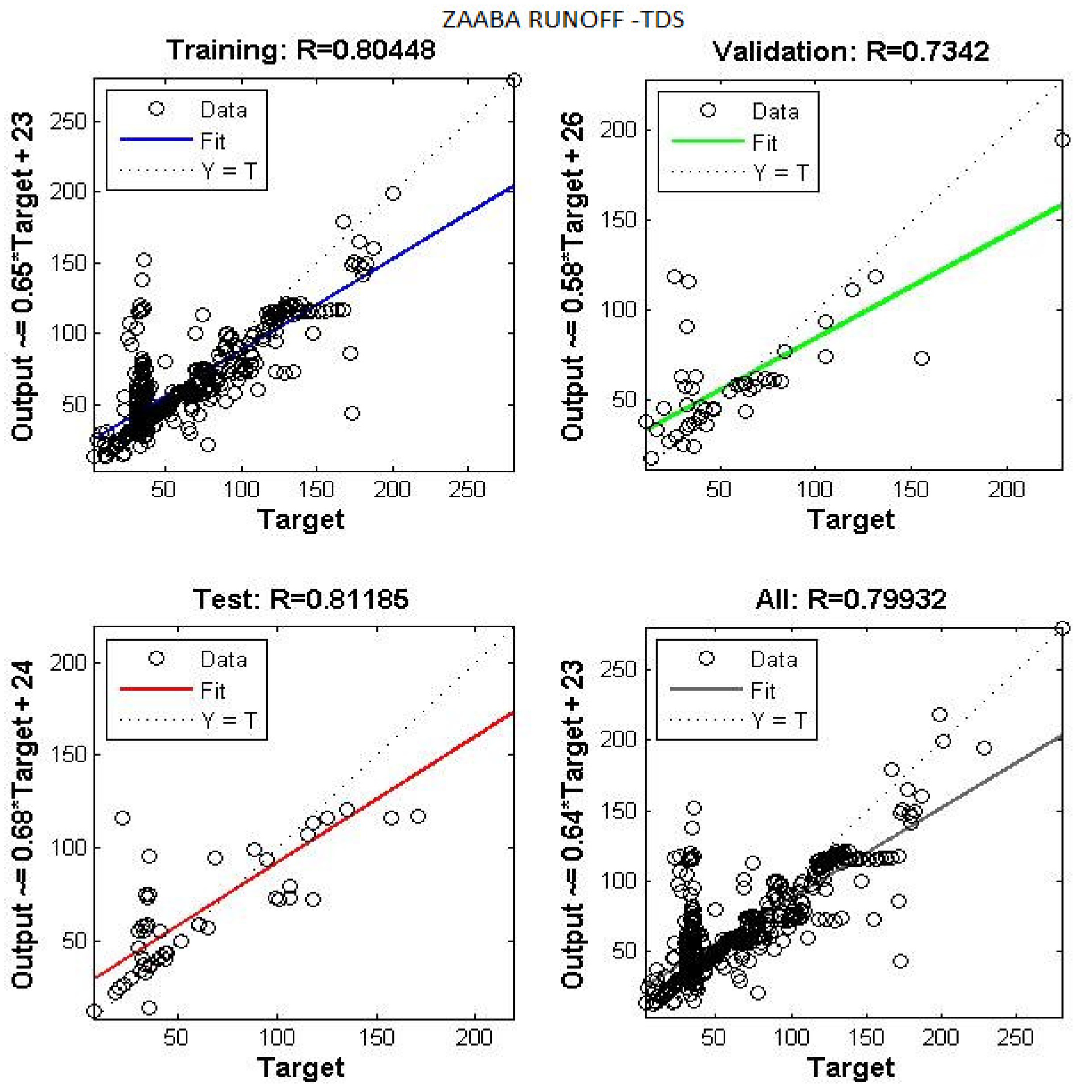


Figure 4. 21: Zaaba Runoff –TDS regression plot.

Garagoli Watershed gave a best fit model for TDS with R for training, Validation and Testing as 0.336, 0.375 and 0.185 respectively as shown below.

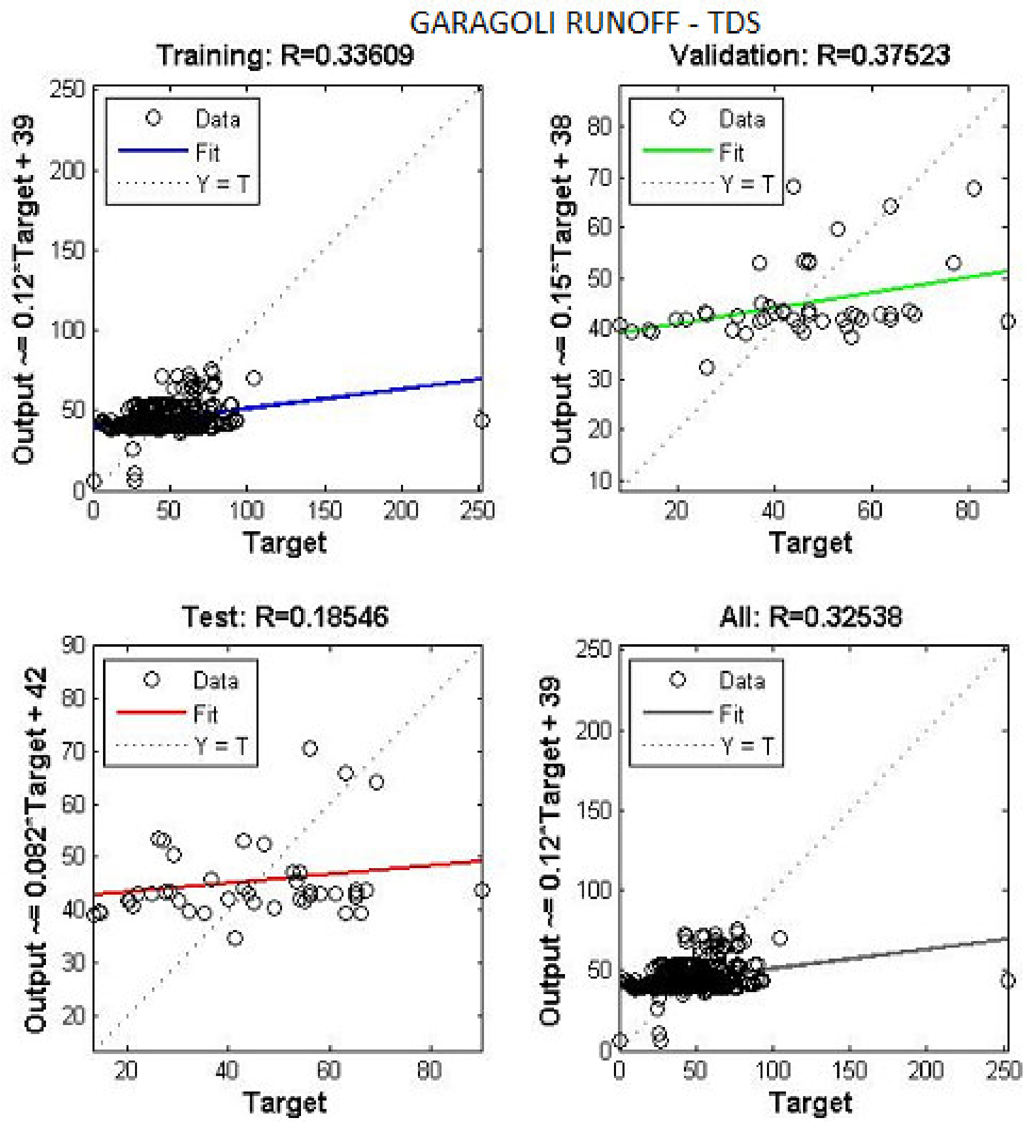


Figure 4. 22: Garagoli Runoff –TDS regression plot.

4.5.4 Regression charts for simulation of runoff and pH

Edzava Watershed gave a best fit model for pH with R for training, Validation and Testing as 0.081, 0.027 and 0.227 respectively as shown below.

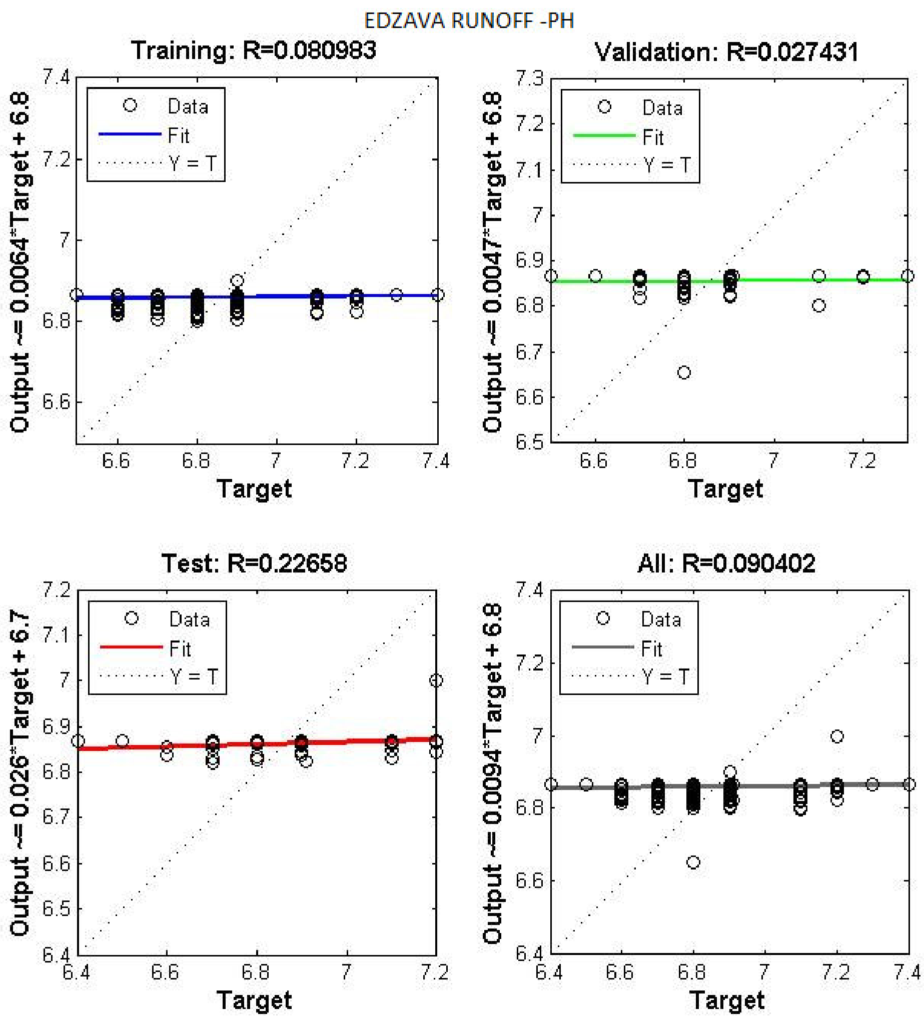


Figure 4. 23: Edzava Runoff –pH regression plot.

Zaaba Watershed gave a best fit model for pH with R for training, Validation and Testing as 0.343, 0.109 and 0.251 respectively as shown below.

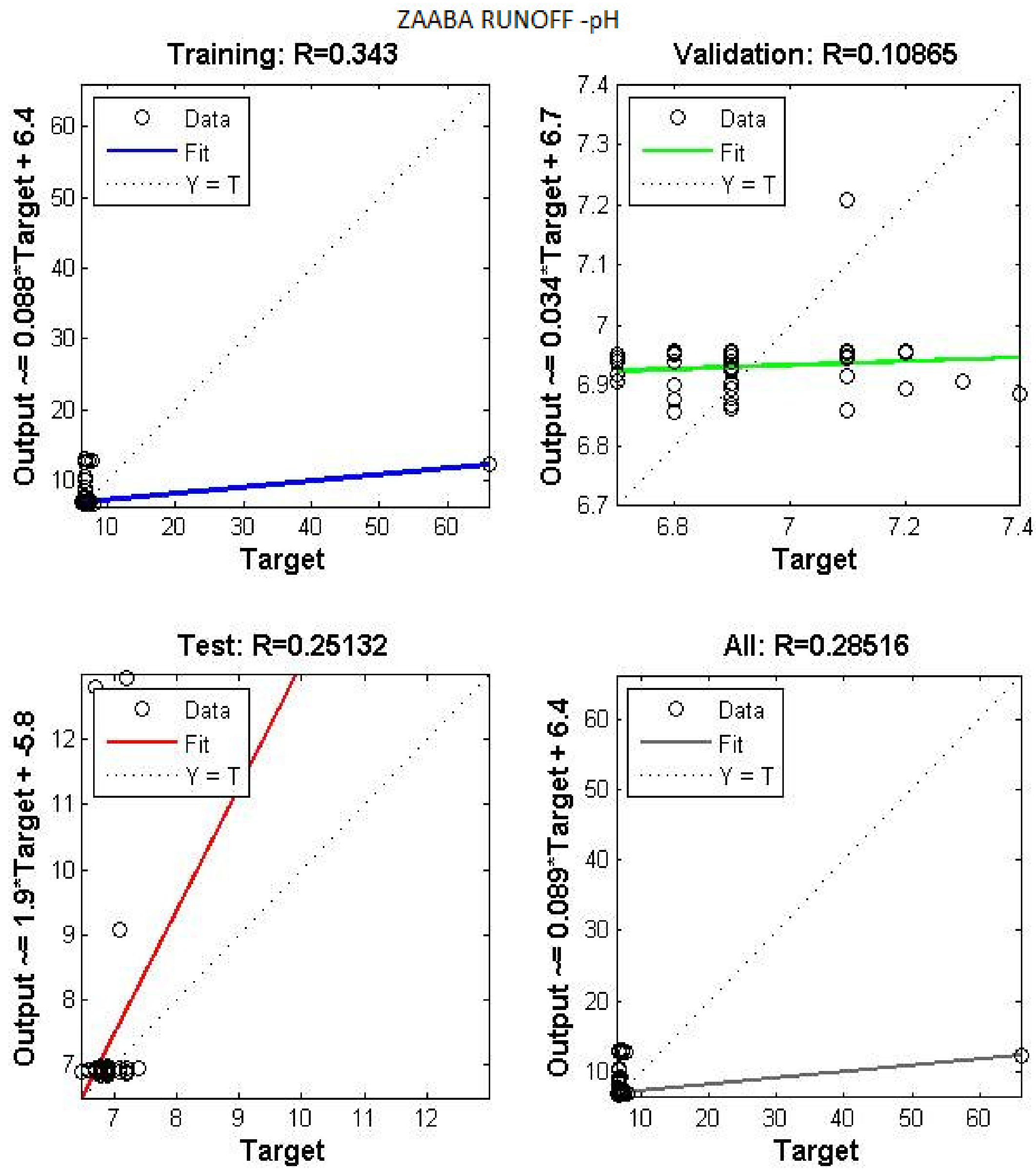


Figure 4. 24: Zaaba Runoff –PH regression plot.

Garagoli Watershed gave a best fit model for pH with R for training, Validation and Testing as 0.618, 0.094 and 0.403 respectively as shown below.

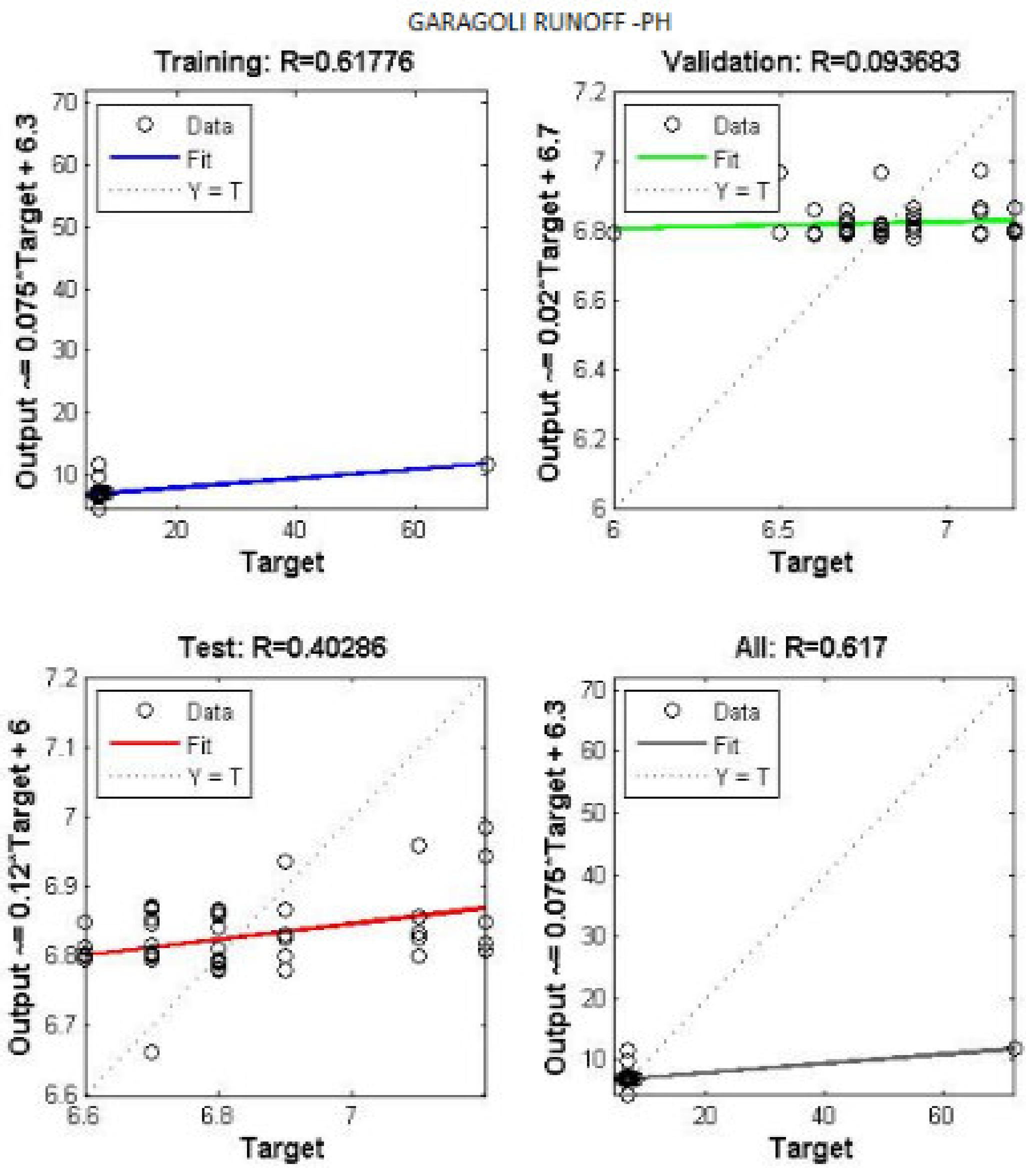


Figure 4. 25: Garagoli Runoff –PH regression plot.

4.5.5 Regression charts for simulation of runoff and Iron

Edzava Watershed gave a best fit model for Iron with R for training, Validation and Testing as 0.151, 0.056 and 0.118 respectively as shown below.

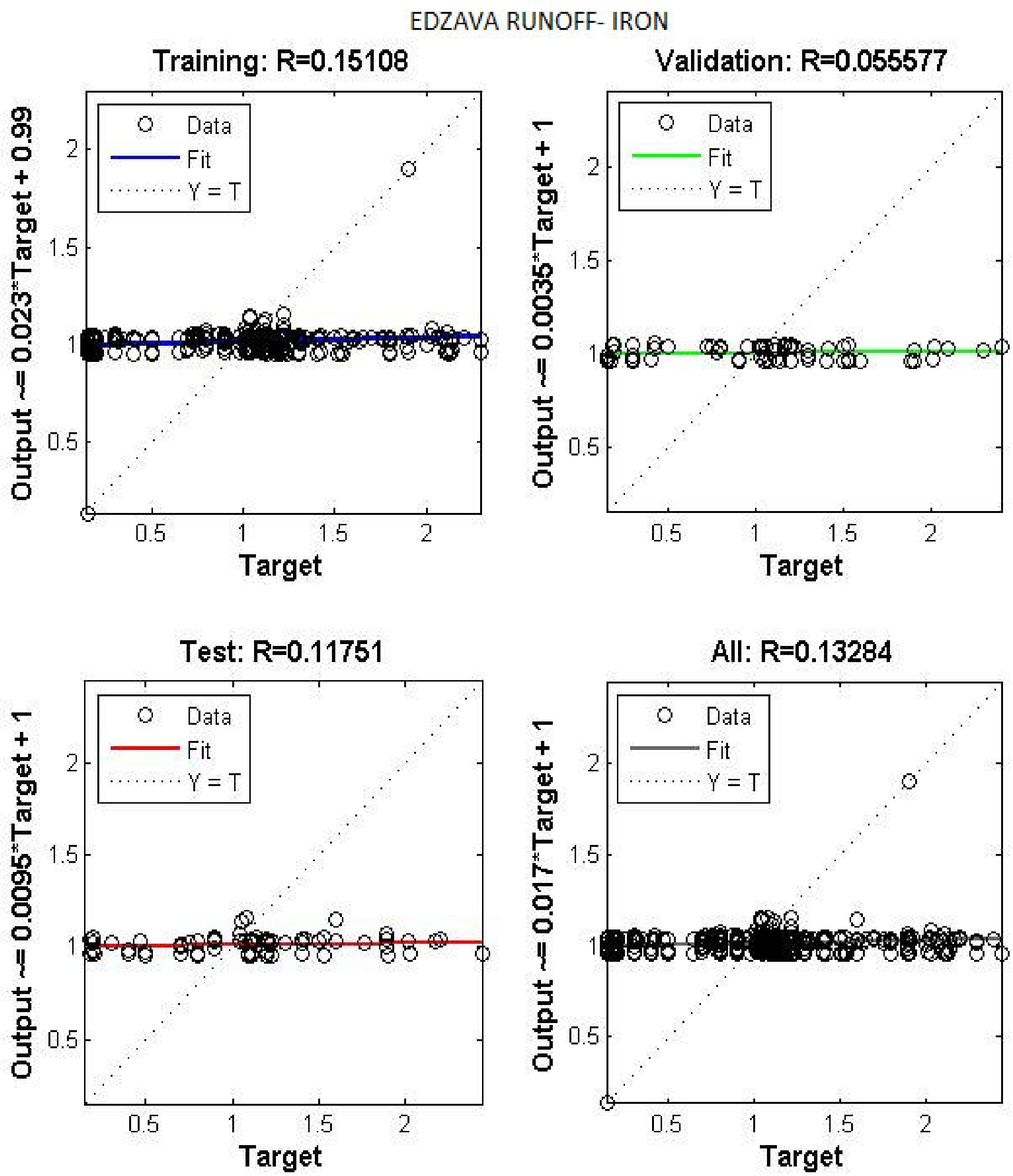


Figure 4. 26: Edzava Runoff –Iron regression plot.

Zaaba Watershed gave a best fit model for Iron with R for training, Validation and Testing as 0.041, 0.586 and 0.183 respectively as shown below.

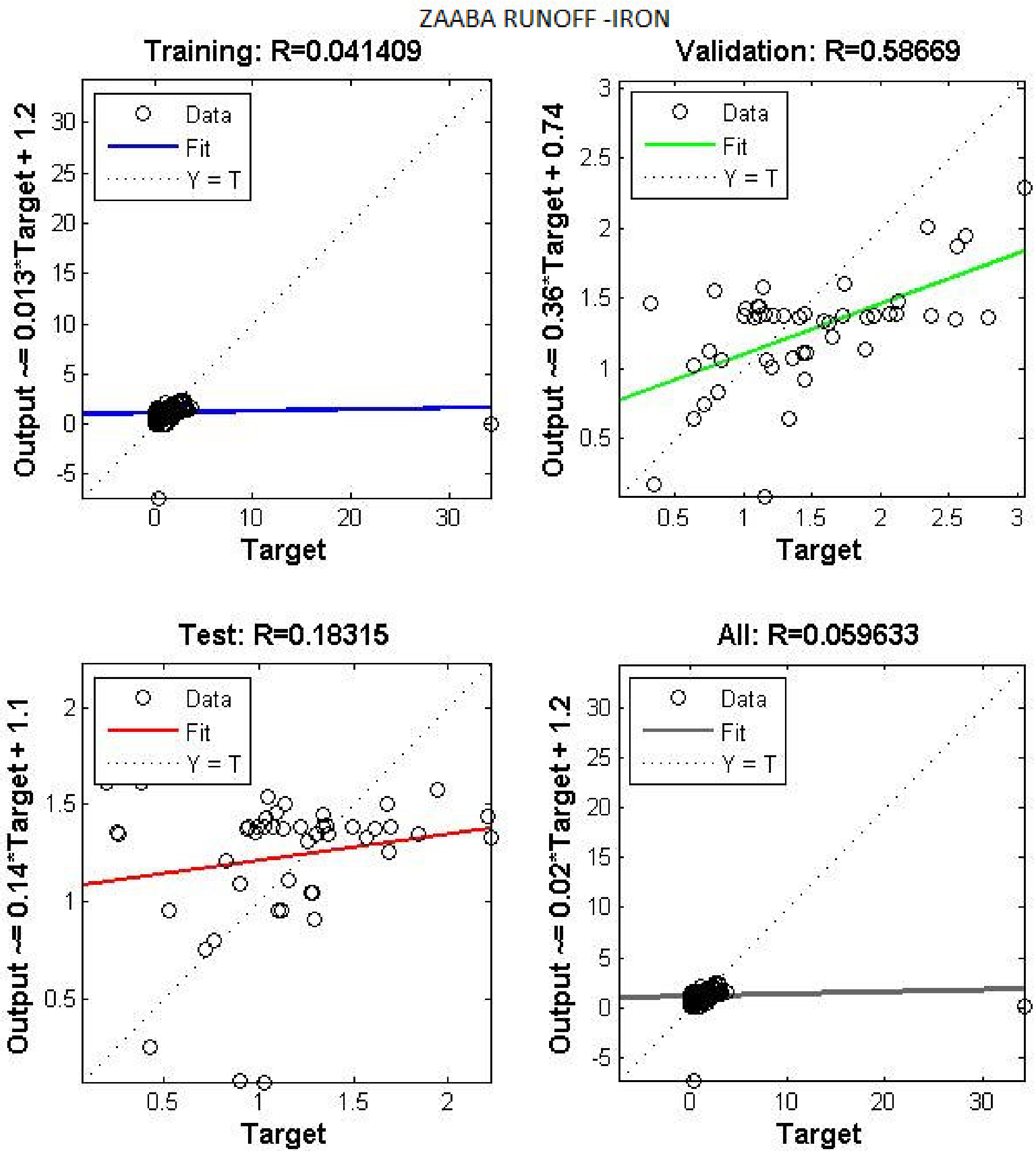


Figure 4. 27: Zaaba Runoff –Iron regression plot.

Garagoli Watershed gave a best fit model for Iron with R for training, Validation and Testing as 0.308, 0.266 and 0.395 respectively as shown below.

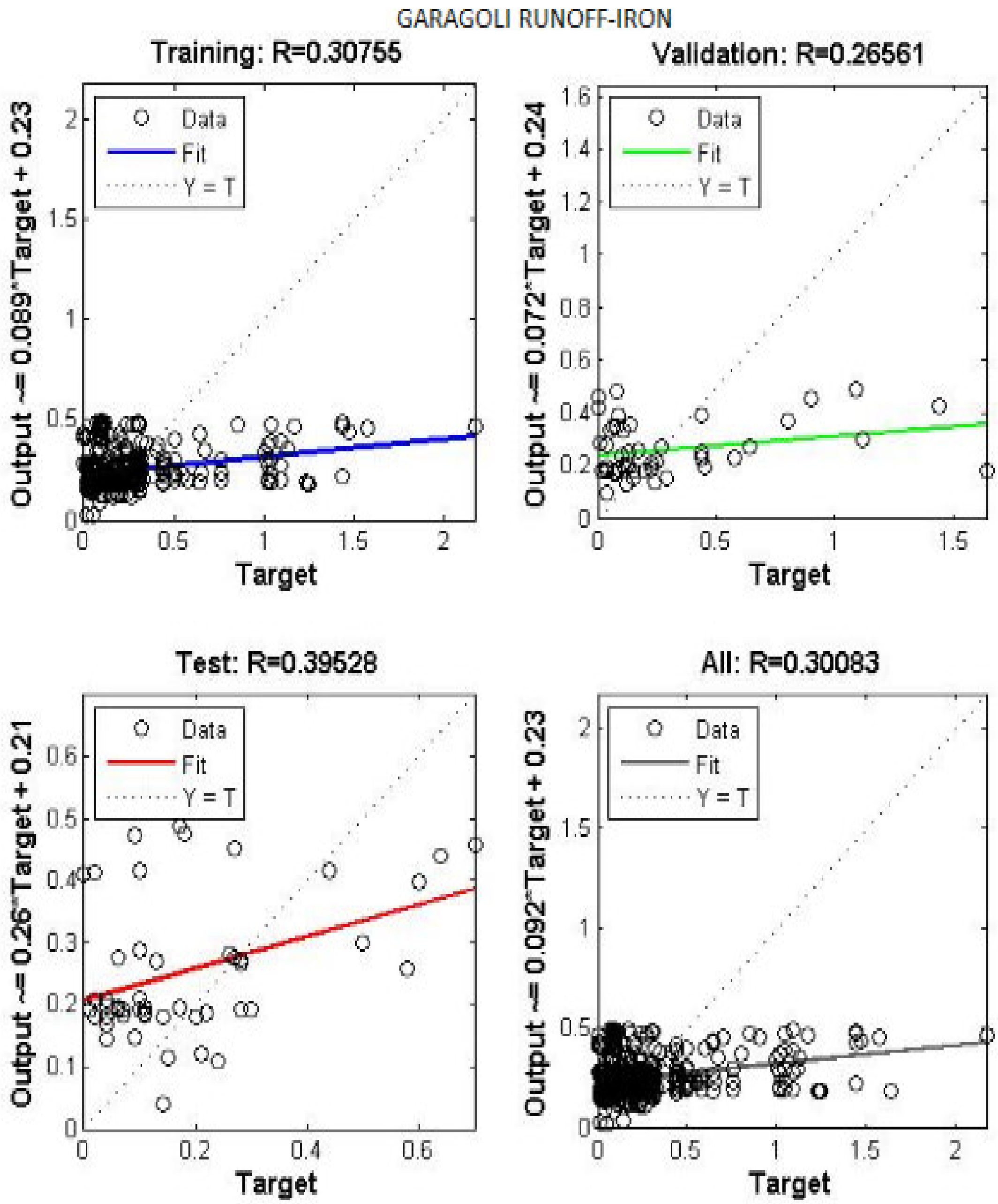


Figure 4. 28: Garagoli Runoff –Iron regression plot.

4.5.6 Model simulation summary:

ANN model was used to simulate runoff- water quality effects in the three river watersheds and the results recorded as discussed. From the analysis, in the following was the summary of the model results.

Table 4. 3: Model Simulation results

Water shed	Model	R- Values				Remarks (Good model ticked)
	Runoff-	**Training**	**Validation**	**Testing**	**Total**	
Turb	**Edzava**	0.734	0.867	0.857	0.750	✓
	Zaaba	0.717	0.857	0.790	0.746	✓
	Garagoli	0.867	0.899	0.928	0.874	✓
Color	**Edzava**	0.734	0.729	0.777	0.736	✓
	Zaaba	0.811	0.858	0.790	0.791	✓
	Garagoli	0.902	0.878	0.841	0.888	✓
TDS	**Edzava**	0.125	0.200	0.150	0.130	x
	Zaaba	0.804	0.734	0.812	0.799	✓
	Garagoli	0.336	0.375	0.185	0.325	X
pH	**Edzava**	0.081	0. 027	0.227	0.090	X
	Zaaba	0.343	0.109	0.251	0.285	X
	Garagoli	0.618	0.094	0.403	0.617	X
Iron	**Edzava**	0.151	0.056	0.118	0.133	X
	Zaaba	0.041	0.587	0.183	0.060	X
	Garagoli	0.308	0.266	0.395	0.301	X

4.5.7 Model performance levels:

Table 4.3 shows individual model performance levels as measured by coefficient of correlation R, for each parameter and the respective river water shed. Turbidity and colour performed well in the three watershed while TDS best fit was in one watershed. The performance of the last two parameter i.e. Iron and PH was very low in all the water sheds. Garagoli registered high performance for both turbidity and colour with R >0.7.

It was only in Zaaba that TDS registered R >0.7 for training, validation and testing.

The above model performance therefore shows that Turbidity and colour had the best fit and thus reliable in the three watersheds.

4.7.8. Training state of the three watersheds

The physical parameter that performed well gave the following results in training:

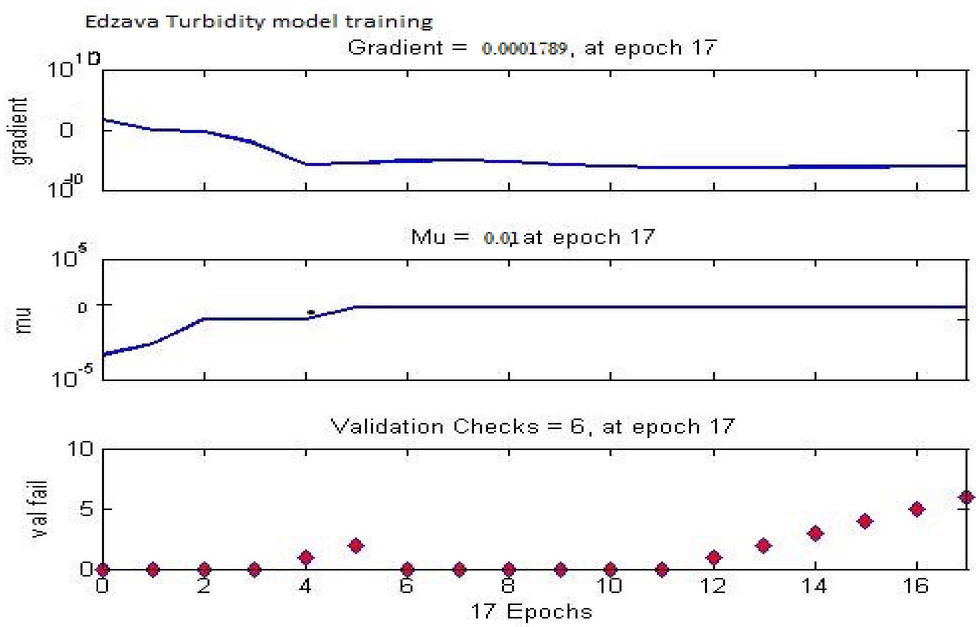


Figure 4. 29: Edzava model training state

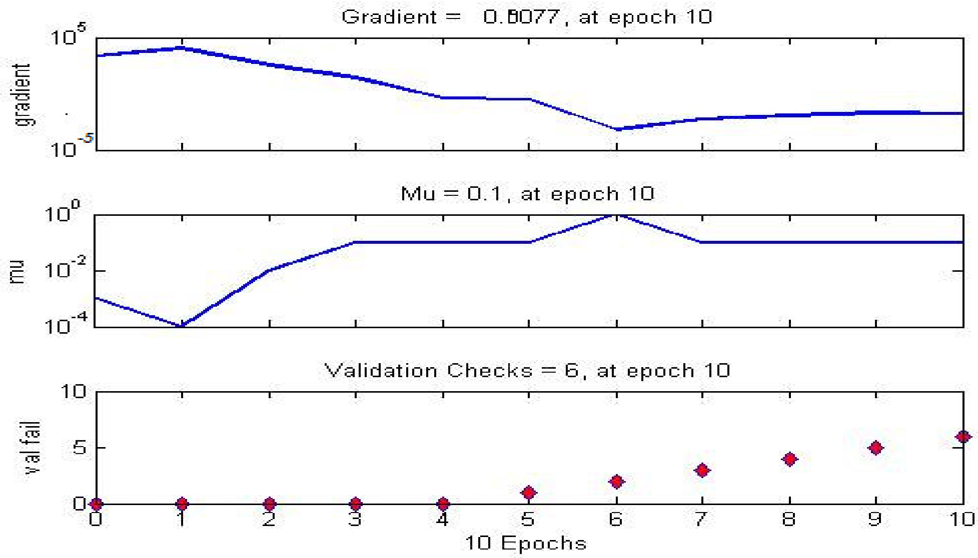


Figure 4. 30: Zaaba model training state

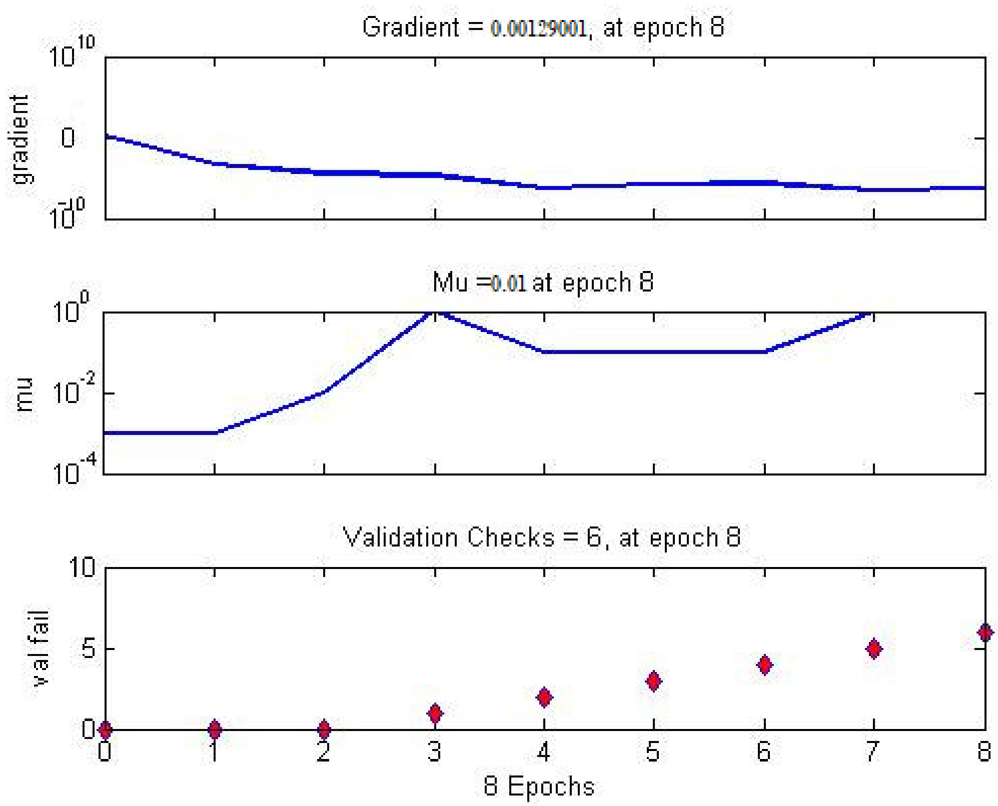


Figure 4. 31: Garagoli model training state.

From the above figures Edzava 4.27, Zaaba 4.28 and Garagoli 4.29, the training state recorded gradient of 0.0001,0.007 ,0.001respectively which represents a MSE of 0.001. This shows that the model performance is good and the error tends to zero (0).

4.7.9. Performance criteria – Mean Square Error graph

The MSE was used to measure the performance of the mode particularly for water quality physical parameters i.e. Colour and Turbidity and the following results for MSE were observed.

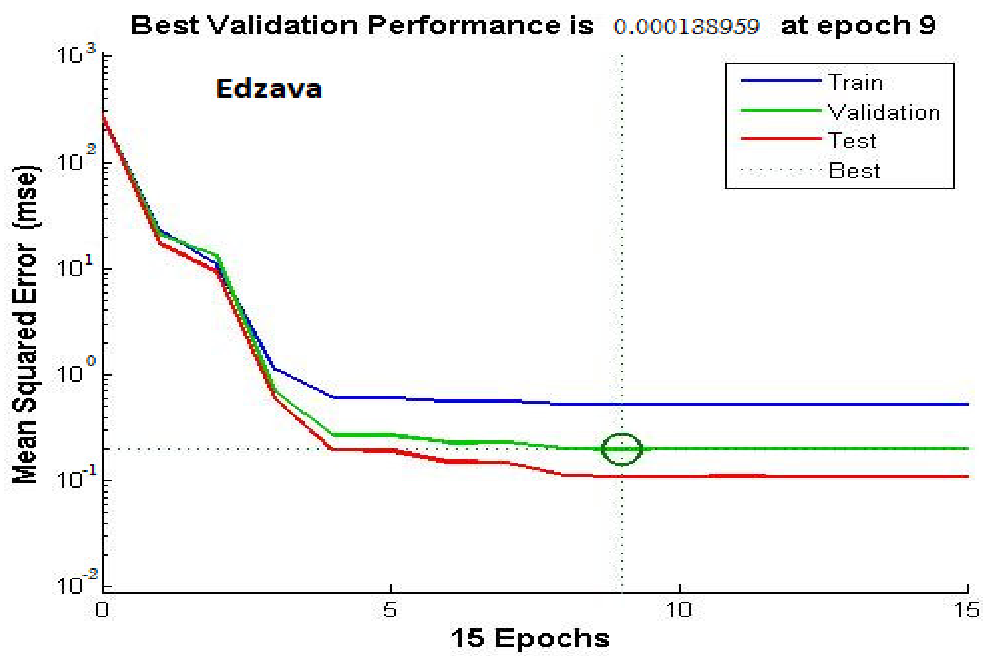


Figure 4. 32: Edzava MSE graph

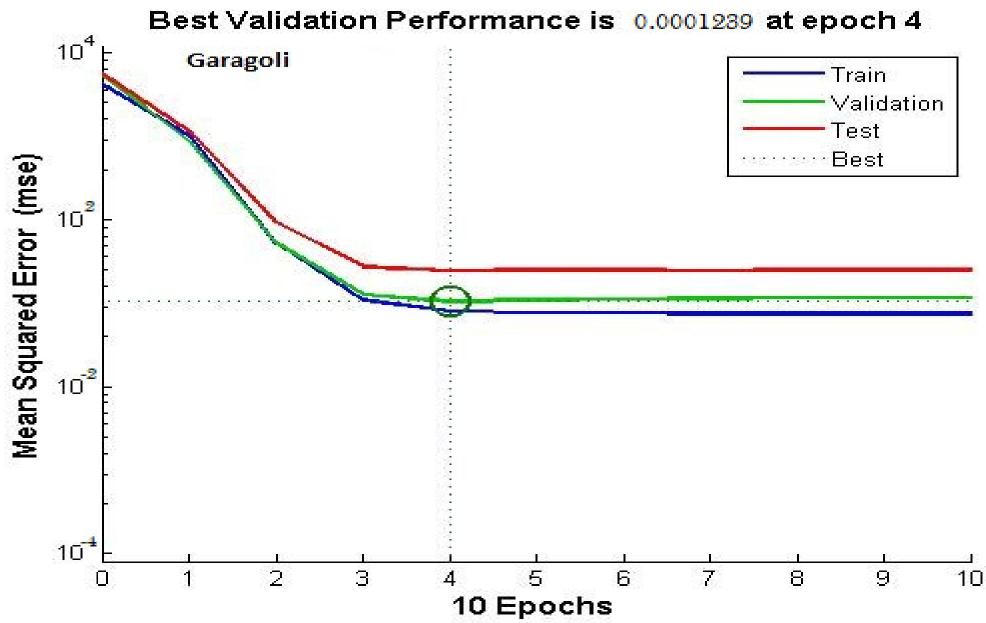


Figure 4. 33: Garagoli model MSE graph

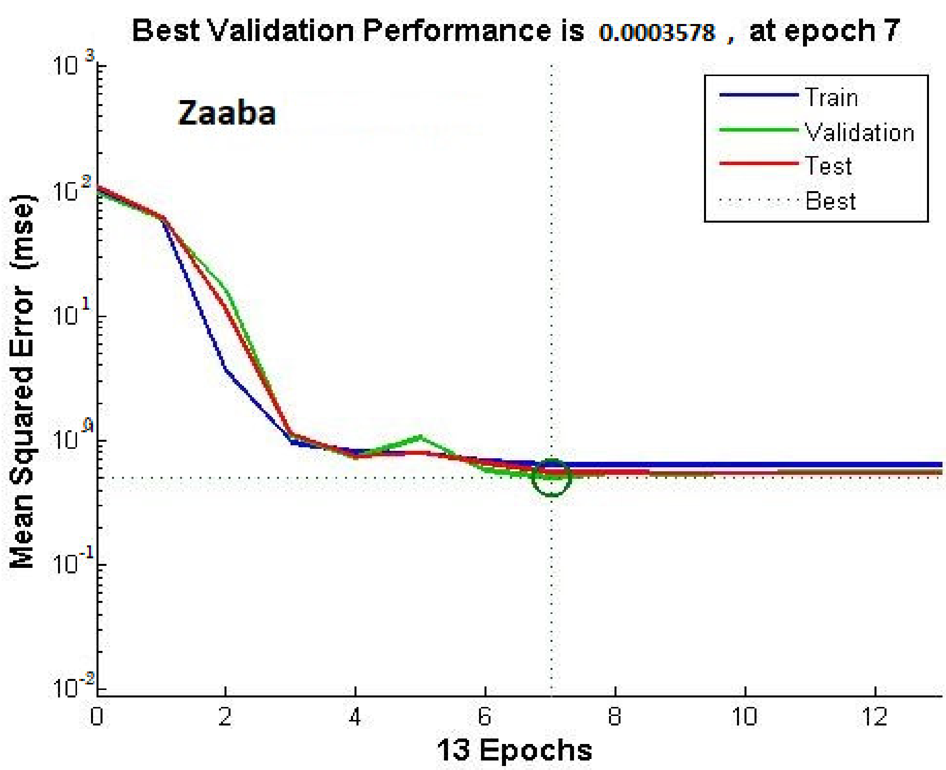


Figure 4. 34: Zaaba model MSE graph

From the above figures; Edzava 4.30, Garagoli 4.31 and Zaaba 4.32, the mean square error values provided from the graph were 0001,0.0001 ,0.0004 which represents a MSE of averagely 0.0001. This shows that the model performed well as the MSE in all the graphs above tends to Zero (0).

4.6: Relationships established from the model

The results of the study summarised the relationships established from the regression model for each parameter. Parametric relationships were:

i. Direct for Turbidity and Colour, which are physical parameters,

ii. Inverse relationship for TDS and

iii. Chemical parameters had no correlation.

Below is a summary of the relationships established:

Colour-

Edzava- $\mathrm{Re} = 0.54Ce + 1.7e^{0.2}$ …………………………………………Equation 4.4

Zaaba - $Rz = 0.79RCz + 13$ ……………………………………..…….Equation 4.5

Garagoli - $Rg = 0.75Cg + 33$ …………………………..………..………Equation 4.6

Turbidity

Edzava- $\mathrm{Re} = 0.52Te + 59$ ……………………………………….……Equation 4.7

Zaaba - $Rz = 0.55Tz + 33$ …………………………………………..………Equation 4.8

Garagoli - $Rg = 0.77Tg + 14$ ……………………………………………Equation 4.9

TDS

Edzava- $\mathrm{Re} = 0.016TDSe + 36$ ……………………………….…………Equation 4.10

Zaaba - $Rz = 0.64TDSz + 23$ ……………………………….…………Equation 4.11

Garagoli- $Rg = 0.12TDSg + 39$ …………………………………………Equation 4.12

PH

Edzava- $\mathrm{Re} = 0.009PHe + 68$ ……………………..………………..…….Equation 4.13

Zaaba - $Rz = 0.89PHz + 64$ ……………………………………..…….Equation 4.14

Garagoli- $Rg = 0.076PHg + 63$ ……………………………..…….Equation 4.15

Iron

Edzava- $\mathrm{Re} = 0.017FEe + 1$ ……………………………………….Equation 4.16

Zaaba - $Rz = 0.02FEz + 12$ ………………………………...……Equation 4.17

Garagoli - $Rg = 0.092FEg + 0.23$ ……………………………...……Equation 4.18

Where,

$R_{e,z,g}$ = Run off in respective water shed

$C_{e,z,g}$ = Color for each water shed

TDSe,s,g =Turbidity for each water shed

pHe,s,g = pH for each water shed

FEe,s,g = Iron Values for each water shed

4.7 Established effects associated with the runoff and water quality in water treatment works

4.7.1 Effect of Runoff on Water quality Parameters

From the results of this study, It was evident that runoff had direct effects on the quality of surface water in the three river watersheds i.e. Edzava, Zaaba and Garagoli. It is shown from the results from ANN model that at least three water quality parameters had a nearly best fit linear regression. This shows that runoff correlated with these parameters which were Turbidity, Color and TDS. It was observed from the results that the increase of runoff in the watershed translated to an increase in the values of parameters i.e. Turbidity, Color and TDS. The other two parameters i.e. Iron and pH, which were also chemical parameters, had a very low values of R whereby Iron had 0.1 in Edzava, 0.2 in Zaaba and 0.1 in Garagoli and pH had R below 0.2 as well in all the river water sheds. Therefore the water supply managers should consider the relationship of the three parameters as established in this study in their day to day running of water supplies.

4.7.2 Effects of runoff on water supply treatment

The results show that in the three water sheds, rainfall is high in the months of March, April, May, September and October. During these months runoff is high relative to rainfall resulting to challenges on the design elements of the water supply from the intake works to the capacity of the water supply treatment plant.

4.7.3 Effects of runoff on water supply operations

Increased values of Turbidity, colour and TDS due to increased runoff, results in increase of treatment time thereby reducing production capacities and increasing dosage of alum and soda ash to facilitate treatment. When there is high runoff from the water shed to the river, water treatment plants that draw water from these rivers, may result to periodic temporary shutdown of treatment plant or diversion the river water that is polluted with high parametric loading during the period of precipitation.

CHAPTER FIVE:

5.0. CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSIONS

The rainfall trends varied on monthly basis in the respective watersheds. The runoff generated coincided with the rainfall trends. The higher the rainfall the higher the runoff and vice- versa.

Most parameters such as Turbidity and Colour had a direct relationship with runoff in all the catchment.

TDS had an inverse correlation with rainfall and runoff. This maybe as a result of other human activities in the catchment.

The three Watersheds Edzava, Zaaba and Garagoli had most of the surface runoff contributing to runoff water to the rivers.

After Simulation of the model for each parameter and respective watershed runoff, the Turbidity and Colour had the best fit in all the watershed while TDS had the best fit in one water shed. The remaining parameters i.e. Iron and pH had very low performance and therefore the model could effectively be used for the two physical parameters.

Increased values of Turbidity, colour and TDS due to increased runoff, increases maintenance and operational costs

The results of the study summarised the relationships established from the regression model for each parameter. Refer to table 4.2 on relationships established. Parametric relationships were:

i. Direct for Turbidity and Colour, which are physical parameters,
ii. Inverse relationship for TDS and

iii. Chemical parameters had no correlation.

These relationships could be used by water supply managers in making decisions on operation and maintenance of water supply.

5.2 RECOMMENDATIONS

The catchment water resources managers should ensure rainfall data and water quality data is collected regularly and consistently to facilitate future research for sustainable resources management.

The results of the study was derived using few parameters i.e. Turbidity, color, TDS, pH and Iron. This left out many more parameters that needs to be considered which also affect the water quality of surface waters. In future, more research should be done with other water quality parameters.

There is need for more research on quantifying and qualifying the runoff from different sources and their quality aspects.

The simulated results from the catchment providing relationship of rainfall-runoff and physical quality parameters could be used by water resources managers for operations and management of water supplies and the entire watersheds

Further research should be undertaken in these watersheds to understand hydrological characteristic of these watersheds for sustainable management of the watersheds.

REFERENCES

Antanasijević, D., Pocajt, V., Perić-Grujić, A., & Ristić, M. (2014). Modelling of dissolved oxygen in the Danube River using artificial neural networks and Monte Carlo Simulation uncertainty analysis. *Journal of Hydrology, 519*, 1895-1907.

ASCE., & Task, C. (2000, April). Artificial Neural Networks in Hydrology. II: Hydrologic Applications. *Journal of Hydrologic Engineering*, 124-137.

Bloschl, G. (2005). Rainfall–runoff modeling of ungauged catchments. In J. W. a. S. M. Anderson (Ed.), *Encyclopedia of Hydrological Sciences* (Vol. 1).

Boye, A., Verchot, L., & Zomer, R. (2008). Baseline Report; Yala and Nzoia River Basins. Nairobi, Kenya: International Centre for Research in Agorforestry.

Chang, J., Wang, G., & Mao, T. (2015). Simulation and prediction of suprapermafrost groundwater level variation in response to climate change using a neural network model *Journal of Hydrology, 529*, 1211-1220.

Chau, K.-w. (2006). A review on integration of artificial intelligence into water quality modelling. *Marine pollution bulletin, 52*(7), 726-733.

Chen, Q., & Mynett, A. E. (2003). Integration of data mining techniques and heuristic knowledge in fuzzy logic modelling of eutrophication in Taihu Lake *Ecol. Modell* (Vol. 162 pp. 55-67).

Chouhan, D., Tiwari, H. L., & Galkate, R. V. (2016). Rainfall Runoff Simulation of Saphira River Basin using AWBM RRL Tool Kit. *International Journal of Engineering and Technical Research (IJETR), 5*(3), 2454-4698

Dearmont, D. (1998). Costs of water treatment due to diminished Water quality: a case study in Texas *Water Resources Research, 34*(4), 849-854.

Donigian, A. S. J. (2002). Watershed Model Calibration and Validation: The HSPF Experience. . 2685 Marine Way, Suite 1314 Mountain View, CA 94043 USA: AQUA TERRA Consultants.

Gao, C., Gemmer, M., Zeng, X., Liu, B., Su, B., & Wen, Y. (2010). Projected streamflow in the Huaihe river basin (2010–2100) using artificial neural network. *Stoch. Environ. Res. Risk Assess, 24*, 685-697.

Githui, F., Gitau, W., Mutua, F., & Bauwens, W. (2009). Climate change impact on SWAT simulated streamflow in western Kenya. *International Journal of Climatology, 29*(12), 1823-1834.

GOK. (2007). *National Policy on Disaster Management*. Nairobi: Government Printers.

GOK. (2013). *Vihiga County Integrated Development Plan* Nairobi: Government Printers.

GOK. (2015). *Impact report , A performance Review of Kenya Water Services Sector, 2013-2014*. Nairobi: Ministry or Water & Irrigation.

Grubert, J. P. (2003). Acid deposition in the eastern United States and neural network predictions for the future. J. . . *Environ. Eng. Sci, 2* (2), 99-109.

Hasan, K., Khan, R. I., Nesha, K., & Masuma, A. H. (2014). Analysis of water quality using chemical Parameters and metal status of Balu River at Dhaka, Bangladesh. *Open journal of water pollution and treatment, 1*(2), Issn (Print):2374-6343, (issn (online): 2374-6351.

ICPAC. (2007). Climate Change and Human Development in Africa: Assessing the Risks and Vulnerability of Climate Change in Kenya, Malawi and Ethiopia. Nairobi: UNDP.

Institute, W. R. (2007). Nature's Benefits in Kenya, An Atlas of Ecosystems and Human Well-Being. Washington, DC and Nairobi:: World Resources Institute.

Integrated Hydrological Modelling System, I. (2008). *User Manual. Version 6.0.*

Jain, S. K., & Chalisgaonkar, D. (2000). Hydrological conceptual models *Journal of Hydrology*.

Jun, D. U., Chang-xing, S., & ZHANG, C. D. (2013). Modeling and analysis of effects of precipitation and vegetation coverage on runoff and sediment yield in Jinsha River Basin. *Water Science and Engineering, 6*(1), 44-58.

Kanda, E. K., Kipkorir, E. C., & Kosgei, J. R. (2016). Dissolved oxygen modelling using artificial neural network: a case of River Nzoia, Lake Victoria basin, Kenya *Journal of Water Security, , 2*.

Kanda, E. K., Odiero, J., Lutta, V., & Ong'or, B. T. I. (2018). Challenges Facing Small and Medium Water Service Providers in Kenya: A Case of Amatsi Water Services Company, Vihiga County. *Journal of the Civil Engineering Forum, 4*(1).

Kazi, T. G., Arain, M. B., Jamali, M. K., & Jalbani, N. (2009). Assessment of water quality of polluted lake using multivariate statistical techniques: A case study. *Ecotoxicology*.

Kiluva, V. M., Mutua, F. M., Makhanu, S. K., & Ong'or, B. T. I. (2010). Rainfall runoff modeling in Yala River basin of Western Kenya *Journal of Meteorology and Related Sciences*.

Lee, J. H. W., Huang, Y., Dickmen, M., & Jayawardena, A. W. (2003). Neural network modelling of coastal algal blooms. *Ecological Modelling, 159*, 179-201.

Liong, S. Y., Lim, W. H., & Paudyal, G. (1999). Real time river stage forecasting for flood Bangladesh: neural network approach. *Comput. Civil Eng. ASCE, 14* (1), 1-8.

Maier, H. R., Jain, A., Dandy, G. C., & Sudheer, K. P. (2010). Methods used for the development of neural networks for the prediction of water resource variables in river systems: current status and future directions. . *Environmental Modelling & Software, 25* (8), 891-909.

Mogaka, H., Gichere, S., Davis, R., & Hirji, R. (2006). Climate variability and water resources degradation in Kenya: improving water resources development and management World Bank.

Needhidasan, S. (2013). Management for Design of Storm Water Drains by Rational Method - an Approach to Storm Water Environmental Protection *International Journal of Engineering and Technology, 5* (4), 3203-3214.

Nkemdirim, L. C. (1979). Spatial and Seasonal Distribution of Rainfall and Runoff in Jamaica. *Geographical Review, 69* (3), 288-301.

Nkemdirim, L. C. (1979). Spatial and Seasonal Distribution of Rainfall and Runoff in Jamaica. *Geographical Review, 69*(3), 288-301.

Olaoye, R. A., Oladeji, O. S., & Olaji, G. (2013). Assessment of rainfall intensity on temporal water quality of Awba Dam, Nigeria. *Civil and Environmental Research, 3*(13).

Ong'or, B. T. I., Shu, L., & Jinning, C. (2009). Groundwater overdraft and impact of artificial recharge on groundwater quality in cone of depression. *Water International, 34*(4), 468-483.

Poggio, T., & Girosi, F. (1990). Networks for approximation and learning. *Proc. IEEE, 78*(9), 1481−1497.

Reckhow, K. H. (1999). Water quality prediction and probability network models. *Fish. Aquat. Sci.Can, 56*, 1150-1158.

Sarda, P., & Sadgir, P. (2015). Computation of Water Quality Parameters and Prediction Tool ANN for Modeling of Water Quality of Reservoir. *International Journal of Innovative Research in Science, Engineering and Technology, 9*, 8906-8911.

Sarkar, A., & Pandey, P. (2015). River water quality modelling using artificial neural network technique. *Aquatic Procedia, 4*, 1070-1077.

Shamsudin, S., & Hashim, N. (2002). Rainfall Runoff Simulation Using Mike11 NAM. Urnal Kejuruteraan Awam. *Journal of Civil Engineering, 15*(2).

Sharma, D., & Mohandatta, S. G. (2017). Classification of watershed and rainfall-runoff modelling using SOM, linear regression analysis and ANN. *International journal of engineering research and general science, 5*(3), 2091-2730.

Shrivastav, M., Haresh, M. G., Ramanuj, P., Chudasama, M. K., & Joshi, J. A. (2014). Prediction of Runoff using Artificial Neural Networks (A Case study of Khodiyar Catchment Area). *International Journal for Scientific Research & Development, 2*(2), 2321-0613.

Suhaila, J., Sayang, M. D., & Jemain, A. A. (2008). Revised Spatial Weighting Method for Estimation of Missing Rainfall Data. *Asia Pacific Journal of Atmospheric Sciences, 44*(2), 93-104.

Tu, J. V. (1996). Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. *Journal of clinical epidemiology,, 49*(11), 1225-1231.

UNEP. (2009). Regional Centre for Mapping of Resources for Development (RCMRD). Government of Kenya (GoK): United States Geological Survey (USGS).

Vos, N. J., & Rientjes, T. H. M. (2005). Constraints of artificial neural networks for rainfall-runoff modelling: trade-offs in hydrological state representation and model evaluation. *Hydrol. Earth Syst. Sci., 2*( ), 365-415.

Wanyonyi, E. S., Wakhungu, J. W., & Kiluva, V. M. (2015). Determination of The Extent of Yala River Flood Flows in The Yala Basin , Kenya *Nile Water Science & Engineering Journal, 8*(1).

Yaseen, Z. M., El-shafie, A., Jaafar, O., Afan, H. A., & Sayl, K. N. (2015). Artificial intelligence based models for stream-flow forecasting. *Journal of Hydrology, 530*, 829- 844.

Zali, M. A., Retnam, A., Hafizan, A. R., & Sharifuddin, M. Z. (2011). Sensitivity Analysis for Water Quality Index (WQI) Prediction for Kinta River, Malaysia. *World Applied Sciences Journal,, 14*, 60-65.

Ziegler, A., Giambelluca, T. W., & Sutherland, R. A. (2002). Improved Method for Modeling Sediment Transport on Unpaved Roads Using KINEROS2 and Dynamic Erodibility. *Hydrological Processes, 16*, 3079-3089.

APPENDIXES I: Soil Group Coefficient Runoff (Reckhow, 1999)

	Runoff Coefficient, C					
	Soil Group A			Soil Group B		
Slope :	< 2%	2-6%	> 6%	< 2%	2-6%	> 6%
Forest	0.08	0.11	0.14	0.10	0.14	0.18
Meadow	0.14	0.22	0.30	0.20	0.28	0.37
Pasture	0.15	0.25	0.37	0.23	0.34	0.45
Farmland	0.14	0.18	0.22	0.16	0.21	0.28
Res. 1 acre	0.22	0.26	0.29	0.24	0.28	0.34
Res. 1/2 acre	0.25	0.29	0.32	0.28	0.32	0.36
Res. 1/3 acre	0.28	0.32	0.35	0.30	0.35	0.39
Res. 1/4 acre	0.30	0.34	0.37	0.33	0.37	0.42
Res. 1/8 acre	0.33	0.37	0.40	0.35	0.39	0.44
Industrial	0.85	0.85	0.86	0.85	0.86	0.86
Commercial	0.88	0.88	0.89	0.89	0.89	0.89
Streets: ROW	0.76	0.77	0.79	0.80	0.82	0.84
Parking	0.95	0.96	0.97	0.95	0.96	0.97
Disturbed Area	0.65	0.67	0.69	0.66	0.68	0.70

Rational Method Runoff Coefficients - Part I

APPENDIXES II: Quality Standards for Sources of Domestic Water

WATER QUALITY STANDARDS IN KENYA (AS ADOPTED FROM WHO)	
PARAMETER	KS-STD Limits
Color (Hazen Units)	15
Turbidity (NTU)	5
pH (pH Scale)	6.5-8.5
Dissolved Oxygen(mg/l)	Nil
Temperature (0C)	Nil
Conductivity (µs)	2000
Total Suspended Matter	Nil
Total Dissolved Solids (mg/l)	1500
Iron (mg/l)	0.3
Manganese (mg/l)	0.1
Flouride (mg/l)	1.5
Magnesium Hardness	2.45
Total Hardness (Mg/l)	500
Calcium Hardness	
Resistivity (Ohms/m)	Nil
Salinity	Nil
Total Coliforms	Nil
Faecal Coliforms	Nil

Source: Environmental Management and Co-ordination (Water Quality) Regulations, (2006)

APPENDIXES III. DPS and Nacosti Approval

MASINDE MULIRO UNIVERSITY OF SCIENCE AND TECHNOLOGY (MMUST)

Tel: 056-30870
Fax: 056-30153
E-mail: sgs@mmust.ac.ke
Website: www.mmust.ac.ke

P.O Box 190
Kakamega – 50100
Kenya

Directorate of Postgraduate Studies

Ref: MMU/COR: 509079

Date: 28th September, 2017

James Odiero
CWR/G/02/15
P.O. Box 190-50100
KAKAMEGA

Dear Mr. Odiero,

RE: APPROVAL OF PROPOSAL

I am pleased to inform you that the Directorate of Postgraduate Studies has considered and approved your Masters proposal entitled: '***Simulation of Runoff-Water Quality effects on Surface Water Supply Treatment Works***" and appointed the following as supervisors:

1. Prof. Basil T.I Ong'or - Department of Civil and Structural Engineering – MMUST
2. Dr. Edward Masibayi - Department Preparedness &Engineering Management - MMUST

You are required to submit through your supervisor(s) progress reports every three months to the Director Postgraduate Studies. Such reports should be copied to the following: Chairman, School of Engineering Graduate Studies Committee and Chairman, Civil and Structural Engineering Department. Kindly adhere to research ethics consideration in conducting research.

It is the policy and regulations of the University that you observe a deadline of two years from the date of registration to complete your Masters thesis. Do not hesitate to consult this office in case of any problem encountered in the course of your work.

We wish you the best in your research and hope the study will make original contribution to knowledge.

Yours Sincerely,

Prof. John Obiri
AG. DIRECTOR DIRECTORATE OF POSTGRADUATE STUDIES