APPLICATION OF ARTIFICIAL NEURAL NETWORKS (ANNs) FOR FORECASTING RAINFALL IN ILORIN, KWARA STATE, NIGERIA

BY

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ABSTRACT

The study is aimed at applying Artificial Neural Networks for forecasting rainfall in Ilorin, Kwara state with a view that artificial neural networks (ANNs) is an emerging computationally powerful technique with very high degree accuracy and widely used as forecasting models in many areas such as engineering, social, finance, economic, stock and foreign exchange problems. The objectives of this study are to examine the rainfall trend and distribution in the study area (1999-2018), to develop a reliable rainfall forecast for the period under study using ANNs and to examine the reliability of the developed rainfall forecast over the study area. In this research, we attempt to study the application of artificial neural networks for forecasting rainfall using some dependent weather variables such as temperature, rainfall, wind speed and sunshine hour in Ilorin metropolis Kwara state from June to October, all for the period of 19 years (1999-2018). The first part of the methodology to carry out this research was the collection of rainfall data (from the Nigerian Meteorological Agency) which serves as the fundamental input for statistical computations. The second aspect was the data processing then followed by the presentation of relevant outputs. From the monthly rainfall data, computation of mean rainfall and percentage mean rainfall for the period under study was carried out. Decadal charts were plotted to ascertain the maximum mean rainfall for each decade and the degree of variation in the amount of fluctuation in rainfall recorded over the period. Developing an artificial neural network (ANNs) as a reliable rainfall forecast essentially involve a nonlinear modeling approach that provides a fairly accurate universal approximation to any function. This is done both visually (using plotted graphs) and statistical measurements such as root-mean-square error (RMSE), mean square error (MSE), Mean Absolute Percent Error (MAPE) and the coefficient of correlation (CORR) to test the degree of error and examine the model performance. The results indicate that the trend and pattern of rainfall movement with respect to its amount and time is such that the rainfall amount either ascends gradually or fluctuates. It was discovered that much of the amount of rainfall in all the years under study is received in the month of June, July, August and September which are largely variant and characterized with fluctuations. Generally, a decreasing trend in rainfall is observed within the first three years of the first decade, with the highest amount of rainfall experienced in the first year of the decade totaled up to 1539.3mm. Also a significant increase in the rainfall amount for the last year of the first decade was observed resulting in an upward trend with values close to what was experienced at the beginning of the decade. The trend in rainfall for the second decade is a little similar to the previous decade with respect to the first, second, eight, ninth and tenth year. However, the eighth year of this decade is most significant as it recorded the highest value of 2552.6mm compared to the previous years in the decade. The highest mean annual rainfall experienced in the first decade was 128.3mm and 212.7mm in the second decade which also correspond to the highest value within the period under study. It was recommended that meteorological stations should be established to cushion the effect and challenge of sparse meteorological data and further reduce the representativeness of a system which can also have significant effect on the results of subsequent analysis. Government should support and encourage private organizations to key into establishment of more automatic weather stations.

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CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

The forecasting of the occurrence of events such as a social phenomenon, a natural disaster, a physical observation, personal research, or otherwise based on historical data has helped individuals and organizations in making informed decisions and adequate arrangements for any eventuality that might occur (Ayuba and Mubarak, 2018). Weather forecasting is one of the most imperative and demanding operational responsibilities carried out by meteorological services, the world over. Rainfall is a stochastic process, whose upcoming events depend on some precursors from other parameters such as temperature, surface pressure and other atmospheric parameters accurate information about rainfall is necessary for the use and management of water resources. Unequivocally, rainfall is one of the most complex and difficult elements in hydrology due to the tremendous range of variation over a wide range of scales both in space and time (Afolayan *et al*., 2016).

Rainfall is one of the most complex and difficult elements of the hydrological cycle to understand and model due to the tremendous range of variation over a wide range of scales both in space and time (French *et al*., 1992). The complexity of the atmospheric processes that generate rainfall makes quantitative forecasting of rainfall an extremely difficult task (Hung *et al*., 2009). Generally, rainfall has strong influence on the operation of dams and reservoirs, sewer systems, traffic and other human activities. Rainfall stands out as perhaps the single, most unique element of all the climatic elements such that it's total amount, intensity, duration, variability, reliability and its spatial and temporal distribution influence phenomenon especially in the tropical region where prevailing economic activity is simply agro-based (Oladipo, 1987, Hyuwa, 2005). Clearly, the rainfall analysis has a substantial role in the successful planning, development and implementation of water resource management, to evaluate engineering projects and environmental problems which include hydropower generation, reservoir operation, flood control and control of water quality (Farah and Hammed, 2018).

The Artificial Neural Networks (ANNs) is an emerging computationally powerful techniques with a very high degree accuracy and widely used as forecasting models in many areas such as engineering, social, finance, economic, stock and foreign exchange problems (Somvansh, *et al*., 2006). The ANNs approach has several advantages due to its robustness and flexibility over conventional methods or semi-empirical models, require known input data set with few prior assumptions (Nagendra and khare, 2006; Gardner and Dorling, 1998)**.** Its robustness, predictability and self-adaptive potential is due to the various distinguishing characteristics which includes, ability to learn a process without any prior knowledge about such phenomenon (i.e. image and sound recognition); ability to capture subtle functional relationships among the data even if the underlying relationships are not known or difficult to describe; ability to infer the unseen part of a population even if data contain noisy information; and many other features of ANNs that make them useful to researchers (Gardner and Dorling, 1998).

Past geographical survey has established that most theoretical analysis for rainfall prediction characteristics in Nigeria has been based on assumption. This is done with the view of rainfall normally in its distributive pattern, especially for an annual series. On the basis of these rainfall attributes, a thorough statistical analysis of rainfall distribution over the study area will not only be imperative but useful to the agricultural, social, commercial and industrial sectors of the economy of the study area but at the same time be a stepping stone to sustainable development of the entire country. Thus, it is imperative therefore to find out if this condition is practically obtainable in Ilorin considering the fact that agricultural practice in Kwara is also rain fed. Also, not just for no other thing to study, but because of the importance of such knowledge for all planning schemes for which rainfall is widely used. Further to this is the fact that such assumption about rainfall condition in the area may have serious and delicate implications on agricultural production. In agricultural production especially in the tropics, rainfall is without doubt a critical climatic factor. It is known fact that one of the two major limiting factors to agricultural production next to soil fertility is nothing but insignificant water supply. Rainfall is the main source of soil moisture in any given environment. Thus an assessment of its distribution be it monthly, weekly, and especially daily distribution) is therefore of great importance in agricultural planning. In Nigeria, the dominant feature of rainfall is its seasonal character. Hence water supply for agricultural practices is highly dependent on precipitation. Moreover, in areas where the climate is greatly influenced by drought and desertification, the condition of precipitation in relation to yield, the rate of evapo-transpiration and soil moisture content may help promote or hinder crop production.

In this research, we attempt to study the application of artificial neural networks for forecasting rainfall using some dependent weather variables such as temperature, rainfall, wind speed and sunshine hour in Kwara state, Nigeria.

1.2 Statement of the Research Problem

It is apparent that many researches have been conducted on rainfall forecasting in Nigeria using Artificial Neural Networks (ANNs) in recent times Ahmad and Mustapha (2018); Ewona *et al*. (2016); Abdulkadir *et al*. (2012); Andrew (2013). Most of these studies reported the suitability of Artificial Neural Network for rainfall forecasting. However, based on the literatures reviewed, little studies were carried in the study area using ANNs for rainfall forecasting.

Even though our computational system is very advanced and we have several software but we cannot forecast the weather as expected. Weather forecasting system is one of the main important applications in agricultural field and it has been technologically and scientifically challenging problem around the world from the past few decades. In recent years, the parameterization and uncertainties associated with process-based models have shifted the drift to the use of data-driven modeling techniques. Thus, smart technology has helped with information abstraction from data in detecting and predicting the likelihood of event trending. Data-driven models are usually numerical based information that employs statistical and mathematical concepts to link a certain input to the model output. Time series (moving average) trending and multiple linear regression analysis have been used to test the variability, homogeneity and trending patterns of rainfall series over a time period. Hence, the challenge posed by the non-linear nature of rainfall has been argued against these methods which use independent variables that are highly correlated with each other. These cannot determine, which independent variables best predict the dependent variable without duplicating characteristics.

1.3 Aim and Objectives

The aim of this research work is to apply Artificial Neural Networks (ANNs) to forecast rainfall in Ilorin, Kwara State. Nigeria.

The specific objectives are to:

i. Examine the rainfall trend and distribution in the study area (1998-2018)

ii. Develop a reliable rainfall forecast for the period under study using ANNs.

iii. Examine the reliability of the developed rainfall forecast over the study area.

1.4 Significance of the Study

This research is to examine and develop the artificial neural network (ANNs) weather forecast on rainfall in Ilorin. Before detailing the trials and results of this experiment, it is beneficial to present a survey revealing how weather forecasting model e.g. artificial neural networks have been applied to weather forecasting. The model was trained yearly for the period of 19 years unlike Abdulkadir *et al* (2012) which was done for 60 years at monthly interval. It will be apt to conclude the research that the ANNs based model is a veritable tool for overcoming the rainfall record paucity, inconsistency, unreliability hampering sustainable water resources development in the study area.

1.5 Scope and Limitation of the Study

The research work will focus on application of artificial neural networks (ANNs) on rainfall forecast in Ilorin metropolis, Kwara State. Also develop¸ examine and determine the efficiency of artificial neural networks for forecasting rainfall using the weather variables such as temperature, rainfall, wind speed, relative humidity and sunshine hour from 1999 to 2018. The study area was chosen because it situated at a strategic point in a densely populated middle belt of Nigeria.

1.6. Study Area Description

1.6.1 Location of the study area

Kwara State is located within the north central geopolitical zone the state capital is Ilorin located at Longitude 4 ^{o} 10'E and 4 ^{o} 36'E and Latitude 8^{o} 24'N and 8 ^{o} 36'N (fig 1.1). It is situated at a strategic point between densely populated middle belt of Nigeria It has an approximate area of about 468sqKm. Ilorin shares southern and eastern boundaries with Ifelodun local government area, while it shares northern boundary with Moro local government area and western boundary with Asa local government area. It is about 300km away from Lagos and 500km away from Abuja the Federal Capital of Nigeria (FCT). Ilorin metropolis is made up of parts of the three local government areas namely, Ilorin west, Ilorin south and Ilorin East. Ilorin is located in the transition zone between the deciduous woodland of the South and dry savannah of North Nigeria (Jimoh 2003).

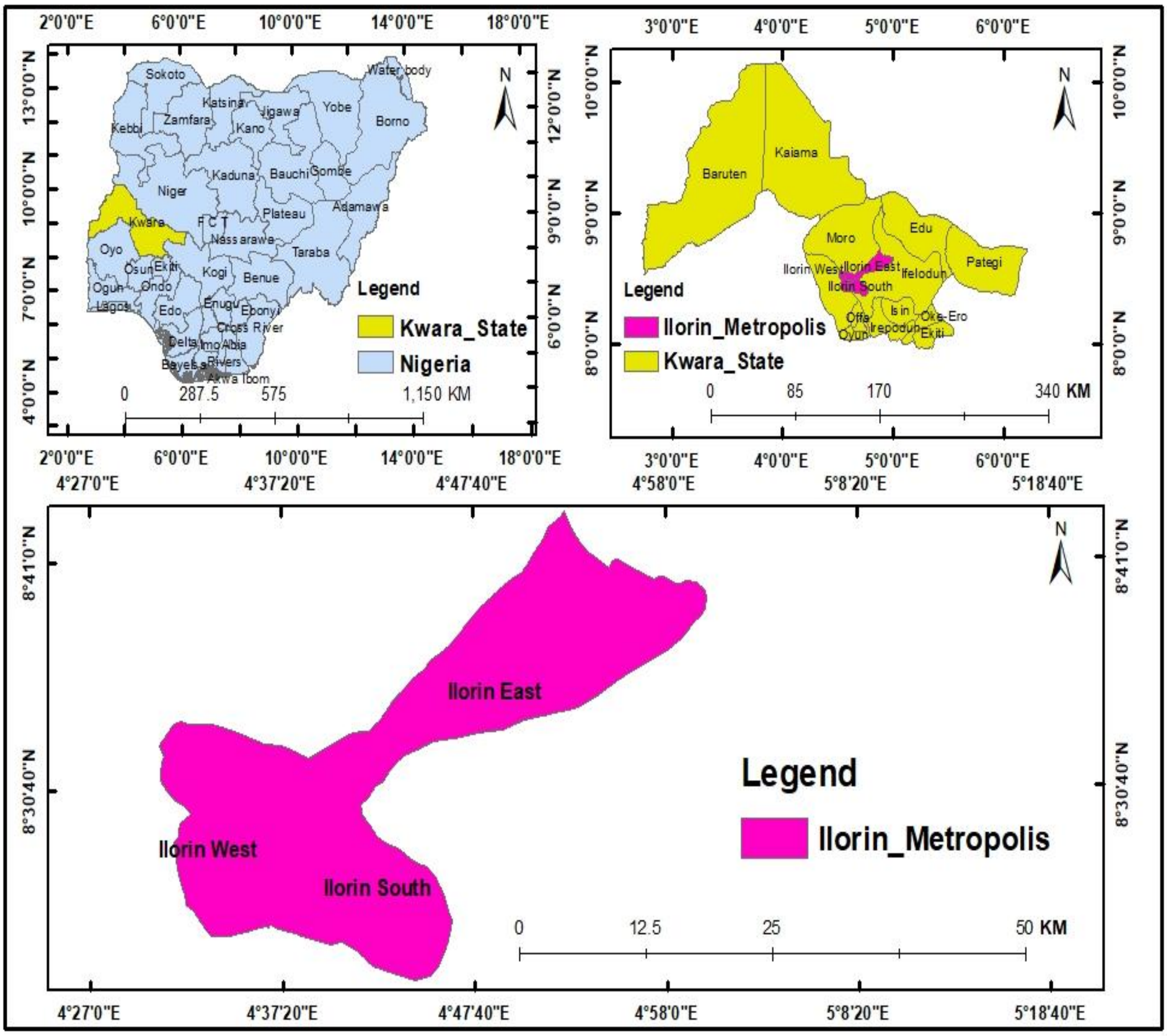

Figure 1.1. The Study Area (Ilorin Metropolis)
Source: Authors GIS mapping 2020.

1.6.2 Climate of the study area

The climate of Ilorin is characterized by both wet and dry seasons. The rainy season begins towards the end of April and last till October while the dry season begins in November and ends in April. The temperature of Ilorin ranges from 33^{o}C to 35^{o}C from November to January while from February to April; the value ranges between 34^{o}C to 37^{o}C. Days are very hot during the dry season. The diurnal range of temperature and the mean monthly temperatures are characteristically high in the area. The total annual rainfall in the area ranges from 990.3mm to 1318mm. Rainfall in Ilorin city exhibits the double maximal pattern and greater variability both temporarily and spatially. The relative humidity at Ilorin city ranges from 75% to 88% from May to October, while in the dry season it ranges from 35% to 80%. The geology of Ilorin consists of Precambrian basement complex rock. The soils of Ilorin are made up of loamy soil with medium to low fertility. Because of the high seasonal rainfall coupled with the high temperature, there is tendency for lateritic soil to constitute the major soil types in Ilorin due to the leaching of minerals nutrients of the soil (Ajibade and Ojelola 2004).

1.6.3 Geology of the study area

Ilorin consists of Precambrian basement complex rock. The soils of Ilorin are made up of loamy soil with medium and low fertility. Because of the high seasonal rainfall coupled with the high temperature, there is tendency for lateritic soil to constitute the major soil types in Ilorin due to the leaching of minerals nutrients of the soil (Ajibade and Ojelola, 2004). Mineral resources in the state are Gold, limestone, marble, feldspar, clay, kaolin, quartz and granite rocks.

1.6.4 Drainage of the study area

The drainage system of Ilorin is dendritic in pattern due to its characteristics. The most important river is Asa River which flows in south-northern direction. The major rivers are Asa, Agba, Alalubosa, Okun, Osere and Aluko. Some of these rivers drain into river Niger or river Asa (Oyegun, 1986). The general elevation of land on the western part varies from 273 m to 364 m (i.e. 900 to 1/200 ft) above sea level. To the north of the western part of Ilorin exists an isolated hill known as Sobi hill which is about 394 m high above sea level (Oyegun, 1986).

1.6.5 Human activities of the study area

Agriculture is well practice in the state and their principal main source of the economy they produce cash crops such as cotton, cocoa, coffee, kola nut, tobacco, bean seed and palm produce. Mineral resources in the state are limestone, marble, feldspar, clay, kaolin, quartz and granite rocks. Industries in the state include; Kwara breweries, Ijagbo Global soap and detergent industry, united match company, Tate and Lyle company, Resinoplast Plastic industry, Pharmatech Nigeria limited, Kwara textile and Kwara furniture company, all in Ilorin. Others are Paper Manufacturing industry, jebba, Okin foam and Okin biscuits, Offa, Kay plastic, Ganmo and Kwara paper converters limited, Erin-de, Sugar producing company, Bacita, Kwara animal feed mall, Ilorin, and the Agricultural products company (Oke 1996).

CHAPTER TWO

LITERATURE REVIEW

2.1 Conceptual Framework

Changes in rainfall and other forms of precipitation will be one of the most critical factors determining the overall impact of climate change. Rainfall is much more difficult to predict than temperature but there are some statements that scientists can make with confidence about the future. A warmer atmosphere can hold more moisture, and globally water vapor increases by 7% for every degree centigrade of warming. How this will translate into changes in global precipitation is less clear cut but the total volume of precipitation is likely to increase by 1-2% per degree of warming. There's evidence to show that regions that are already wet are likely to get wetter, but details on how much wetter and what impacts there will be on a local scale are more difficult to ascertain. The dry regions of the subtropics are likely to get drier and will shift towards the poles. It is the changes in weather patterns that make predicting rainfall particularly difficult.

While different climate models are in broad agreement about future warming on a global scale, when it comes to predicting how these changes will impact weather and consequently rainfall there is less agreement at a detailed level. It is likely that in a warmer climate heavy rainfall will increase and be produced by fewer more intense events. This could lead to longer dry spells and a higher risk of floods. So far, any impact that climate change may have had generally on regional rainfall cannot be distinguished from natural variations. Rainfall is a climatic phenomenon characterized by extremely irregular space-time distribution. Rainfall forecasting is a challenging task especially in the modern world where we are facing major environmental problems such as global warming. Owing to global warming, the change in rainfall patterns directly affects the agriculture sector as the rainfall plays a vital role in both the growth and production of crops.

According to (Oladipo, 1987; Hyuwa, 2005) rainfall stands out as perhaps the single, most unique element of all the climatic elements such that it's total amount, intensity, duration, variability, reliability and its spatial and temporal distribution influence phenomenon especially in the tropical region where prevailing economic activity is simply agro-based. Accurate information on rainfall is essential for the planning and management of water resources. Additionally, in the urban areas, rainfall has a strong influence on traffic, sewer systems, and other socio economic activities. Nevertheless, rainfall is one of the most complex and difficult elements of the hydrology cycle to understand and to model due to the complexity of the atmospheric processes that generate rainfall and the tremendous range of variation over a wide range of scales both in space and time (French *et al.,* 1992). Thus, accurate rainfall forecasting is one of the greatest challenges in operational hydrology, despite many advances in weather forecasting in recent decades.

Kumar *et al.* (2012) described weather forecasting as the application of science and technology to predict the state of the atmosphere for a given location. Weather forecasts are made by collecting quantitative data about the current state of the atmosphere and using scientific understanding of atmospheric processes to project how the atmosphere will evolve. The chaotic nature of the atmosphere, the massive computational power required to solve the equations that describe the atmosphere, error involved in measuring the initial conditions, and an incomplete understanding of atmospheric processes mean that forecasts become less accurate as the difference in current time and the time for which the forecast is being made increases. Weather warnings are important forecasts because they are used to protect life and property. Forecasts based on temperature and rainfall are important to agriculture, and therefore to traders within commodity markets Kumar and Singha *et.al* (2011) emphasis on weather forecasting has an important field of research in the last few decades.

According to Hung *et al.* (2009), an artificial neural networks (ANNs) is an interconnected group of artificial neurons that has a natural property for storing experiential knowledge and making it available for use. The first simplest form of feed-forward neural network, called perceptron has been introduced by (Rosenblatt in 1957). This original perceptron model contained only one layer, inputs are fed directly to the output unit via the weighted connections. Although the perceptron initially seemed promising, it was eventually proved that perceptron could not be trained to recognize many classes of patterns. After that, multilayer perceptron (MLP) model was derived in 1960 and gradually became one of the most widely implemented neural network topologies. Multilayer perceptron means a feed forward network with one or more layers of nodes between the input and output nodes. The MLP overcomes many limitations of the single layer perceptron, their capabilities stem from the non-linear relationships among the nodes (Lippmann, 1987).

In their study of nonlinear dynamics, Lapedes and Farber (1987) have pointed out the importance that the MLP is capable of approximating arbitrary functions. Two important characteristics of the MLP are: its nonlinear processing elements (PEs) which have a nonlinearity that must be smooth (the logistic function and the hyperbolic tangent are the most widely used); and their massive interconnectivity (i.e. any element of a given layer feeds all the elements of the next layer). Artificial neural networks are computational models that are capable of machine learning and pattern recognition. They are usually presented as systems of interconnected "neurons" that can compute values from inputs by feeding information through the network. Like other machine learning methods, neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming, including computer vision and speech recognition. Artificial neural networks have been applied in non-linear system modeling with enormous applicability in time series analyses of recent (Dunis and Williams, 2002).

Artificial neural network can be chosen for rainfall forecasting. Artificial neural networks are a method which can be easily adapted to the types of data with few limiting hypotheses against classical or conventional methods. For ANN, there exists a general functional structure that can be generalized. An artificial neural network is a network of interconnected elements which are inspired in producing an output pattern using an input pattern. Connectionist models, such as ANN, are well suited for machine learning where connective weights are adjusted to improve the performance of network. ANN approaches to rainfall modeling are more efficient than the conventional flow forecasting models whenever explicit knowledge of the hydrological balance is not required and when the system may be treated as a black box. Be it as it may, recent experiments have reported that ANN may offer a promising alternative for rainfall modeling (Smith and Eli, 1995; Tokar and Johnson, 1999). The ANN is based on the perceptron a compound word combining the role of neurons and recognition. The perceptron consists of one input layer and an output layer, and each layer contains nodes for data operations corresponding to a cell body. By adding a hidden layer and nodes inside the input layer and the output layer of the perceptron, the network expands to a multilayer perceptron structure. In general, an artificial neural network refers to a multilayer perceptron structure. The three-layered feed-forward neural network has been widely used in hydrologic forecasting models. The input data in the input layer is transferred to each neuron in the hidden layer through a linear sum operation, and the result of inputting the linear sum to the activation function is the result of the hidden layer neuron.

2.2 Literature Review

2.2.1 Weather forecasting.

Weather forecasting is one of the important science applications in our day-to-day planning activities. This is one prominent application that has played a significant role to humankind from long way back. Wherever humans have settled around the world, weather forecasting has always been part of their life for man has always been actively involved in their surroundings. Early human kind relied on their philosophical experience and other reoccurring weather phenomena to predict the weather and infer what was coming their way. This was the knowledge gathered over many years of observations and passed from one generation to another. Wiston *et al* (2018).

However, it became evident that natural knowledge was inadequate to precisely gauge the atmospheric changes; a growing number of scientists realized the need for more advanced and better ways of predicting weather. Weather forecasting was particularly revolutionized in the 1920s by Norwegian scientists the leading proponent being Vilhem Bjerknes (1862-1951) introducing empirically observed conditions and described precipitation formation, cyclones and atmospheric circulation systems. He combined all the sciences needed to conduct numerical weather predictions: meteorology, physics and numerical mathematics, although it took several years before his ideas could be put into practice.

Climatic data on rainfall, evaporation, relative humidity, temperature and sunshine hours were collected for a period of 10 years alongside agricultural data on rice, sorghum, maize, cowpea and yam. Multiple regression, trend analysis and correlation analytical techniques were employed to analyze the data. The result obtained shows that the selected climatic parameters have a weak correlation on urban agriculture within the years the result obtained from the regression and correlation statistics reveals that climate has little impact on crop productivity within the years under review. In other word, the result implies that, though there are variations in climatic parameters within the years, such variation has little impact on the selected crops. This suggests that variation in crop yield could be as a result of other factors. Such factors could be soil or farm techniques (Ajadi, *et al* 2011). Weather forecasting has become an important field of research in the last few decades. In most of the cases the researcher had attempted to establish a linear relationship between the input weather data and the corresponding target data. But with the discovery of nonlinearity in the nature of weather data, the focus has shifted towards the nonlinear prediction of the weather data. Although, there are many literatures in nonlinear statistics for the weather forecasting, most of them required that the nonlinear model be specified before the estimation is done. But since the weather data is nonlinear and follows a very irregular trend, Artificial Neural Network (ANN) has evolved out to be a better technique to bring out the structural relationship between the various entities (Amanpreet, *et.al* (2011).

Bjerknes approach was a more explicit analysis of the weather prediction from scientific perspective. He believed that the problem of predicting the future atmospheric evolution could be formulated mathematically in terms of seven variables (three components of air velocity, pressure, temperature, density and humidity) each being a function of time and space. Weather forecasting models comprise of fundamental laws and parameterized physical and chemical components of the atmosphere. The state of the atmosphere is described at a series of 'grid-points' by a set of variables such temperature, pressure, velocity and humidity. The laws are expressed as mathematical equations, averaged over time and grid volumes describing the evolution of such variables. They are solved by replacing time-derivatives by finite differences, and spatially either finite difference schemes or spectral methods (i.e. state of the body as a function of time). They are converted into a computer program, defining among other things, possible integrations between the variables with other formulations, and integrated forward in discrete time steps (i.e. making them predictive) to simulate changes in the atmosphere. In this context, the model is a computer program that produce meteorological information at given locations. All numerical models are based on the same set of governing laws used to predict the physics and dynamics of the atmosphere. There are many types of parameterization schemes used in different models. These are important aspects that strongly influence model forecasts and interact with each other in the atmosphere.

Parameterization needs to account for computational costs. (e.g. model running time, resolution used and or any other resource specification), especially when using or increasing the complexity of the choice. There must be a 'balance' between the type of scheme chosen and the computational cost. For example, using one particular scheme can result in more [simulation] time than another choice of scheme. However, these developments can be hampered by inadequate observations (data voids), limited understanding of the atmospheric physical processes and the chaotic nature of the atmospheric flow. Therefore, uncertainties will always exist in both initial conditions and/or numerical prediction results. Many models are developed to improve precision and to accommodate more complex processes. Many scientists realized that atmosphere could be modeled from the physics laws that could alter its state. But it was the pioneering work of Bjerknes and Richardson in the 1920s that kicked off the development of modern weather forecasting. Notwithstanding weather forecasting is a complex and challenging science, depending on the efficient interplay of weather observation, data analysis, computers and rapid communication. Generating weather information involves a vast infrastructure of space, earthbound observations, numerical weather models and scientific knowledge requiring significant coordination.

2.2.2 Artificial neural networks (ANNs) model.

Khan and Maqsood (2004) describe a model that predicts the hourly temperature, wind speed and relative humidity 24 hour ahead. Training and Testing is done separately for winter, spring, and summer and fall season. The authors have made a comparison of Multilayer Perceptron Networks (MLP), Elman Recurrent Neural Network (ERNN), Radial Basis Function Network (RBFN) and the Hopfield Model (HFM) and ensembles of these networks. MLP was trained by back propagation. RBFN has natural unsupervised learning. The authors have suggested one hidden layer and 72 neurons for the MLP network and 2 hidden layers with 180 neurons for RBFN as the optimal architecture. The accuracy measure used is the mean absolute percentage error (MAPE). RBFN has the best performance. RBFN and MLP have about the same accuracy, but the MLP learning process is more time consuming. However, the performance of ensembles outperformed all single networks.

The work described by Sanjay (2007) focuses on maximum and minimum temperature forecasting and relative humidity prediction using time series analysis. The network model used is a Multilayer feed forward ANN with back propagation learning. Direct and statistical input parameters and the period are compared. For minimum/maximum temperature forecasting the optimum seems to be a 15-week period of input data. Input features were features of maximum and minimum, respectively. Namely these features are moving average, exponential moving average, oscillator, rate of change and the third moment. For the 15-week period the error was less than 3%. The main result is that in general statistical parameters can be used to extract trends.

Franses and Griensven (1998) examine the performance of artificial neural networks (ANNs) for technical trading rules for forecasting daily exchange rates. The main conclusion of the attempt was that ANNs perform well, and that they are often better than linear models. Furthermore, the precise number of hidden layer units in ANNs appears less important for forecasting performance than is the choice of explanatory variables. Another short-term temperature forecasting system was described by Hayati (2007) a three-layer MLP network with 6 hidden neurons, a sigmoid transfer function for the hidden layer and a pure linear function for the output layer was found to yield the best performance. The scaled conjugate gradient algorithm was used for training. The following input parameters were measured every three hours: wind speed, wind direction, dry bulb, temperature, wet bulb temperature, relative humidity, dew point, pressure, visibility, amount of cloud. The other input parameters were measured daily: gust wind, mean temperature, maximum temperature, minimum temperature, precipitation, mean humidity, mean pressure, sunshine, radiation, evaporation.

According to Kumar *et al.* (2012), most Artificial Neural Networks approaches preprocess the input and target data into a range -1 to +1 or 0 to 1 and then post-process it. However, investigation on finding model that can reduce this processing cost by working on raw data. Since we have 10 inputs, a 5 hidden-layer network with 10 or 16 neurons/ layer and a tan-sigmoid transfer function for hidden layers seemed to do generalize much better over 750 and 1460 samples as compared to a single hidden-layer network with the same number of neurons. However, the most important conclusion that the study resulted to was on the behavior of increased hidden layers on performance and generalization. Finally, the prediction that was made for the maximum temperature can be extended to other weather factors like humidity, wind speed etc. using the same model and precautions. Further measures to optimize the performance of such a weather forecasting model can be based on various macro and micro-environmental factors. The model used to develop supportive statistical plots and concentrate on the trend of weather over a long period of time in a particular area.

2.2.3 Application of artificial neural networks in forecasting.

According to Folorunsho (2002) in application of ANNs for forecasting rainfall in Zaria, several models have been developed for forecasting yet, the artificial neural network (ANN) model provides a quick and flexible means of creating reasonable output. It has higher performance level when compared with conventional methods. The data used to carry out the research done by Folorunsho were obtained from the Nigerian meteorological agency, Zaria and Meteorological Unit, Soil Science Department, Ahmadu Bello University, Zaria on a monthly average basis over a twelve (12) years period (1990 – 2002). As part of the ANN model development procedures, the data sets of 84 raining months in the study area (April – October) was partitioned into two parts with 70% of the entire data sets used as the training data while the remaining used as the testing and the validation data.

The results revealed that the developed ANN based model in the Predict Demo Neural Ware environment shows a correlation value of 81% when the original rainfall values of the study area were compared with the forecasted rainfall value. The primary data used for the work include the monthly averages of the temperature, relative humidity, wind speed and sunshine hours of the study area which was used as the input data. These were obtained from the Nigerian College of Aviation Technology (N.C.A.T.) Zaria, while the monthly average rainfall data series for Samaru spanning 1990 to 2002 was obtained from the Meteorological Department, Institute of Agricultural Research, (I.A.R), Ahmadu Bello University, Samaru, Zaria. The data Analysis carried out on the research explained that the artificial neural network based model development using the Neural Ware Predict Demo interface was used to achieve the desired operations. Employing the six (6) basic procedures: launching of the model and loading the data sets partitioned into 70% of the data sets for training and 30% for the testing and validation; configuration of the model; training of the model using four (4) sets of variables for input; model performance testing; model validation for reliability for forecasting the rainfall and, graphical plots of the actual and forecasted rainfall output in order to certify the ability of the model to learn the trend, cycles and pattern of the rainfall of the study area.

The key indicator of such the ANNs model is the performance of the model when subjected to the standard procedures and statistical tests outlined earlier. For this study, these values were actually found to be similar with the correlation value (R) between the actual and forecasted mean monthly data shown as 81%, root mean square error (RMS) is 52.5, accuracy of 96.4%, and the confidence interval of 107.7 at 0.05 significant level. From the obtained test results generated by the ANNs based model, there are indications that the model has learned both the trend and cycle of the actual data. This further confirms the reliability of the model for sustainable water resources development and management in the study area.

However, in order to validate the ANN based model developed, the performance of the developed model to forecast mean monthly rainfall from the actual mean monthly rainfall data was tested. From the test result, a comparison of the actual mean monthly rainfall output and the ANN based model output was tested and the developed model has a high-performance level (with R value of 81%) having learned both the trend and cycle of the Samaru mean monthly rainfall. This present a good effect on the reliability of the ANN model developed for forecasting rainfall series that can improve formulation of policies that can promote sustainable development of all the rain-fed activities in the study area. From the foregoing, it will be apt to conclude the research that the ANN based model is a veritable tool for overcoming the rainfall record paucity, inconsistency, unreliability hampering sustainable water resources development in the study area.

John and Jennifer (2017) carried out a research on the application of artificial neural networks to forecasting monthly rainfall one year in advance in Australia. Much of Australia regularly experiences extremes of drought and flooding, with high variability in rainfall in many regions of the continent. Development of reliable and accurate medium-term rainfall forecasts is important, particularly for agriculture. Monthly rainfall forecasts 12 months in advance were made with artificial neural networks (ANNs), a form of artificial intelligence, for the locations of Bathurst Deniliquin, and Miles, which are agricultural hubs in the Murray Darling Basin, in southeastern Australia. Two different approaches were used for the optimization of the ANN models. In the first, all months in each calendar year were optimized together, while in the second approach, rainfall forecasts for each month of the year were made individually. For each of the three locations for most months, higher forecast skill scores were achieved using single-month optimizations. In the case of Bathurst, however, for the months of November and December, the root mean square error (RMSE) for all-month optimization was lower than for single-month optimization. The best overall rainfall forecasts for each site were obtained by generating a composite of the two approaches, selecting the forecast for each month with the lowest forecast errors. Composite model skill score levels of at least 40% above that of climatology were achieved for all three locations, whereas skill level derived from forecasts using general circulation models is generally only comparable to climatology at the long-lead time of 8 months. The research indicates that it is possible to make skillful monthly rainfall forecasts with a 12 months lead time for locations in the Murray Darling Basin. Our previous approach of forecasting has also been refined by examining the skill corresponding to the optimization of individual months, as well as the overall.

Ahmad and Mustapha (2018) applied Artificial Neural Network to predict monthly rainfall over Kano, Kano State, Nigeria. Three months lagged climate indices for monitoring El Nino-Southern Oscillation (ENSO) namely: Southern Oscillation Index (SOI), Nino 1+2, Nino 3.4 and Nino 4 monthly values for 37 years were used as predictors. A Linear Model (LM) was first used as a yardstick. The ANN was trained using neural package in R statistical software, 25 years' data (1981-2005) was used for model training, while the remaining twelve years data (2006-2017) was used for model evaluation. The study developed the Linear Model and the ANN models via linear model and neural net available in R statistical software. The model evaluation was carried out using Correlation Coefficient (r), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The results showed that Nino 1+2, Nino 3, Nino 3.4 and Nino 4 indices exhibited a similar trend, although with some disparities. Higher values of monthly rainfall were observed from 1996-2005 as compared to earlier years of (1981-1995). A correlation coefficient *r* value of 0.70 was recorded between the actual monthly rainfall values and the predicted monthly rainfall values from (2006-2017) by the traditional Linear Model (LM) after evaluation. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values of 72.21 and 106.0 were also recorded for Linear Model respectively. There was an improvement in correlation coefficient by 0.03 when ANNs was applied. Mean Absolute Error and Root Mean Square Error of 64.73 and 100.77 were reported, respectively. A higher *r,* lower MAE and RMSE produced by ANNs results indicated higher accuracy as compared with the Linear Model. The study concluded that forecast made using ANNs was more accurate and was there for recommended for rainfall prediction in the study area. However, the study equally recommended that further studies should be carried out over other regions due to wide spatial and temporal variability of rainfall in Nigeria.

Ewona *et al.* (2016) predicted rainfall in Nigeria using Artificial Neural Network (ANN). Rainfall data from the Nigerian Meteorological Agency, Oshodi, Lagos collected over thirty (30) years and from twenty-three weather measuring stations spread across Nigeria were used for the study. By applying stochastic and data reduction procedures, the data was filtered to fast track the actual variables that were used for modeling rainfall. Three hundred and sixty (360) monthly mean rainfall data points, representing a thirty-year period were used for the analysis. Out of the 360 monthly mean rainfall data points, 300 data points representing 25 years were used for training the network. The remaining 60 data points representing 5 years were used to cross validate the model. Each set of data was trained for five different sets of epochs. The number of epochs was chosen at intervals of 500, 1000, 1500, 2000 and 3000 epochs. By varying the weights and learning cycles, 5 different sets of predicted values were obtained. The predicted values were then correlated with actual values for corresponding periods. The values of the correlation coefficients were used to determine the most suitable network among the five different settings and learning processes. The artificial neural network employed for the analysis was used in conjunction with Excel Software to model 330 data sets covering ten meteorological parameters and 23 weather stations in Nigeria.

The results showed that the ANNs could not account for the extreme rainfall in the months of August and September. This was attributed to the general variation in the other meteorological parameters used for modeling it. This was seen as poor fit between predicted and actual data between June and October. The network predicted rainfall less accurately for the two months. Correlation coefficients were generally between 0.20 and 0.80. However, the network fared better in the middle belt, especially at Lokoja. Except Lagos, all other weather stations in the southern part of the country recorded poor correlation values between the two sets of values. The study concluded that the prediction of rainfall using Neuro XI is better at higher latitudes.

2.2.4. ANNs modeling of rainfall.

Abdulkadir, *et al.* (2012) made some findings and clear explanations that accurate information about rainfall is essential for the management of water resources, disaster prevention, and agricultural production. This ANN model is designed to run a real time task in which the input to the model is a consecutive data of the rainfall. The neural network was trained with sixty years (1952–2011) total monthly historical rainfall data. The trained network yielded 76% and 87% of good forecast for the training and testing data set respectively. The correlation coefficient of 0.88 was obtained which showed that the network is fit to be used for the subsequent quantitative prediction of rainfall. Rainfall is one of the key entities of hydrological cycle that strongly influence the operation of dams and reservoirs, flood control, drought mitigation, operation of sewer systems, agricultural practice, traffic conditions and other human activities. The neural network summary yielded 76% of good forecasts for rainfall in the study area with correlation coefficient of 0.88. This showed that the trained network is reliable and fit to be used for the subsequent quantitative prediction of rainfall. It can therefore be concluded that forecasting using ANNs is a very versatile tool in water resources management modeling.

Hung *et al.* (2009). The researchers present a new approach using an artificial neural networks technique to improve rainfall forecast performance. A real world case study was set up in Bangkok; 4 years of hourly data from 75 rain gauge stations in the area were used to develop the ANNs model. The developed ANNs model is being applied for real time rainfall forecasting and flood management in Bangkok, Thailand. Aimed at providing forecasts in a near real time schedule, different network types were tested with different kinds of input information. Preliminary tests showed that a generalized feed forward ANNs model using hyperbolic tangent transfer function achieved the best generalization of rainfall. Especially, the use of a combination of meteorological parameters (relative humidity, air pressure, wet bulb temperature and cloudiness), the rainfall at the point of forecasting and rainfall at the surrounding stations, as an input data, advanced artificial neural networks model to apply with continuous data containing rainy and non-rainy period, allowed model to issue forecast at any moment. Additionally, forecasts by artificial neural networks model were compared to the convenient approach namely simple persistent method. Results show that artificial neural networks forecasts have superiority over the ones obtained by the persistent model. Rainfall forecasts for Bangkok from 1 to 3 h ahead were highly satisfactory.

Sensitivity analysis indicated that the most important input parameter besides rainfall itself is the wet bulb temperature in forecasting rainfall. Historical rainfall data was collected from

104 stations of the BMA and TMD rain gauge networks for the period from 1991 to 2005. After analyzed data, the period from 1 January 1997 to 31 December 1999 was selected to train artificial neural network models, and the data of the year 2003 were used as a testing set. The research focus on the Bangkok area only, so total 75 stations inside Bangkok area were selected, while the other 29 stations which are located outside Bangkok were discarded, it roughly made each selected station representing for an area around 21 km^2. The collected meteorological data which contained hourly measurements of six parameters observed in the mast station, that is: relative humidity, wet bulb temperature, dry bulb temperature, air pressure, cloudiness, and wind speed for the same period as rainfall data. As an additional variable, the average hourly rainfall intensity of all the rain gauges was simply arithmetically average computed and provided with the meteorology data.

The meteorological data from 1991–2004 was that the average annual relative humidity (RH) is about 81% with the average maximum RH of 93% and the average minimum RH of 52%. The average annual temperature is 26.8$^{\circ C}$, with the average maximum temperature of 33.4$^{\circ C}$ in April and the average minimum temperature of 20.4$^{\circ C}$ in December. The average annual rainfall is 1869.5 mm with the highest average monthly rainfall of approximately 381 mm observed in October, and the lowest average monthly rainfall of about 12 mm occurring in December, usually the driest month of the year.

Artificial Neural Networks model was employed to forecast rainfall for Bangkok, Thailand, with lead times of 1 to 6 h. Comparison of 1 h ahead rainfall forecast of the six models considered in the preliminary test showed that a combination of meteorological parameters such as relative humidity, air pressure, wet bulb temperature, and cloudiness, along with rainfall data at the forecasting station and other surrounding stations, as an input for the model could significantly improve the forecast accuracy and efficiency. Results of preliminary tests also concluded that the generalized feed forward network and hyperbolic tangent function performed well in their work. With the appropriate network architecture and especially with the use of auxiliary data, the ANNs model was able to learn from continuous input data which contained both rain and dry periods, thus the model can be adopted to run for real time forecasting. The superiority in performance of the ANNs model over that of the persistent model again confirmed that the real advantage of a continuous ANNs model is that it can provide a satisfactory rainfall forecast at any moment. It is important to determine the dominant model inputs, as this increases the generalization of the network for a given data.

Furthermore, it can help reduce the size of the network and consequently reduce the training time. With their clarification in the research sensitivity analysis was used to rank the input parameters with respect to their importance in forecasting rainfall based on the model performance. Results of the sensitivity analysis indicated that the most important input parameter, besides rainfall itself, is the wet bulb temperature; further study over the entire rain gauge network could be carried out for more significant conclusions. The ANN model was found to be efficient in fast computation and capable of handling the noisy and unstable data that are typical in the case of weather data. The predicted values of all 75 rain gauge stations matched well with the observed rainfall for forecasts with short lead times of 1 or 2 h. Not only that, the rainfall forecasting for 3 h ahead using the ANNs model also provided reasonably acceptable results. The efficiency indices were gradually reduced as the forecast lead time increased from 4 to 6 h. Although the model performance of 6-hour forecasting was low and the forecasting was not as accurate as expected, the developed model can still be used for practical applications such as rainfall forecasting and flood management for the urban areas.

2.2.5 Using neural networks to provide local weather forecasts.

Andrew (2013) examined the use of neural networks for providing local weather forecast artificial neural networks (ANNs) have been applied extensively to both regress and classify weather phenomena. While one of the core strengths of neural networks is rendering accurate predictions with noisy datasets, there is currently not a significant amount of research focusing on whether ANNs are capable of producing accurate forecasts of relevant weather variables from small-scale, imperfect datasets.

Also, there is not a significant amount of research focusing on the forecasting performance of neural networks applied to weather datasets that have been temporally rolled-up from a base dataset, an experiment in which neural networks are used to regress and classify minimum temperature and maximum gust weather variable and a dataset containing weather variables recorded every 15 minutes over the course of a year by a personal weather collection station in Statesboro, Georgia was used. Data cleansing and normalization were applied to this dataset to subsequently derive three separate datasets representing 1-hour, 6-hour, and 24-hour time intervals. Three different NN (neural networks) structures were then applied to these datasets in order to generate minimum temperature regressions at 15-minute, 1-hour, 3-hour, 6-hour, 12-hour, and 24- hour look-ahead ranges. Maximum gust regressions were also generated for each dataset 2 at 1-hour, 3-hour, 6-hour, 12-hour, and 24-hour look-ahead ranges. Finally, neural networks were applied to these datasets to classify freezing events and gusty events at 3- hour, 6-hour, 12-hour, and 24-hour look-ahead ranges.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Data Types and Sources

This research work adopted some key climatic data ranging from monthly maximum and minimum air temperature, relative humidity, wind Speed and total monthly rainfall and sunshine hour from June to October, all for the period of 19 years (1999-2018) over the study area (Ilorin Metropolis). The datasets were acquired from the Nigerian Meteorological Agency (NIMET).

3.2. Characteristics of the Data Sets

Table 3.1: Characteristics of Datasets for the study

S/N	Data type	Acquisition date	Format	Source
1	Monthly Rainfall	1999 - 2018	Text	NIMET
2	Maximum /Minimum Air Temperature	1999 - 2018	Text	NIMET
3	Relative Humidity	1999 - 2018	Text	NIMET
4	Wind Speed	1999 - 2018	Text	NIMET
5	Sunshine	1999 - 2018	Text	NIMET

The characteristics of all the climatic dataset used in the study are summarized on Table above. See appendix 1

3.3 Methods of Data Collection;

Before beginning the network design process, there was collection and preparation of sample data. It is generally difficult to incorporate prior knowledge into a neural network therefore the network can only be as accurate as the data that are used to train the network. It is important that the data cover the range of inputs for which the network will be used. Multilayer networks can be trained to generalize well within the range of inputs for which they have been trained. However, they do not have the ability to accurately extrapolate beyond this range, so it is important that the training data span the full range of the input space. After the data have been collected, there are two steps that need to be performed before the data are used to train the network: the data need to be preprocessed, and they need to be divided into subsets.

3.3.1 Creating neural network:

To create a neural network, the network creation functions were used. Using the “feed forward net” command, a simple, two-layer feed forward network is created;

3.3.2 Configuring neural network:

After a neural network has been created, it must be configured. The configuration step consists of examining input and target data, setting the network's input and output sizes to match the data, and choosing settings for processing inputs and outputs that will enable best network performance. The configuration step is normally done automatically using the model software, when the training function is called. However, it can be done manually, by using the configuration function.

3.3.3 Network training:

After the network has been configured, the adjustable network parameters (called weights and biases) need to be tuned, so that the network performance is optimized. This tuning process is referred to as training the network with the Neural Ware Predict Demo interface.

3.3.4 Neural network validation:

This algorithm is to assess how well neural networks (NN) predict a modeled system when they are trained by the developed algorithms. A trained network generalizes well if it is able to predict correctly both data that were used for training and data that were not used during training. This process is called network validation. During the validation process, tests are performed to access to what extend the developed model represents the operational dynamics of the underlying system.

3.3.5 Network usage:

After the network is trained and validated, the network object can be used to calculate the network response to any input.

3.4 Methods of Data Analysis

3.4.1 Rainfall trend and distribution

For this study, the knowledge on the spatial distribution and pattern of rainfall is essential for efficient understanding of the rainfall trend in the study area.

The first part of the methodology to carry out this research was the collection of rainfall data (from the Nigerian Meteorological Agency) which serves as the fundamental input for statistical computations. The second aspect was the data processing then followed by the presentation of relevant outputs. From the monthly rainfall data, computation of mean rainfall and percentage mean rainfall for the period under study was carried out. Rainfall anomaly was calculated by adding the annual yearly rainfall amount then subtracts the average values from the total annual rainfall. Decadal charts were plotted to ascertain the maximum mean rainfall for each decade and the degree of variation in the amount of fluctuation in rainfall recorded over the period. Standardized precipitation Index (SPI) shall then be computed in other to further understand and confirm the distribution and trend of rainfall in the entire study area under the period of study. Microsoft Excel Software was used to calculate the Standardized Precipitation Index using the formula below;

$$\text{SPI} = \frac{(P_{ij} - \bar{p}_i)}{\sigma} \tag{1}$$

$$\sigma = \sqrt{\frac{\sum_1^n (P_{ij} - \bar{p}_i)^2}{N}}. \tag{2}$$

where (σ) is standard deviation and $(P_{ij} - \bar{p}_i)$ is rainfall anomaly.

12 months Standardized Precipitation Index was calculated for period under study 1999 to 2018 and this is based on the method of McKee, (1993), using the precipitation data from the Nigeria Meteorological Agency (NIMET) to analyze the degree of wetness or dryness as the case may be during the period under study.

3.4.2 Development of reliable rainfall forecast using ANNs

For the purpose of this objective, the Artificial Neural Network (ANN) will be used. ANN is a non-statistical data forecasting tool which is contained in any version of "MATLAB tool box". An artificial Neural Network is a highly interconnected network of many simple processing units called neurons, which are analogous to the biological neurons in the human brain (Andy et al., 2004; Hung et al., 2008; Kumarasiri and Sonnadara, 2006; and Luk et al., 2001). Neural networks essentially involve a nonlinear approach that provides a fairly accurate universal approximation to any function. Its approximation power comes from the parallel processing of the information from the data. ANNs is characterized by a network of three layers of simple processing units, which are connected to one another. The layers are input, hidden and output layer.

3.4.2.1 Workflow for neural network design

The work flow for the neural network design process has seven primary steps which are outlined below;

i. Collect data
ii. Create the network
iii. Configure the network
iv. Initialize the weights and biases
v. Train the network
vi. Validate the network
vii. Use the network

3.4.3 Examination of the reliability of the artificial neural network in forecasting rainfall in the study area

The reliability of the artificial neural network is determined in the results of its prediction when compared to the observed data obtained from meteorological stations. This is done both visually (using plotted graphs) and statistical measurements such as root-mean-square error (RMSE), mean square error (MSE), Mean Absolute Percent Error (MAPE) and the coefficient of correlation (CORR) to test the degree of error and examine the model performance.

3.4.3.1 Root mean square error (RMSE):

The RMSE has become one of the most frequently used measures to establish the differences between values predicted and the values observed. The RMSE represents the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences. These deviations are called residuals when the calculations are performed over the data sample that was used for estimation and are called *errors* (or prediction errors) when computed out-of-sample.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \qquad (3)$$

Where $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are predicted values while $y_1, y_2, \ldots, y_n$ are observed values and n is the number of observation.

3.4.3.2 Mean square error (MSE):

Mean Square Error is a statistical approach that measures the average of the squares of the errors i.e. the average squared difference between the estimated values and the actual value.

MSE is a measure of the quality and reliability of the forecast. It is always non-negative, and values closer to zero are better.

The formula below is used to compute the MSE;

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \tag{4}$$

Where $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are predicted values while $y_1, y_2, \ldots, y_n$ are observed values and n is the number of observation.

3.4.3.3 Mean absolute percentage error (MAPE):

This is used statistically to measure the accuracy of a forecasting method based on the results of its prediction. MAPE is also referred to as mean absolute percentage deviation (MAPD). It usually expresses the accuracy as a ratio defined by the formula:

$$\text{M} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|, \tag{5}$$

Where A_t is the actual value and F_t is the forecast value.

3.4.3.4 Correlation coefficient:

The correlation coefficient is a very good statistical measure that is used to test the strength of the relationship existing between the relative variables. The threshold values range between -

1.0 and 1.0. A correlation of -1.0 shows a perfectnegative correlation, while a correlation of 1.0 shows a perfect positive correlation.

$$r = \frac{\Sigma(x - \bar{x})(y - \bar{y})}{\sqrt{[\Sigma(x - \bar{x})^2 (y - \bar{y})^2]}} \quad (6)$$

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Rainfall Trend and Distribution

The first result presented involves the examination of the rainfall pattern and distribution in both annual and decadal trend in the study area. From the monthly rainfall data collected, total rainfall for each year, mean rainfall and percentage mean rainfall were first calculated for the period under study (Tables 4.1). The data was further used to plot a decadal chart to ascertain the maximum mean rainfall for each decade (Figure 4.1).

As observed from the result (Table 4.1) shows that the percentage mean rainfall in 1999 was 5.5% (128.3 mm) which declined to 3.6% in the year 2000 and further declined to 2.5% in

2001. There was slight increase in 2002 to 3.1% which then significantly went up to 4.6% (107.2mm) in 2003 and subsequently sustained the increased again to 4.7% (110.6 mm) in 2004. The percentage mean rainfall values were maintained between 2004 and 2006 (4.7%) before decreasing a little to 4.6% in 2007 and increased by 0.4% in 2008 (5%). The out pour of rain between 2008 and 2013 was characterized by upward and downward fluctuations ranging from 5% to 4.5% respectively. There was however an unprecedented out pour of heavy rains in 2014 (8.2% (191.3)). The quantity of rain later dropped to 6.1% in 2015 before attaining the highest peak value of 9.1% in 2016. Consequently, a sharp decline (5.3%) was experienced in 2017 (123.6mm) before finally increased to 7.9% in 2018.

Table 4.1: Total and mean monthly rainfall from 1999 to 2018.

Year	Annual Total Rainfall (mm)	Monthly Mean (mm)	% Mean
1999	1539.3	128.3	5.5
2000	993.3	82.8	3.6
2001	697.7	58.1	2.5
2002	957.1	71.8	3.1
2003	1286.7	107.2	4.6
2004	1327.1	110.6	4.7
2005	1317.1	109.8	4.7
2006	1303.8	108.7	4.7
2007	1292.2	107.7	4.6
2008	1401.4	116.8	5
2009	1343.1	111.9	4.8
2010	924.3	77	3.3

2011	1086.5	90.5	3.9
2012	1071.1	89.9	3.9
2013	1275.5	105.9	4.5
2014	2296.5	191.3	8.2
2015	1701.1	141.8	6.1
2016	2552.6	212.7	9.1
2017	1483	123.6	5.3
2018	2195	182.9	7.9
		Total: 2329.3	

Source: Author's data analysis 2020

Considering the results on the decadal level, Figure 4.1 shows the trend in rainfall with the minimum rainfall increasing gradually from 697.7mm in the first decade to 924.3mm in the second decade. On the other hand, the maximum rainfall was not steady as it fluctuates from 1539.3mm in the first decade which later increased drastically to 2552.6mm in the second decade.

The result shows slight similarity in the pattern and trend of rainfall for the first two years and last three years in both decades. As seen from figure 4.1, a decreasing trend in rainfall is observed within the first three years of the first decade, with the highest amount of rainfall experienced in the first year of the decade totaling up to 1539.3mm. The value dropped to 993.3mm and 697.7mm for the second and third year respectively. The fourth year however experienced slight increase in rainfall amount of up to 957.1(mm). This increasing trend continues for the fifth and sixth year before almost maintain a uniform pattern for the seventh, eighth and ninth year with just slight difference in the quantity of rainfall received for the years. Figure 4.1 also shows a significant increase in the rainfall amount for the last year of the first decade resulting in an upward trend with values close to what was experienced at the beginning of the decade.

The pattern and trend in rainfall for the second decade is a little similar to the previous decade with respect to the first, second, eight, ninth and tenth year. The eighth year of this decade is very significant as it recorded the highest value of 2552.6mm compared to the previous years in the decade. It was also observed (Figure 4.1) that this decade shows some degree of difference in the fifth, sixth and seventh year when compared to the previous decades as its rainfall trend was characterized with upward and downward fluctuations against the previous decade where almost uniform trend was observed for the fifth, sixth and seventh year respectively.

Figure 4.2 shows the annual rainfall trend for Ilorin for the period under study. The highest mean annual rainfall experienced in the first decade was 128.3mm and 212.7mm in the second decade which also correspond to the highest value within the period under study.

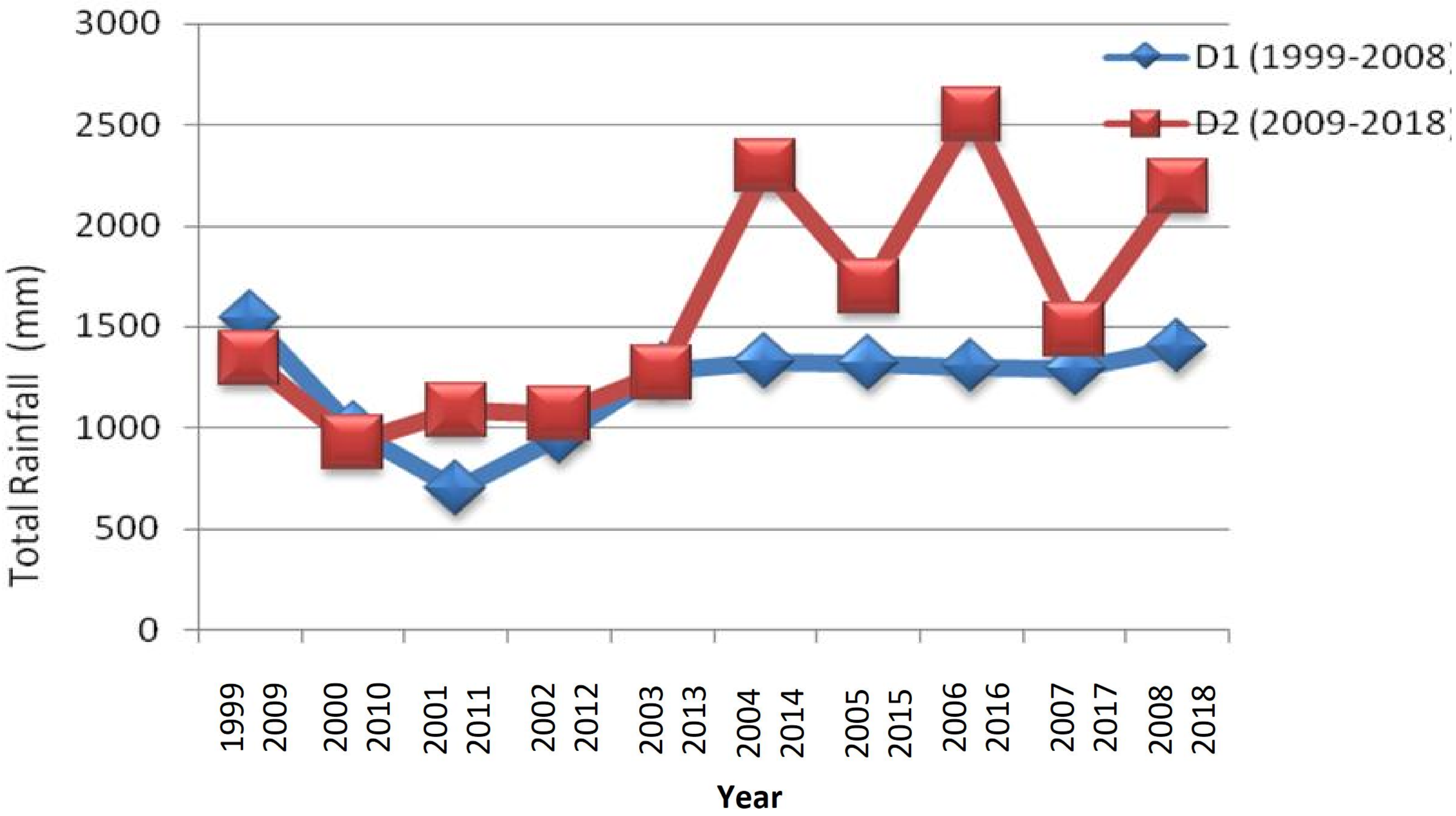

Figure 4.1: Trend in decadal rainfall

Source: Author's data analysis 2020

Figure 4.2: Annual rainfall trend of Ilorin for 19 years (1999-2018).

Source: Author's data analysis 2020

4.2. Standardized Precipitation Index (SPI)

In other to further understand and confirm the distribution and trend of rainfall in the entire study area under the period of study, standardized precipitation index (SPI) analysis were carried out so as to understand the sensitivity of the SPI to actual rainfall / rainfall deviation and the behavior in wet and normal years. This study adopts the Mc Kee *et al*. (1993) SPI principle and the result is as presented in table 4.2 and figure 4.3.

Table 4.2: Anomaly and Standardized Precipitation Index (SPI) from 1999 to 2018

Year	Annual Total Rainfall (mm)	Rainfall Anomaly	SPI
1999	1539.3	137.08	+0.3
2000	993.3	-408.92	-0.89
2001	697.7	-704.52	-1.53
2002	957.1	-445.12	-0.97
2003	1286.7	-115.52	-0.25
2004	1327.1	-75.12	-0.16
2005	1317.1	-85.12	-0.19
2006	1303.8	-98.42	-0.21
2007	1292.2	-110.02	-0.24
2008	1401.4	-0.82	-0.00
2009	1343.1	-59.12	-0.13
2010	924.3	-477.92	-1.04
2011	1086.5	-315.72	-0.69
2012	1071.1	-331.12	-0.72
2013	1275.5	-126.72	-0.28
2014	2296.5	894.28	+1.94
2015	1701.1	298.88	+0.65
2016	2552.6	1150.38	+2.5
2017	1483	80.78	+0.18
2018	2195	792.78	+1.72

Source: Author's computation 2020

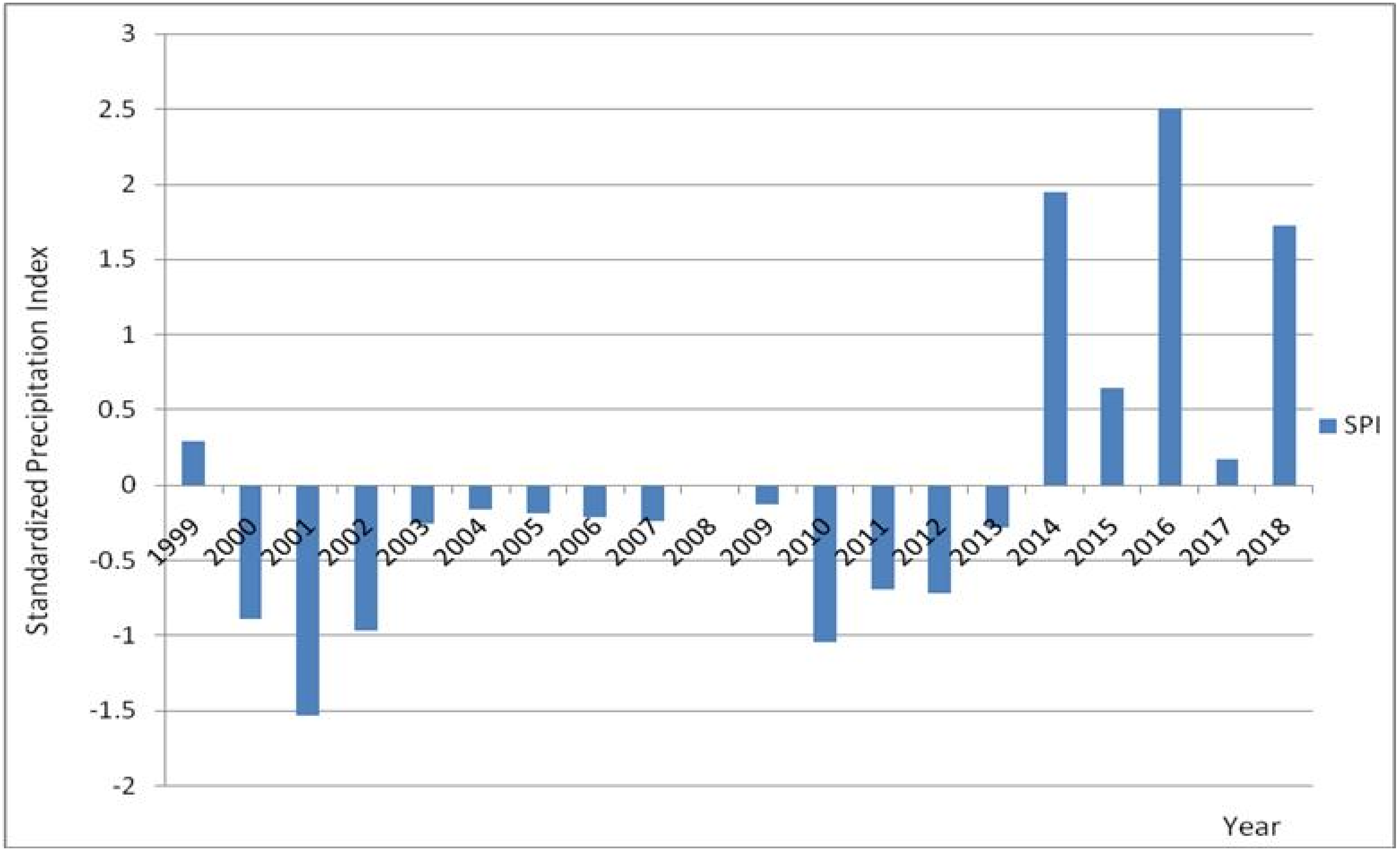

Figure 4.3: Standardized precipitation index (SPI) of Ilorin 1999-2018
Source: Author's data analysis 2020

The result of the time series analysis of SPI as shown in (figure 4.3) indicated that year 1999, 2014, 2015, 2016, 2017 and 2018 are wet years with different degree of wetness. The SPI values were observed to increase from +0.3 in 1999 to +1.94 in 2014, signifying a very sharp transition from a near normal condition to a severely wet condition respectively. The wetness condition also decreased greatly to a near normal condition in 2015 with SPI value of +0.65 before increasing unprecedentedly with an SPI value reaching as high as +2.5 in 2016. This signifies extremely wet condition. The reverse was however the case in 2017 as the SPI value was observed to experience a drastic decrease to +0.18 signifying a near normal condition. Progressing in 2018, Figure 4.3 also shows that the study area was characterized with a severely wet condition as the SPI value rose drastically to +1.72. Considering the Standardized Precipitation Index in terms of dryness, moderately dry and near normal conditions were observed for fourteen consecutive years (2000-2013) except for 2001 where a severely dry condition was observed with SPI value of -1.53. SPI values of -0.89, -0.97, -0.25, -0.16, -0.19, -0.21, -0.24, -0.0, -0.13, -0.69, -0.72, -0.28 were recorded for year 2000,2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2011, 2012 and 2013 signifying near normal condition. SPI value of -1.04 was recorded for the year 2010 signifying a moderately dry year.

The results of SPI suggest that the trend of rainfall over the entire study area for the period under study is such that first decade was majorly characterized with near normal rainfall conditions. This same condition was maintained into the first five years of the second decade before a sharp and drastic change was experienced resulting into a trend that is characterized by severely wet and extremely wet conditions.

4.3. Development of Reliable Rainfall Forecast Using ANNs

The monthly rainfall amount and other important parameters during dry and wet (rainy) seasons in Ilorin were obtained from the Nigerian Meteorological Agency for the period under study and were analyzed using Artificial Neural Networks (ANNs).

Figures 4.4, 4.5 and 4.6 shows the results of the predicted rainfall as generated from the Artificial Neural Network for 1999, 2008 and 2018 using the 'Feed- Forward back propagation' algorithm with Figure 4.4 (year 1999) serving as the base map for comparison for 2008 and 2018.

Base on the output of the result, it shows that in 1999 the peak rainfall value was predicted to be 262.6mm and occurs in the month of June. The actual value as observed for the same month was 296.2mm and the flow is such that it fluctuates from January to April before maintain a steady increase from May to June and fluctuates up and down between July and September until October when it now starts decreasing to December.

In 2008 the peak rainfall as predicted is seen to be between the month of July and September with rainfall accumulation of 306.1mm and 306.7mm respectively. The actual value is 318.6mm and 290.3mm as observed. Also, the flow is similar to that in 1999 as it fluctuates in the first four to five months from January to Apr/May before experiencing sharp upward increase from June to October before descending almost completely around December period.

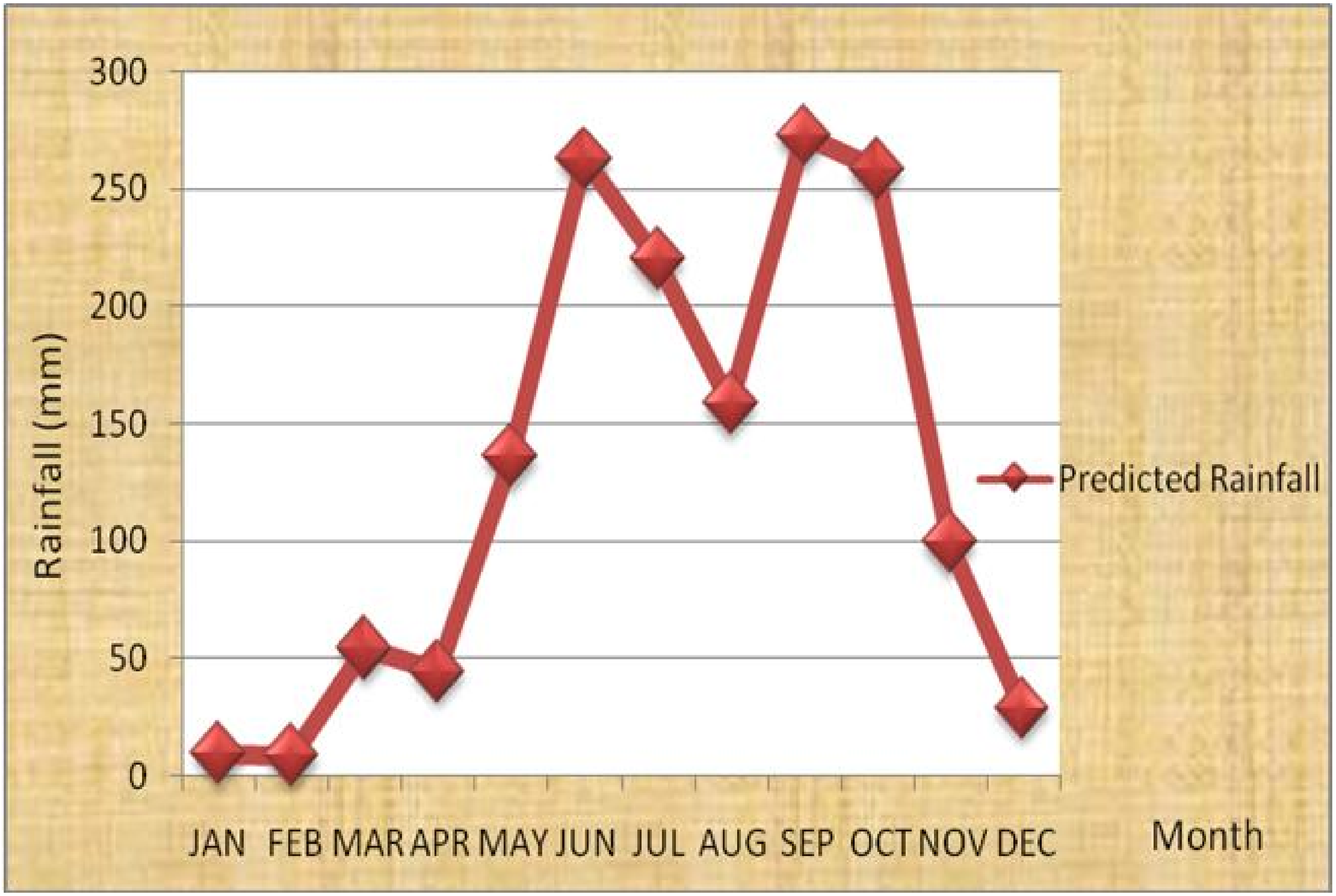

Figure 4.4: Mean monthly rainfall for 1999 as predicted using ANNs

Source: Author’s data analysis 2020

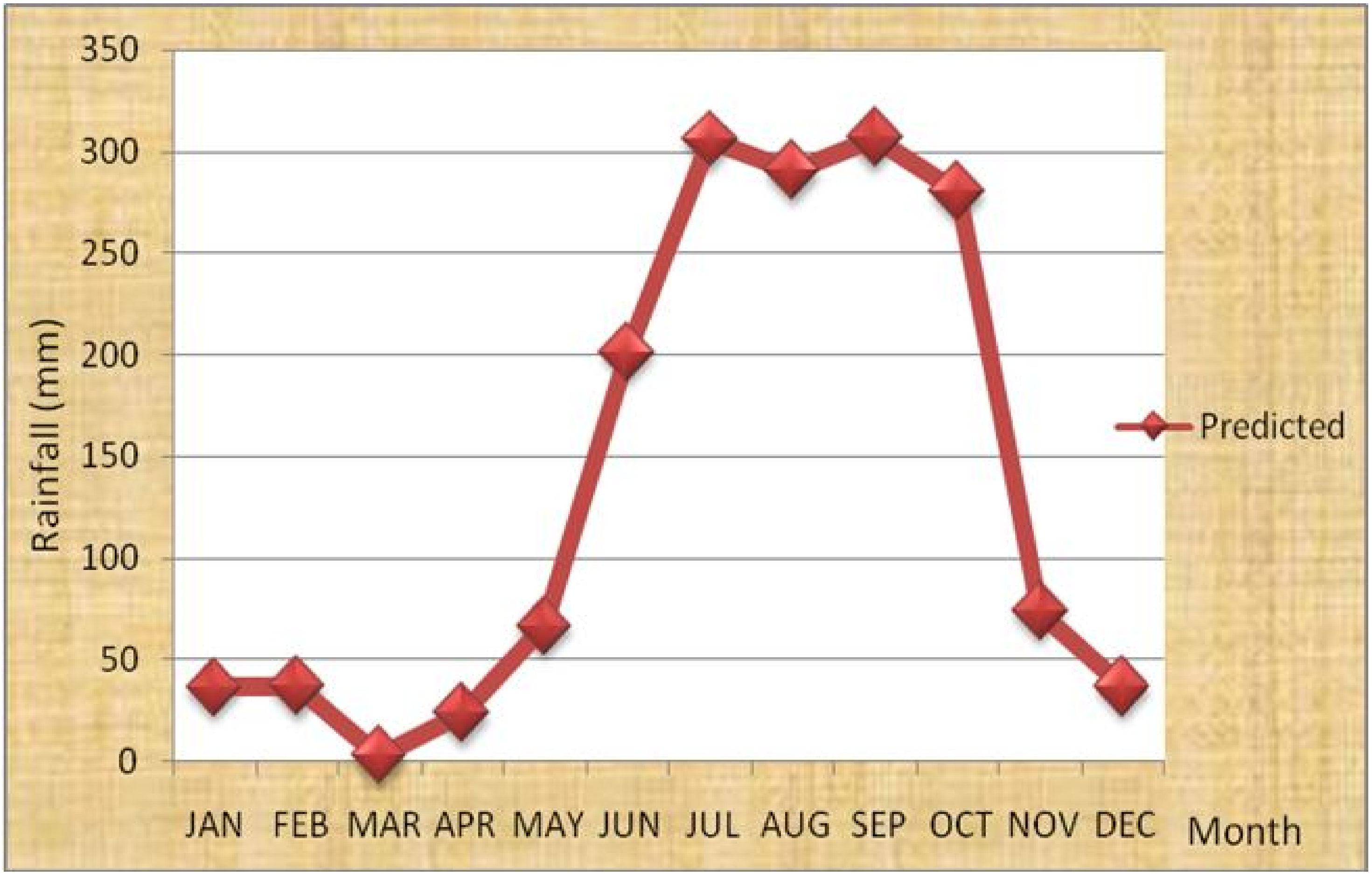

Figure 4.5: Mean monthly rainfall for 2008 as predicted using ANNs

Source: Author's data analysis 2020

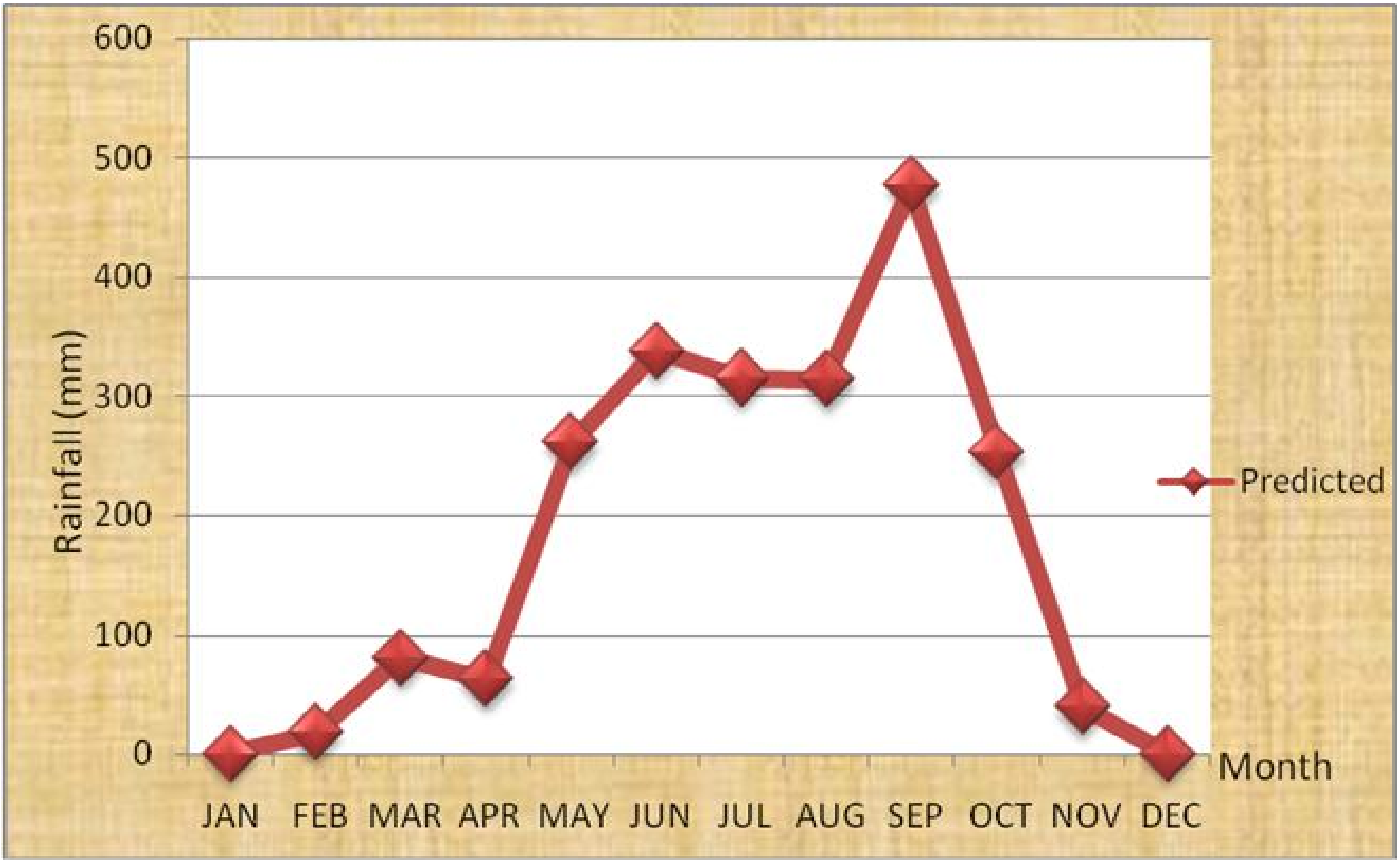

Figure 4.6: Mean monthly rainfall for 2018 as predicted using ANNs

Source: Author's data analysis 2020

Furthermore, the result of the prediction for 2018 (figure 4.6) shows significant increase in rainfall amount relative to the previous epochs. The peak rainfall amount was experienced between the month of June and September with the month of September recording the highest value 477mm (actual value was observed to be 542.7mm). Rainfall accumulation of 338.1mm, 315.2mm and 314.2mm were recorded for June, July and August respectively.

4.3.1 Comparison of actual rainfall with ANNs forecast rainfall

Tables 4.3, 4.4 and 4.5 shows the summary of the results obtained from the ANN forecast rainfall and Figures 4.7, 4.8 and 4.9 present the patterns of the observed rainfall (blue line) and ANN forecast rainfall (red line) in order to understand how well ANNs could predict and present rainfall pattern especially for the month of June, July, August, September and October over the study area. Base on the result, it was observed that the pattern and trend of ANN forecast rainfall matched with the actual rainfall time series which implies that the selected meteorological variables used in training the network are significant in bringing about the resultant output over the study area.

In 1999, the Artificial Neural Network forecasted the peak rainfall value to be 262.6mm while the observed peak rainfall value is seen to be 296.2mm (figure 4.7). Peak rainfall value forecasted for 2008 was 306.7mm as against 318.6mm of actual rainfall value. (Figure 4.8). 2018 on the other hand shows great significance in terms of the behavior in the quantity of rainfall and the accuracy of the forecast. The Artificial Neural Network (ANN) forecasted the highest peak rainfall value of 477mm whereas the actual peak rainfall value was 542.7mm (figure 4.9).

Table 4.3: Rainfall Prediction using ANNs for 1999

Month	Observed Rainfall (mm)	Predicted Rainfall (mm)
January	0	9.6
February	15.1	8.8
March	68	54.3
April	118.3	44.7
May	171.3	135.8
June	296.2	262.6
July	179.4	219.9
August	138.1	158.4
September	268.9	272.2
October	248.3	258
November	35.7	99.6
December	0	28.9

Source: Author's data analysis 2020

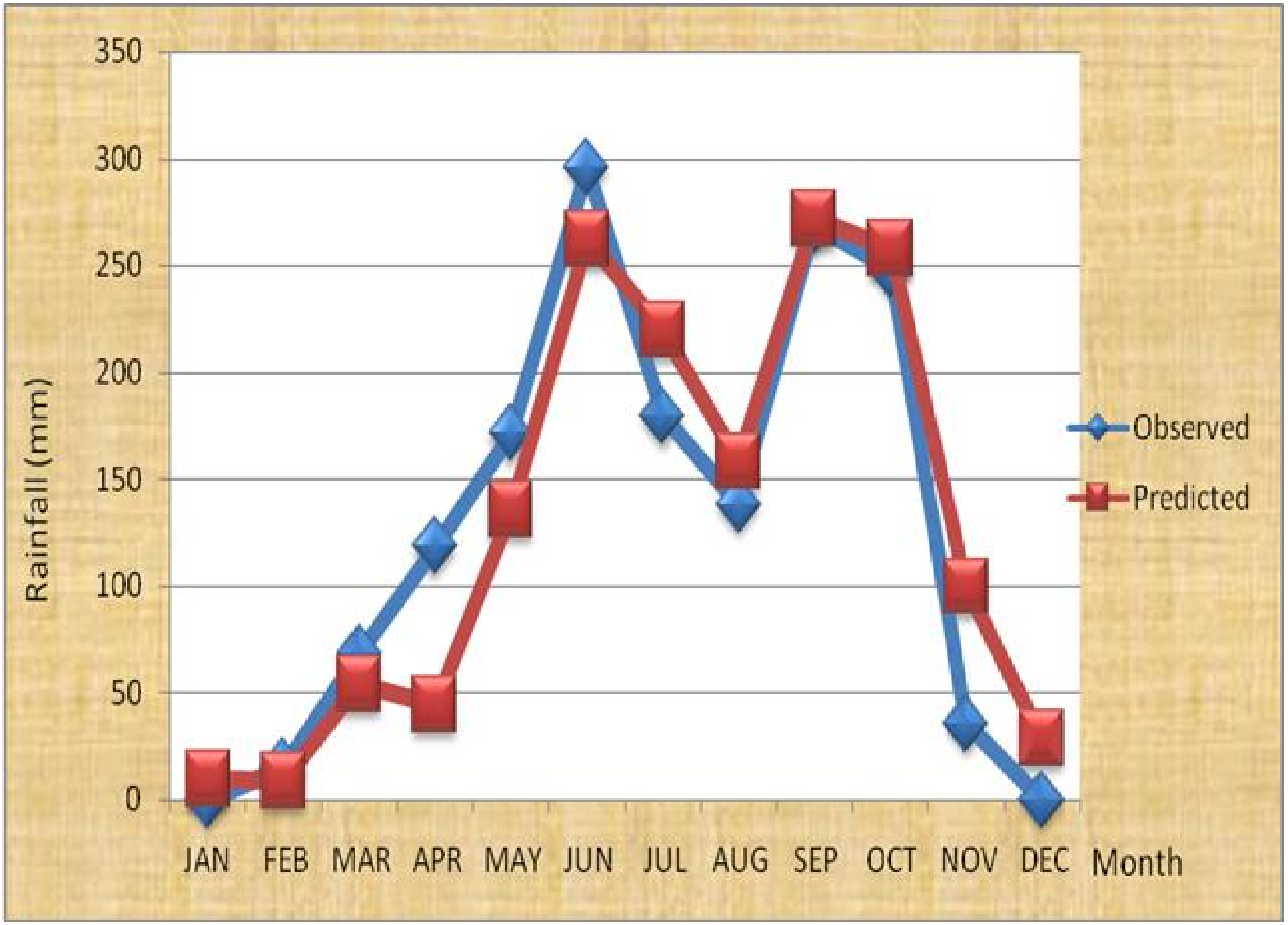

Figure 4.7. Observed mean monthly rainfall with ANNs predicted rainfall for 1999.

Source: Author's data analysis 2020

Table 4.4: Rainfall Prediction using ANNs for 2008

Month	Observed Rainfall (mm)	Predicted Rainfall (mm)
January	0	36.6
February	0	36.9
March	0	2.9
April	95.8	23.5
May	38.3	66.8
June	218.5	201.4
July	318.6	306.1
August	214.7	290.6
September	290.3	306.7
October	225.2	280.1
November	0	74.2
December	0	36.7

Source: Author's data analysis 2020

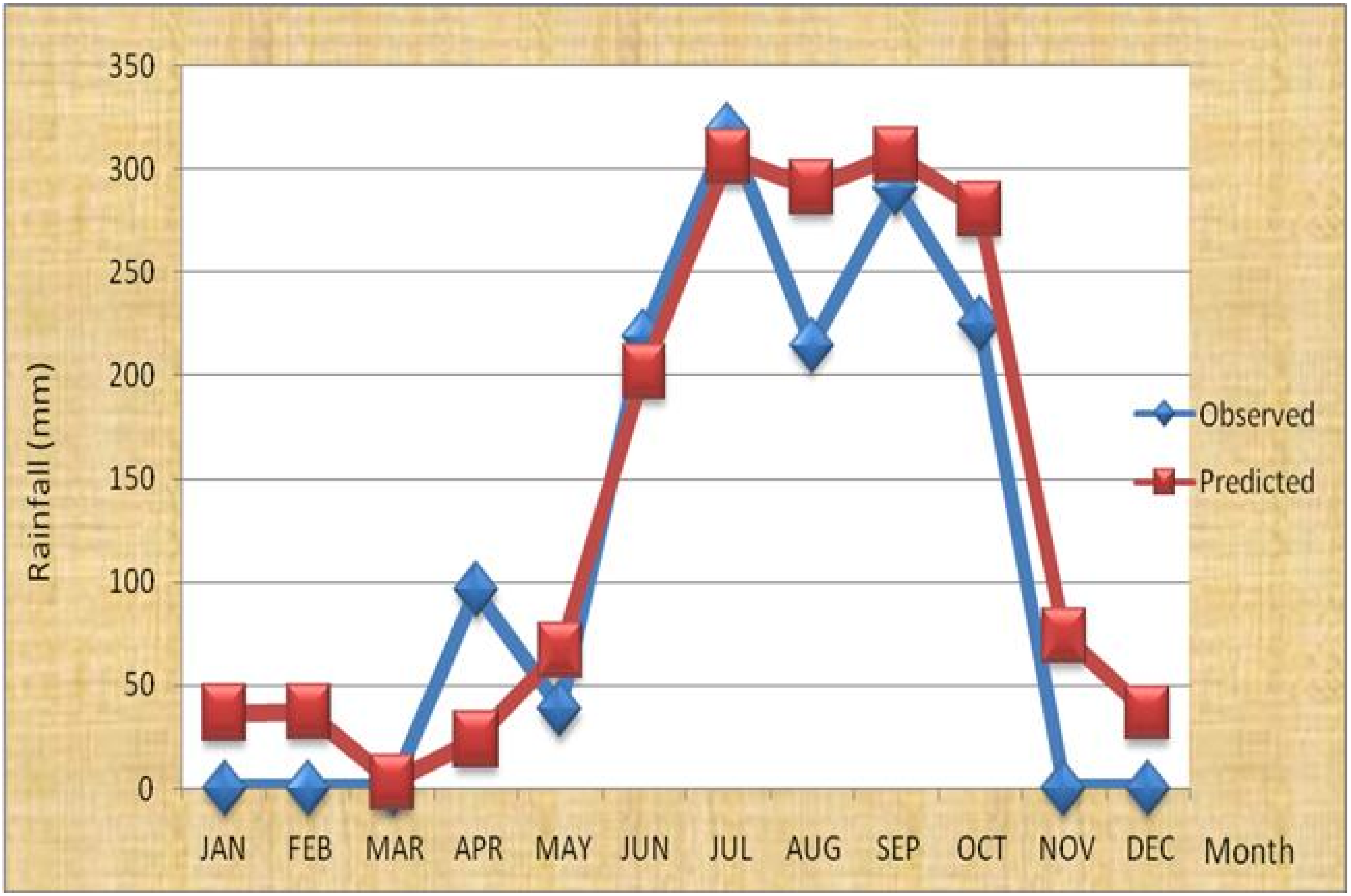

Figure 4.8. Observed mean monthly rainfall with ANNs predicted rainfall for 2008

Source: Author's data analysis 2020

Table 4.5: Rainfall Prediction using ANNs for 2018

Month	Observed Rainfall (mm)	Predicted Rainfall (mm)
January	0	0
February	78.8	17.7
March	15.3	80.6
April	66.2	62.7
May	284.6	261.3
June	301.6	338.1
July	289.5	315.2
August	287.9	314.2
September	542.7	477
October	264.8	252.5
November	63.6	39.4
December	0	0

Source: Author's data analysis 2020

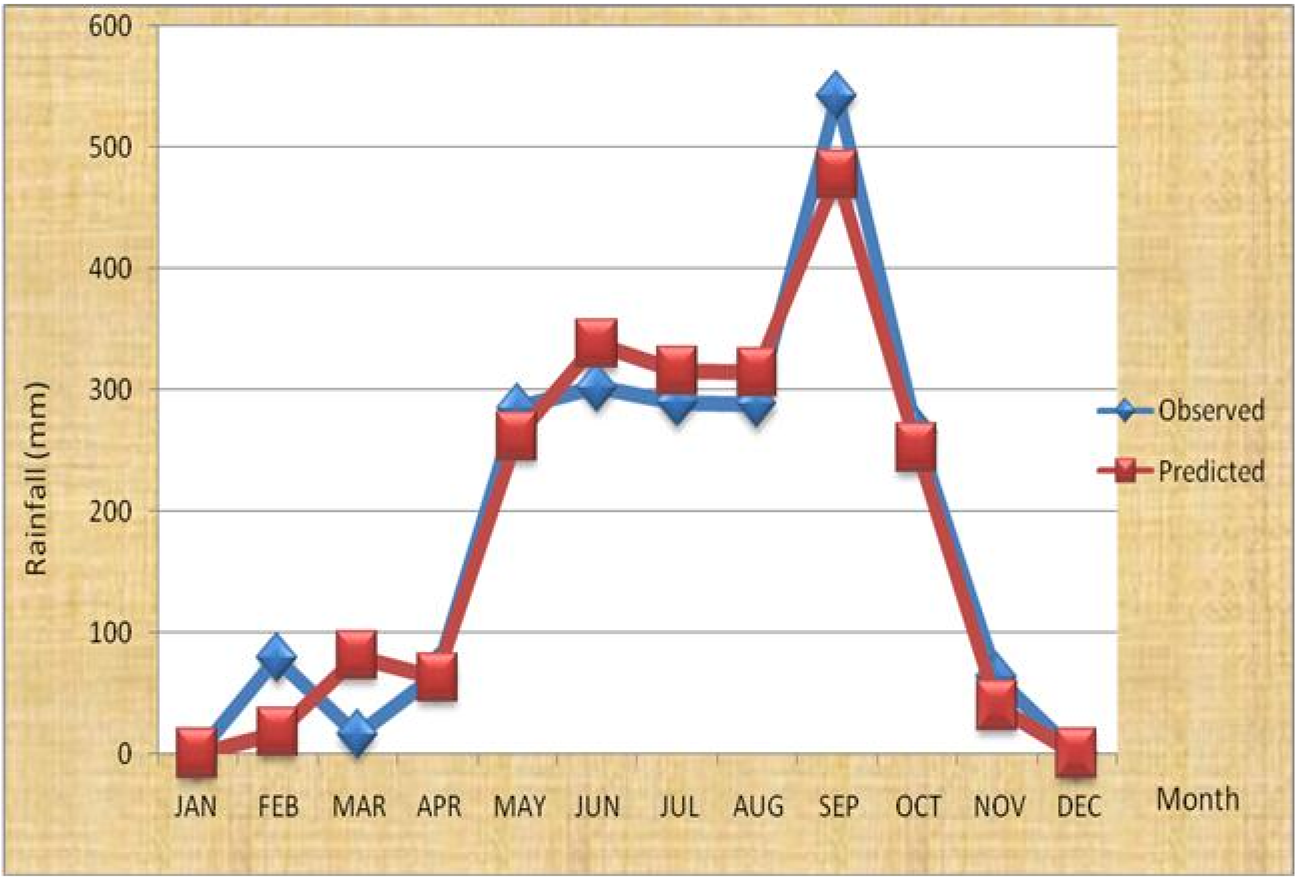

Figure 4.9. Observed Mean Monthly Rainfall with ANNs predicted Rainfall for 2018.
Source: Author's data analysis 2020

4.4. Reliability and Performance of the ANNs

In other to test the reliability of the Artificial Neural Network (ANN) forecast, the following statistical measure were employed to evaluate the performance of the network output with the validation data over the study area; root mean square error, mean squared error and regression analysis. Figures 4.10, 4.12 and 4.14 shows the result of the Regression analysis as computed, while figures 4.11, 4.13 and 4.15 displayed the mean squared error performance for the period under study. The Regression value for;" training, validation and test" for all the epoch (1999, 2008 and 2018) were not more than 1. This implies that the performance of the statistical measure in line the predicted forecast was good. Going forward, it also means that the entered variables used can successfully explain the rainfall distribution and dispersal pattern over the study area. In line with the investigation of the forecast, results showed that the difference between actual rainfall and predicted rainfall is minimal and acceptable which therefore means that the ANN forecast can predict the amount of rainfall thus giving it some degree of reliability.

The result obtained in this study compared with other researches Mekanik. *et al* (2011) showed that ANN techniques are efficient in the rainfall forecast and they can successfully predict amount of rainfall.

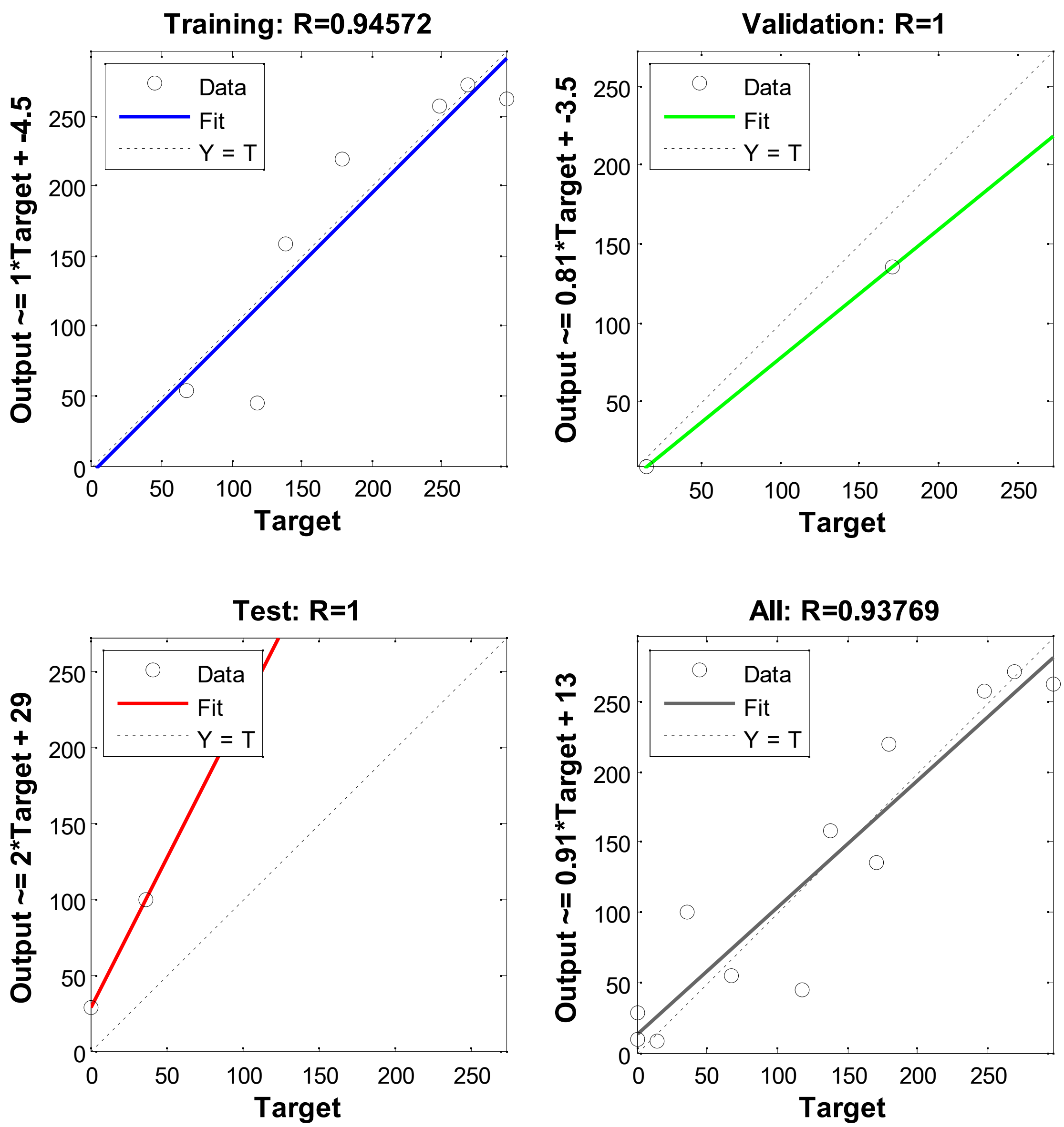

Figure 4.10. Regression analysis for reliability of the ANNs observed and predictated rainfall in Ilorin for 1999

Source: Author's data analysis 2020

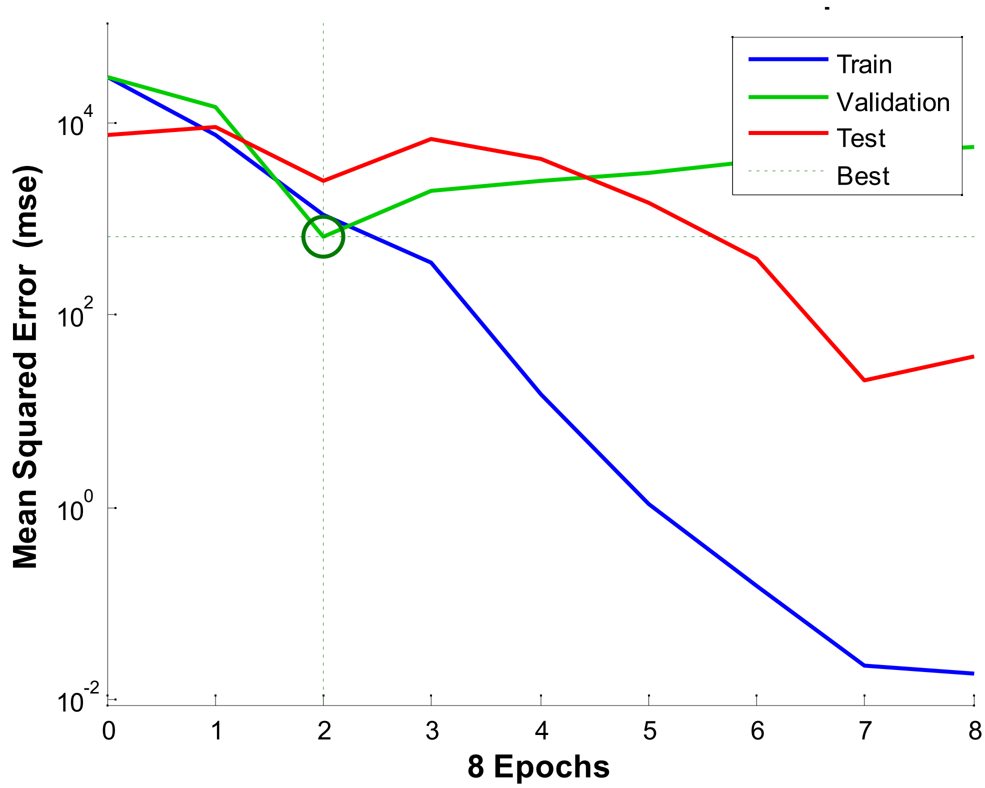

Figure 4.11. MSE for neural network training performance of 1999

Source: Author's data analysis 2020

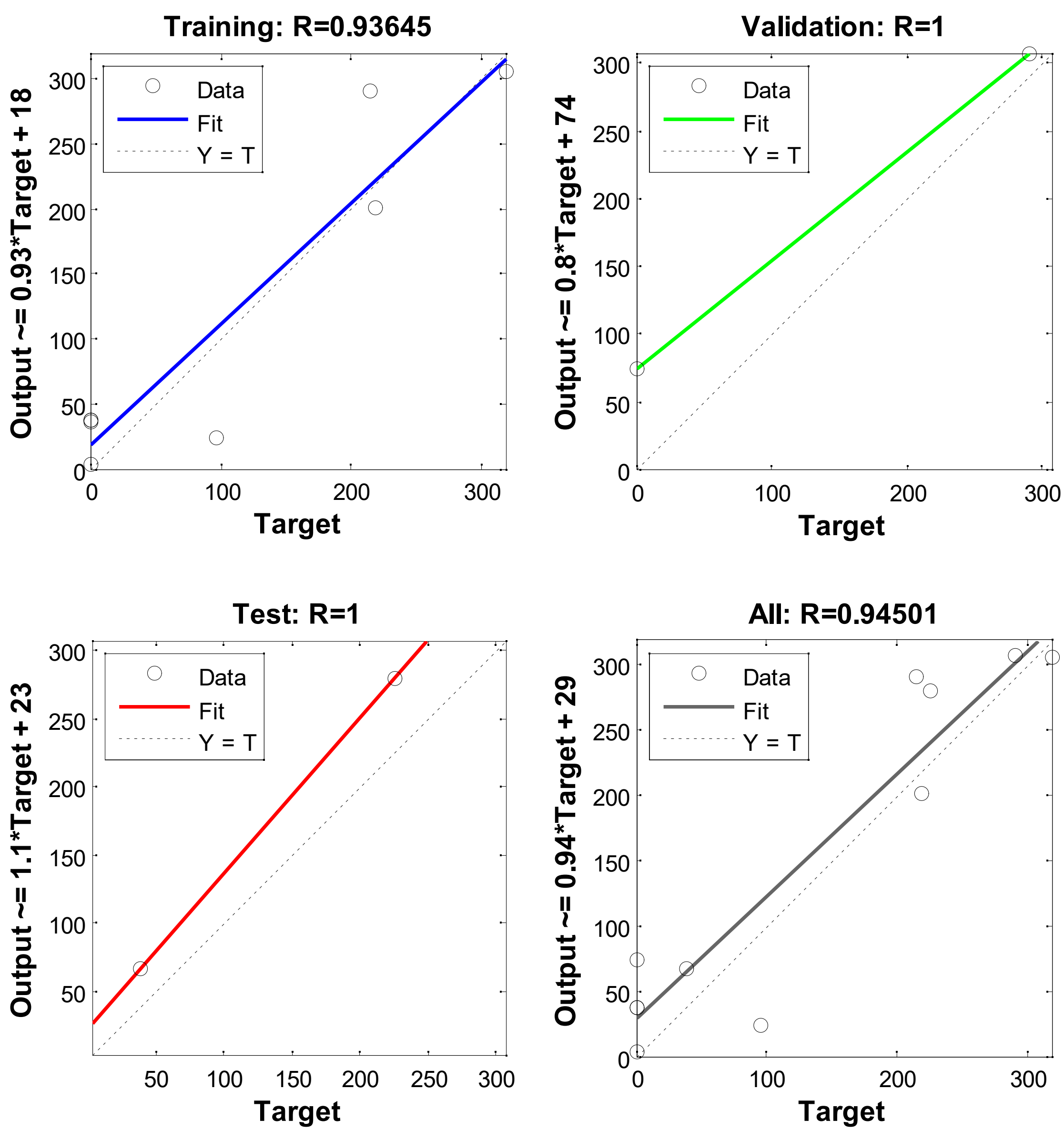

Figure 4.12 Regression analysis for reliability of the ANNs observed and predictated rainfall in Ilorin for 2008

Source: Author's data analysis 2020

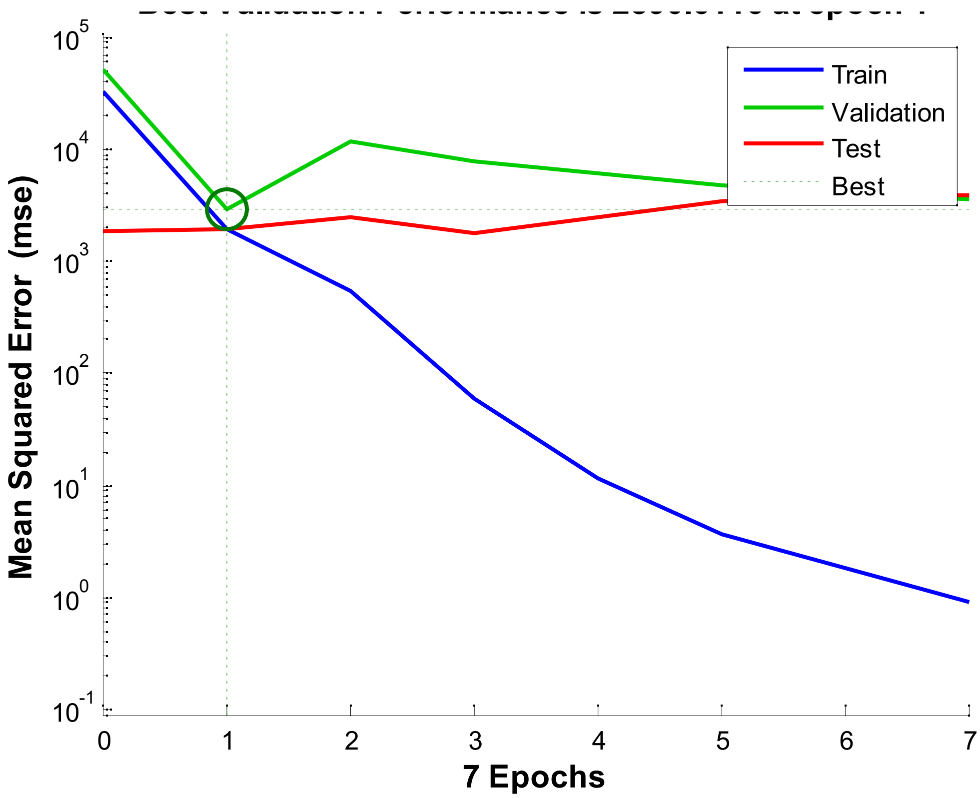

Figure 4.13. MSE for neural network training performance of 2008

Source: Author’s data analysis 2020

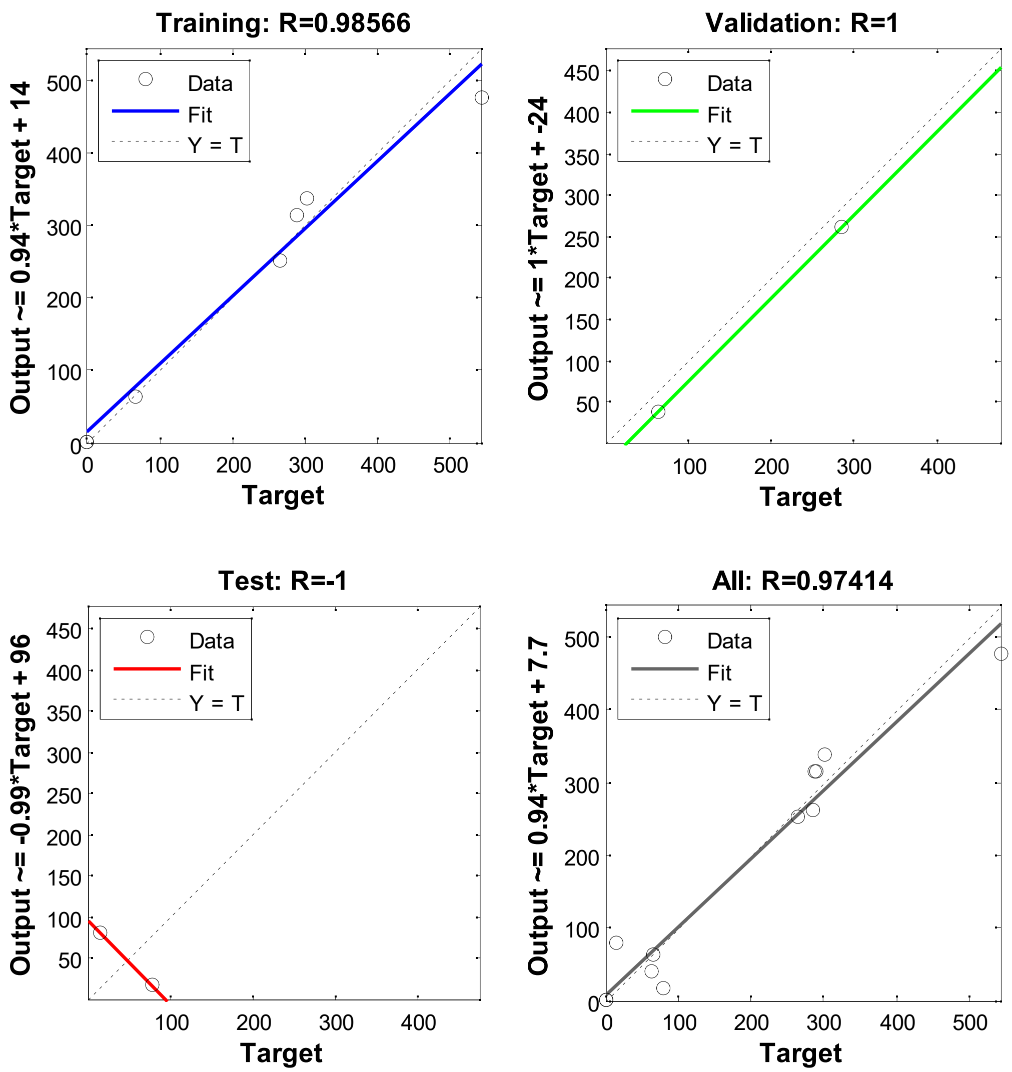

Figure 4.14. Regression Analysis for reliability of the ANN observed and predictated rainfall in Ilorin for 2018

Source: Author's data analysis 2020

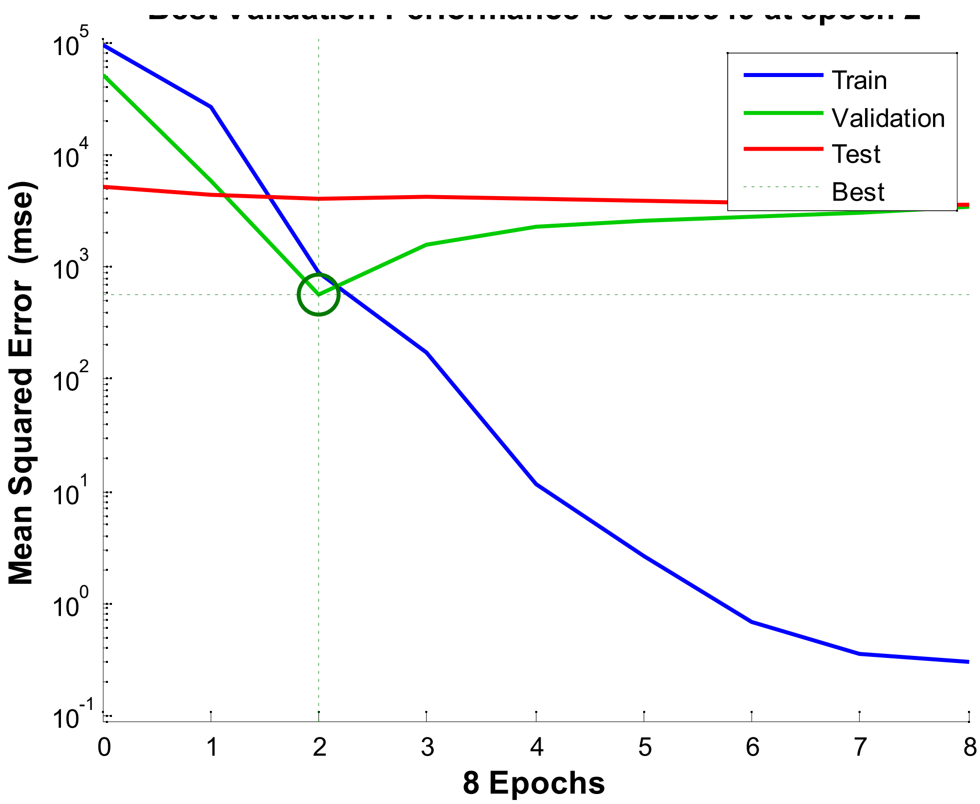

Figure 4.15. MSE for neural network raining performance of 2018

Source: Author’s data analysis 2020

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study has established that with the availability of relevant and necessary weather parameters serving as inputs, the Artificial Neural Network (ANN) rainfall forecast has the capability to forecast accurate rainfall amount over a given location. The results from this study no doubt provide information that aids agriculture, water resource and other related sectors of the economy. The study utilizes key meteorological data to examine the rainfall trend over Ilorin, develop a reliable rainfall forecast using ANNs and examine the reliability of the developed rainfall forecast over the study area.

To address the first objective, the monthly rainfall distribution in Ilorin from 1999 to 2018 were gotten from the Nigerian Meteorological Agency Abuja (NIMET) and were converted into charts to show the trend and pattern of rainfall movement with respect to its amount and time. From the monthly rainfall data collected, total rainfall for each year, mean rainfall and percentage mean rainfall were calculated for the period under study. The data was further used to plot a decadal chart to ascertain the maximum mean rainfall for each decade.

In developing a reliable rainfall forecast using the ANN, the relevant sample data were first collected. Owing to the fact that it is generally difficult to incorporate prior knowledge into a neural network and that networks can only be as accurate as the data that are used to train them, it is therefore important that the data covers the range of inputs for which the network was used. To create the neural network, the network creation function was used. Using the “feedforwardnet” command, a simple, two-layer feedforward network is created. After the neural network was created, it was then configured. The configuration step consists of examining input and target data, setting the network's input and output sizes to match the data, and choosing settings for processing inputs and outputs that will enable best network performance. The network configuration was then followed by network training before proceeding to validating the network.

Finally, the results of the prediction were compared to the observed data obtained from meteorological stations. This is done both visually (using plotted graphs) and statistical measurements such as root-mean-square error (RMSE), mean square error (MSE) and regression analysis to test the degree of error and examine the performance. The findings from the study showed that the trend and pattern of rainfall movement with respect to its amount and time is such that the rainfall amount either ascends gradually or fluctuates. It was discovered that much of the amount of rainfall in all the years under study is received in the month of June, July, August and September which are largely variant and characterized with fluctuations.

Generally, a decreasing trend in rainfall is observed within the first three years of the first decade, with the highest amount of rainfall experienced in the first year of the decade totaled up to 1539.3mm. Also a significant increase in the rainfall amount for the last year of the first decade was observed resulting in an upward trend with values close to what was experienced at the beginning of the decade. The trend in rainfall for the second decade is a little similar to the previous decade with respect to the first, second, eight, ninth and tenth year. However, the eighth year of this decade is most significant as it recorded the highest value of 2552.6mm compared to the previous years in the decade

The highest mean annual rainfall experienced in the first decade was 128.3mm and 212.7mm in the second decade which also correspond to the highest value within the period under study.

5.2. Recommendations

The result of this study has shown that ANNs is capable of forecasting complex non-linear problems and therefore has the ability to predict accurate rainfall amount. Based on the outcome of this study, the following recommendations should be considered;

i. More meteorological stations should be established to cushion the effect and challenge of sparse meteorological data and further reduce the representativeness of a system which can also have significant effect on the results of subsequent analysis

ii. Government should support and encourage private organizations such as Agro allied companies, private airlines and private media house to key into establishment of more automatic weather stations.

iii. More funding and grants should be made available to interested individual and research institutions to embark on relevant research that will translate into better economic and social development.

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