NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF CIVIL ENGINEERING

CORRECTING AND MODELLING MONTHLY RAINFALL BASED ON CLIMATE PARAMETERS: CASE STUDY SOMALIA

Msc. THESIS

Abdifatah Mohamoud YUSUF

Nicosia

June, 2022

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Supervisor
Prof. Dr. Hüseyin Gökçekuş

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Approval

We certify that we have read the thesis submitted by Abdifatah Mohamoud Yusuf titled **" Correcting and Modelling monthly rainfall based on climate parameters: Case study Somalia.** " and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Civil And Environmental Engineering.

Examining Committee	Name-Surname	Signature
Head of the Committee :	Prof. Dr. Aşkın Kiraz	…………………………
Committee Member :	Assoc. Prof. Dr. Hüseyin Çamur	…………………………
Committee Member :	Assıst. Prof. Dr. Mustafa Alas	…………………………
Supervisor:	Prof. Dr. Hüseyin Gökçekuş	…………………………
Co-Supervisor:	Assoc. Prof. Dr. Youssef Kassem	…………………………

Approved by the Head of the Department

29/06/2022

Prof. Dr. Kabir Sadeghi

Head of Department

Approved by the Institute of Graduate Studies

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Prof. Dr. Kemal Hüsnü Can Başer

Head of the Institute

Declaration

All of the information, including the data, papers, analyses, and results, that are presented in this thesis was compiled and presented in a manner that is compliant with the academic regulations and ethical guidelines of the Graduate School at Near East University. In accordance with these standards of conduct, I confirm that all information and data that is not original to this work has been properly attributed and cited. This includes any information and data that has been taken from another source.

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Abdifatah Mohamoud YUSUF

Abstract

CORRECTING AND MODELLING MONTHLY RAINFALL BASED ON CLIMATE PARAMETERS: CASE STUDY SOMALIA

YUSUF, Abdifatah Mohamoud

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Floods and droughts have a huge impact on Somalia's agriculture, environmental conditions and infrastructure as well as the economy. Rainfall is the major source of water for groundwater and surface water in Somalia. Therefore the aims of this study is to increase the accuracy of rainfall data and then predict the amount of rainfall to show the relationship between Rainfall and other climate parameters such as wind speed and temperature using machine learning models. there are a variety of climatic parameters that affect rainfall amounts, including latitude, altitude, topography, seasons, and distance from the ocean and the sea surface temperature along the coast. Meteorological offices around the world find it difficult to predict rainfall because of its uncertainty. Rainfall forecasting in four Somali cities is the focus of this research. To begin, a nine-year period of meteorological data was gathered between 2009 and 2017. Minimum, maximum and mean temperature, as well as the maximum wind speed, are used as inputs, with the monthly precipitation serving as the output variable. After comparing the Actual and predicted data for the four cities, The Cascade Neural Network produced the best results. In Mogadishu city the Cascade's R squared and RMSE were both 0.668 and 0.232. R squared and RMSE in Garowe and Berbera were 0.751, 0.361 and 0.593, 0.226, respectively. respectively. The Cascade NN was at best in Burao city with RMSE of 0.0005074 and Rsquared of 0.566. Cascade Neural Network is more accurate than other NN models when it comes to predicting rainfall. Further studies into rainfall forecasting can benefit from the use of Cascade Neural Network.

***Key Words**:* Somalia, machine learning, neural networks, parameters, Precipitation

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List of Abbreviations

CFS: Climate Forecast System

MERRA-2: Modern-Era Retrospective Analysis For Research And Applications Version 2

ECMWF: European Centre for Medium-Range Weather Forecasts

ERA5: ECMWF Re-Analysis

CHIRPS: Climate Hazards Group InfraRed Precipitation with Station

UNFPA: United Nations Fund for Population Activities

GDP: Gross Domestic Product

ANN: Artificial Neural Network

ITCZ: Inter-Tropical Convergence Zone

WHO: World Health Organization

UNDP: United Nations Development Programme

MAE: Mean Absolute Error

MSE: Mean Squared Error

SPI: Standardized Precipitation Index

DDI: Difference Drought Index

PNI: Percent of Normal Index

SPEI: Standardized Precipitation Evapotranspiration Index

IPCC: Intergovernmental Panel on Climate Change

CORDEX: Coordinated Regional Climate Downscaling Experiment

RCM: Regional Climate Model

GCM: Global Climate Model

UNFCCC: United Nations Framework Convention On Climate Change

FFNN: Feed Forward Neural Network

TDNN: Time Delay Neural Network

ANFIS: Adaptive Network-Based Fuzzy Inference System

SWALIM: Somalia Water and Land Information Management System

UNICEF: United Nations Children's Fund

CFNN: Cascade Forward Neural Network

RMSE: Root Mean Square Error

ENN: Elman Neural Network

CHAPTER I

Introduction

There are a variety of climatic parameters that affect rainfall amounts, including latitude, altitude, topography, seasons, and distance from the ocean and the sea surface temperature along the coast. Flooding may have a devastating effect on the environment. A major impact on agriculture, the environment, infrastructure, social life, and gross domestic product can be found in droughts and floods (Divas Basnyat, 2007). Somalia is suffering from a severe water deficit as a result of its reliance on unpredictable annual rainfall. freshwater supplies may become more scarce as a result of climate change and this is a major problem (Abdifatah Yusuf et al., 2022). It is the goal of this study to fill a void in research by using current (regional) climate change data and hydrological modeling to simulate possible future climatic scenarios in terms of rainfall variability. As a result, agricultural expansion and long-term infrastructure planning can be improved by the use of hydrological modeling with climate change scenarios. Predicting monthly precipitation and understanding how climate change occurred in the past is always critical. Extensive testing is necessary for climate models to acquire confidence in their forecasts and to find areas for improvement (Caiming shen et al.,2006).

In data-scarce countries like Africa, reanalysis products are frequently used in place of observational weather and climate data. An Artificial Neural Network is being used to establish the optimal precipitation product and the link between precipitation and climate parameters in the absence of any actual data (ANN). Climate change impacts can be mitigated by making judgments and policies based on the unpredictable nature of the climate. According to research by Guillermo Obregón et al (2014), large-scale weather patterns have an effect on the variability of rainfall at all three time scales: daily, interannual, and decadal.

1.1. Aim Of The Study

Africa's ground-based measurements are insufficient because of geographical and temporal inconsistencies (Schreck and Semazzi, 2004). Accordingly, there are numerous free satellite-based and numerical model outputs that may be validated before being used. These data not only fill in the data gaps between ground-based radar stations and rain gauges, but they also provide information on when, where, and how much precipitation falls all over the world. There is always underestimating of data derived from satellites in dry seasons, which could be due to an overestimation of the depth of precipitation. This study aims to correct the value of space-based rainfall data to increase the accuracy of the data. Additionally the study is predicting Monthly rainfall in order to show the relationship between Rainfall and other climate parameters such as wind speed and temperature using machine learning models.

1.2. Climate Of Somalia

In Somalia, the climate is mainly dry or semi-dry. Throughout the year, rainfall can occur in a variety of locations and at various times.The intertropical convergence zone (ITCZ) migrates north-south through Somalia, affecting the country's climate. Because of this, most of Somalia experiences two distinct rainy seasons: the Gu (March to June), which occurs as the zone travels north, and the Deyr (October to December), which occurs when the zone moves south. Moist air from the Indian Ocean in the southerly air flow causes rain in both cases. There isn't a lot of precipitation coming from the north-east winds that come from Asia and Arabia. In Somalia, rainfall is by far the most important meteorological component and seasonal fluctuations and variations within each season impact the success of agricultural activities. The northern Plateau experiences the greatest winds, averaging between 0.5 and 10 meters per second. April and May is when southern Somalia experiences its lowest winds; from June through August, it experiences the highest winds.

1.3. State Of Water Resources In Somalia

The overall land area of Somalia is 637,700 square kilometers, of which around 45% is used for grazing, 30% is desert, 14% is forested, and 11% is arable (Houghton-Carr et al, 2011). The Juba and Shabelle River basins, which are Somalia's few permanent rivers flow through Ethiopia, Kenya, and the rest of the country (Mesenbet Yibeltal Sebhat,2015).

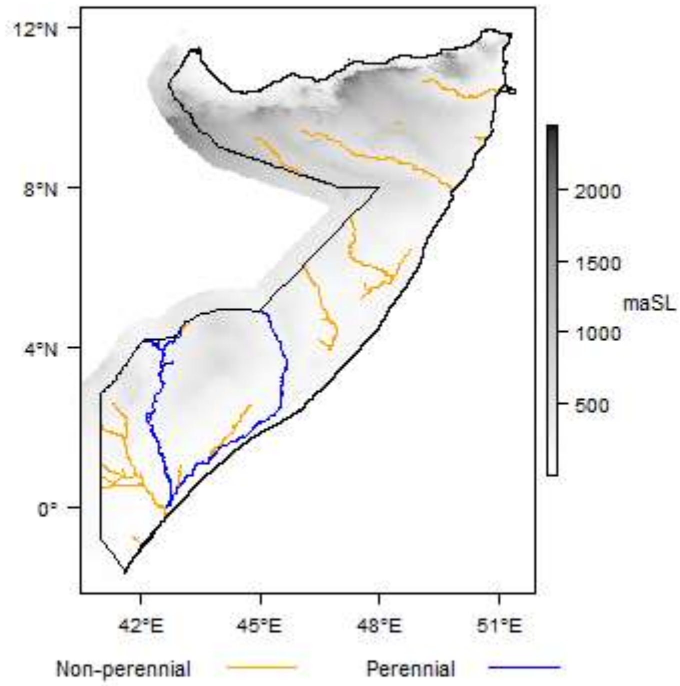
1.3.1. Surface Water Resources In Somalia

Somalia relies heavily on water supplies that originate outside of the country. River basins in Somalia are all located within a single region of the country.In addition to the Gulf of Aden and the Indian Ocean, the East African Rift Valley and the Tana River basin intersect it on its west and south.

The Shabbele and the Juba are the only two year-round rivers. When there is a lot of rain, there is a lot of surface water in other rivers and drainages. Toggas, which originate in the Andes Mountains, are smaller streams. Northern Somalia has plateaus and mountains with perennial flows, while groundwater recharge and springs can be found in the higher portions of the plateaus and mountains. Additionally, floods can occur in the Juba and Shabelle rivers. Even a modest flood every five years has been shown to cause flooding issues. The strong flash floods that occur in the northern alpine regions of the little toggas are also well-known. 2 to 3 hectare (ha) plots along the toggas are irrigated with surface and groundwater. (Divas Basnyat, 2007).

Figure 1

country's most important surface waters. Developed World Wildlife.



1.3.2 Juba River.

The Juba River is known by its Ethiopian name, Genale Dawa. Each of the three major tributaries has a catchment area between 24,860 km2 and 59,020 km2. The Juba River is formed by the junction of Ethiopia's Gestro and Genale rivers just north of Dolo, while the Dawa flows into Ethiopia's Juba River at Dolo after crossing the Kenya-Ethiopia boundary and the Somalia-Ethiopia border west of Dolo. There are roughly 1,808 kilometers of the Juba River in Ethiopia and 1,004 kilometers in

Somalia according to USGS SRTM 30m estimated streams(Basnyat and Gadain,2009).

Table 1.

Summary of Annual Maximum Discharge for the Juba River

Year	Luuq	Bardheere	Jammame	Marere
Maximum (m^3/s)	1,823	1,762	553	804
Minimum (m^3/s)	250	365	241	201
Std. Deviation (m^3/s)	335	367	54	141
CV	18%	21%	10%	18%

1.3.3. Shabelle River.

The Shabelle River rises at a height of 4,230 meters in Ethiopia's eastern highlands, on the edges of the country's eastern highlands. About 297,000 square kilometers (based on watershed delineation using SRTM 30m from Juba River; USGS) of the Shabelle River's catchment area is in Ethiopia (188,700 square kilometers); the remainder is in Kenya and Somalia (108,300 km2). The basin's elevation ranges from 20 meters above sea level in the south to 40 meters above sea level in the north. The Eastern Ethiopian Plateau has an elevation of more than 3,000 feet. Approximately 47 percent of the basin is below 500 meters, 41 percent is between 500 and 1,500 meters, and 13 percent is below 1,500 meters. Fewer than 1% of the world's people live below an elevation of 3000 meters. The catchment area for Somalia's water supply is below 700 meters (Basnyat and Gadain,2009).

Table 2.

Annual Maximum Discharge Summary For The Shabelle River

Year	Belet Weyne	Bulo Burti	Mahadey Weyne	Afgoi	Awdegle
Maximum (m^3/s)	473.6	489.3	176	112.7	95.6
Minimum (m^3/s)	138.5	144.5	130.2	81.1	72.2
Std. Deviation (m^3/s)	88.6	78.3	12.4	7.0	7.1

Table 2 (Continued).

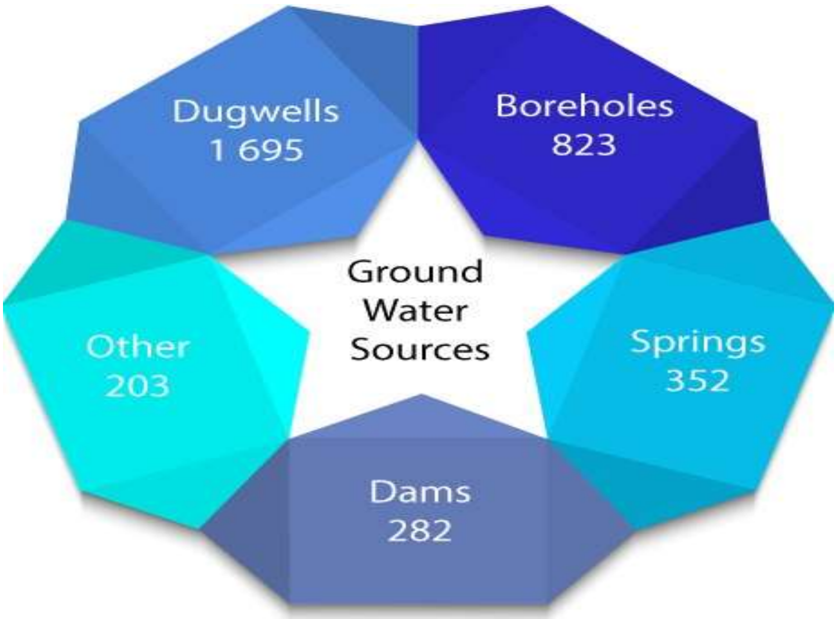
CV	19%	16%	7%	6%	7%

1.4. Groundwater Resources In Somalia

Groundwater is the principal source of water for most Somalis. Except for those who live near rivers like the Juba and Shabelle, most people in the country rely on groundwater from wells, boreholes, and springs to meet their water needs. Residential, animal, and small-scale irrigation demands are all met by groundwater in both rural and urban areas. These deliberately placed boreholes are used to draw water from deeper aquifers, which are crucial during the dry season. Somalia relies heavily on shallow hand-dug wells for its groundwater supply. Groundwater quality, on the other hand, is frequently assessed as poor (Faillace and Faillace, 1986). At seasons of high flow, a minor freshwater lenses in the downstream parts of rivers are replenished and partially drained in the dry season (Houghton-Carr et al., 2011).

Figure 2

Ground Water Sources As At September 2014



Posted from SWALIM (2014).Somalia's underground water resources http://www.faoswalim.org/water/water-resources/ground-water .

Somalia's primary water source is the borehole, which provides year-round water and can be relied on when other sources have run out. While most boreholes are between 90 and 250 meters deep, some may reach 400 meters. Shallow wells are those with a depth of less than 20 meters. Depending on the aquifer, these sources produce different amounts of water in different regions. Although the majority of shallow wells generate between 2.5 and 10 m3/hr, most boreholes may produce between 5 and 20 m3/hr (Swalim,2014).

1.5. Water Quality

Several factors influence quality of groundwater and pollution, including the soil and geological formations through which it travels, time spent in each location, recharge efficiency, depth below ground, and pollution in the catchment region as a whole. Groundwater in Somaliland and Puntland states has a wide range of physical and chemical qualities depending on where and how the water is sourced (spring, dug well, drilled well). The pH ranged from 6 to 10, the temperature ranged from 19 to 38°C, and the electrical conductivity ranged from 160 to 11 000 S/cm, all based on measurements taken on the ground. Researchers say that groundwater salinity can be extremely high in some areas. Despite the fact that 511 samples exceeded WHO-approved drinking water quality limits for hardness, calcium, magnesium, salt, potassium, and other elements, acceptance of these waters is vital because there is generally no alternative. It's not always dangerous to drink water that has concentrations over the statutory limit, However, in areas where hazardous water forms present a concern to humans and animals, effective water treatment should be studied.

The groundwater in the study region can be contaminated by a variety of chemical contaminants. In some areas, the civil conflict has led to the discovery of explosives and other potentially harmful materials.Their existence in a highly permeable karstic aquifer is quite hazardous. Bacterial tests show that shallow aquifers, like those in Somaliland and Puntland, are frequently contaminated and can lead to widespread water-related illnesses. Polluted water and poor sanitation are deadly in this country, where waterborne infections are a common cause of illness and death. There are just 30 percent of Somalis who have access to potable water, putting the majority at risk for a wide range of illnesses (Oxfam International, 2014).

1.6. Water Demand In Somalia

Water is essential for both human consumption and the consumption of animals across all of Somalia's regions.

1.6.1. Domestic Demand

Families in the area have not conducted any research on the water usage patterns or the availability of water. Using the UNDP's population predictions, a rough estimate of the amount of water used in households can be derived (2005). In metropolitan areas, the rate is 50 lpcd per capita, whereas in rural areas it is 20 lpcd. According to Table 3, each day there is a need for a minimum of 140,250 m3 of water to satisfy the water demands of residential properties.

Table 3.

Water Demand For Domestic Use In The Rural And Urban Areas Of South-Central Somalia

Zone	Region	Population estimates		Water demand estimates m^3/d		
		Urban	Non-urban	Urban	Non-urban	Total
Central	Hiiran	69,113	260,698	3,456	5,214	8,670
	Middle shabele	95,831	419,070	4,792	8,381	13,173
Banadir	Banadir	901,183		45,059		45,059
	Lower shabele	172,714	677,937	8,636	13,559	22,194
South	Bay	126,813	493,749	6,341	9,875	16,216
	Bakool	61,438	249,189	3,072	4,984	8,059
	Gedo	81,302	247,076	4,065	4,942	9,007
	Middle Juba	54,739	184,138	2,737	3,683	6,420

Table 3 (Continued).

	Lower Juba	124,682	261,108	6,234	5,222	11,456
	Total	1,687,815	2,792,965	84,391	55,859	140,250

CHAPTER II

Literature Review

2.1. Climate Change Issues

Due to its location which is close to the equator, Somalia does not experience a significant number of distinct seasons. There have only been a few occasions of rainfall that has been particularly erratic. In addition to the constant high temperatures, monsoon winds and rain showers can occur throughout the year (periodic seasonal reverse winds, followed by corresponding precipitating fluctuations). Higher elevations and the east coast, where the daily maximum temperature ranges between 30 and 40 degrees Celsius (86 and 104 degrees Fahrenheit), are able to experience a possible cold offshore current due to the presence of an offshore current (Abdikarin Ibrahim Awale, 2021). It has an MAE of 1.11, which represents reduced error compared to other models, and it has an MSE of 4.56. It has an R2 of 0.92. The first 10 rows of the weather prediction data set can be used to generate a line plot by comparing the actual values to the expected ones.

An examination of several drought indicators, such as the SPI and the DDI, revealed that the Somali region of Puntland State experienced droughts in 2007, 2008, 2009, 2011, 2015, 2016, and 2017. These years were included in the study. Both the SPI and the PNI were found to have produced comparable results, and it was discovered that there were two further droughts in 2010 and 2014. (Abdullahi Ali Said and a number of other researchers, 2019).

According to another study, the most severe drought epidemic in Somalia occurred between May 2011 and January 2013, lasted for an entire year, and had a severity score of -0.55. This information was selected from SPEI 12, which was used by researchers. A considerable number of people in Somalia's southern areas have also been impacted negatively by drought, and mild to severe droughts have had a devastating effect across the entire nation (Sylus Kipngeno Musei, 2020). As a result of trend analysis, it has been demonstrated that both the minimum and maximum temperatures are on the rise in the Greater Horn of Africa more often. Studies conducted by the Intergovernmental Panel on Climate Change (IPCC) and others have proven a connection between growing global temperatures and the heat brought on by climate change. Due to the short amount of time that the temperature data were collected over, this study was unable to provide conclusive evidence that there is a connection between observed temperature variations and changes in the climate. The statistics on the amount of precipitation showed only slight but statistically significant shifts. There were just a few noticeable patterns that remained consistent throughout a vast area (Linda Ajuang Ogallo, 2017).

2.2. Rainfall Issues

In comparison, Lower Jubba receives an average of about 250 millimeters of rain during the Deyr season, whereas it receives approximately 350 millimeters of rain during the Gu season. Between 1981 and 2015, the total quantity of Gu precipitation in Lower Jubba saw a general downward trend, whereas the total amount of Deyr precipitation showed an upward trend (Ogallo et al., 2017). These two weather phenomena are more frequently related with the drought than they are with the floods that has been occurring in the Lower Jubba region since there has been an increase in below-average rainfall and a decrease in rainfall that is above-average (Ogallo et al., 2017). The GHA is seeing a decline in the amount of precipitation that falls over the course of a year, but an increase in the amount that falls within a week (Omondi, P.A et al., 2009; Omondi, P.A et al., 2010). Temperature rises in Lower Jubba have been recorded by Ogallo et al, (2017), and these findings are in line with those of other recent pieces of study conducted on a worldwide scale (IPCC, 2014; King'uyu et al., 2000; and Easterling, 2009). Because to the rise in temperature, there is a possibility of an increase in the number of deaths and cases of disease among humans and animals (IPCC, 2014; Matthew Young et al, 2020; Neelam Mishra et al., 2018). Using the estimates that the government has made regarding the effects of climate change, an analysis of the likelihood that Somalia would be affected by extreme weather will be carried out. In addition to that, the development of a strategy for adaptation is possible with the assistance of this. The scope, the data, and the techniques of the study are discussed in these parts.

A location-dependent drop in the relationship between interannual rainfall variability at the regional and local levels and the POD for the lowest tercile group is observed as the geographic scale is raised. Examining these metrics at a spatial scale of 5 typically used for regional forecasts shows that representativeness varies by location. As can be shown from the large positive correlations in regional local precipitation (> 0.9) and the relatively high POD values at three sites (Zambia, Somalia, DRC), regional variability is highly uniform and hence accurately represents local variation. Lower correlations show that the regional scale is less representative at Fort Portal, Uganda, and the Jos Plateau, Nigeria, due to orographic characteristics and the singularity of convective systems. (Matthew Young et al, 2020).

Somalia's food production and water scarcity: a summary The production of reliable food sources will continue to be hampered by unpredictable elements such as precipitation. In Somalia, the amount of rain that falls varies substantially (Devin Franzen, 2012). The annual rainfall averaged 584 millimeters from 1963 to 1990, however it was 800 millimeters in 1977, the wettest year on record.

Evapotranspiration (PET) is measured in millimeters per hour, with a range of 1,000 to 3,010. As a result, the soil's water content drops by 200 millimeters over time. It is possible to cultivate crops during only a few months of the year when PET readings are lower than precipitation.

An article named "Climate Change Projections, and the Associated Potential Impacts for Somalia" discovered that there was concordance between the yearly rainfall cycle that was projected by an ensemble of CORDEX RCMs and CHIRPS data. The paper was written about Somalia. RCMs are afflicted by an early peak and an overestimation of monthly precipitation, particularly during the Deyr season. This problem is especially pronounced. According to the findings of a number of studies, GCMs have a tendency to exaggerate the amount of rainfall that occurs in the Horn of Africa during the months of October and December (IPCC, 2014; Anyah and Qiu,2012). Due to the nonlinear and unstable structure of the climate system, it is impossible to predict rainfall with precision(IPCC, 2014).

According to the findings of the study, observed climate events were found to closely match the group models. This was one of the main findings of the study. This study provides essential information on the trends in rainfall in Lower Jubba, which is needed for the sixth IPCC assessment report on the effects of regional climate change in Africa. This study is necessary in order for Somalia to develop strategies for reducing disaster risks and adapting to climate change that are in line with the Sustainable Development Goals, the Paris Agreement, Other worldwide, regional, national, and local frameworks for enhancing resilience include the Sendai Framework.

2.2.1. Rainfall Issues Using Machine Learning

Drought and flood concerns can be detected earlier with the help of time series data analysis and accurate rainfall projections. The Artificial Neural Network (ANN) approach was used to create one-month and two-month rainfall forecasting models using monthly precipitation estimates from Northern India. Feed Forward Neural Network (FFNN) and the Back Propagation Algorithm (BPA) were used in these models, along with the Levenberg-Marquardt training function. In order to analyze both models, regression analysis and the Mean Square Error (MSE) were used. Both the one-month forecast and the two-month forecast performed well using the proposed ANN model. Research areas for future development in rainfall forecasting and time series data processing are also outlined in this study (Neelam Mishra, 2018).

Various meteorological applications have made use of neural networks, each with a different lead time and a different location throughout the world. Periods such as these are among the many that may be found here. The Paramatta catchment in Sydney, Australia, was shown by Luk, Ball, and Sharma to be able to predict rainfall 15 minutes in advance using a neural network (Ball and Sharma, 2001). Only precipitation data were used as input features in the prediction challenge. The most accurate neural network topology was the Time Delay Neural Network (TDNN).

Zanyar rzgar ahmed (2018) In his thesis titled "Rainfall prediction using machine learning methodologies," stated that the program can anticipate monthly precipitation data employing temperature, wind direction, wind speed, air pressure, and humidity as system inputs. Additionally, the use of neuro-fuzzy models to train and test data resulted in the reduction of errors to RMSE values between 0.011-0.015 and RMSE values of 0.025-0.025. According to the research, ANFIS is the best artificial network for predicting precipitation. In a comparing of the observed data and the projected data, the ANFIS system's outputs exhibited maximum accuracy with little error.

2.3. Water Resources Issues

SWALIM, the Somali government's water authority, and the United Nations' Water, Sanitation, and Hygiene Cluster have all collaborated on the development of systems that can monitor the country's various water sources (Water, Sanitation, and Hygiene). In 2006, the Somalia Water Sources Information Administration System, often known as SWIMS, was established in order to keep track of the country's many water sources. After eight years of operation and extensive input from partners, the SWIMS platform underwent a comprehensive makeover in 2014 to become a dynamic, graphical web application. According to the 2014 SWALIM Groundwater Report, the majority of shallow wells in Somalia are located at depths that are less than twenty meters. The amount of water that may be extracted from diverse sources varies greatly according to the aquifer. Boreholes normally produce between 5 and 20 m3/hr of water per second, whereas shallow wells typically produce between 2.5 and 10 m3/hr of water per second.

The vast majority of people rely heavily on groundwater wells (also known as dug wells and boreholes) as their primary source of drinking water. In 1999, the United Nations Children's Fund worked in many regions of Somalia, including Puntland, to acquire significant data on the places of water sources. SWALIM is an contraction that stands for the Somalia Water Source Information Management System. This system was developed by SWALIM and its collaborators with the assistance of other organizations (SWIMS). In order to make appropriate preparations for the future, it would be beneficial to have an understanding of how water levels change over the course of time and whether or not there are any drawdowns.

Catchment water, also known as rainwater, is gathered in berkads and wars (which are dams and reservoirs), which is another significant source of water in Somalia. The majority of streams and drainages in the region are dry, and the only periods when they have adequate flow are at times when there has been significant rainfall. This is due to the dry environment of the region, as well as the irregular rainfall patterns and high liability for evaporation. The usage of water taken from more insignificant catchments is required for these wars or berkads.

Kammer and Win conducted a case study, and the focus of their investigation was on storm water collection stations (1989). The research provides a comprehensive description of the catchment as well as the rainfall circumstances that contribute to the formation of runoff. Rainwater collection systems that are based on catchment runoff can be constructed with the assistance of the findings from this research.

CHAPTER III

Methodology

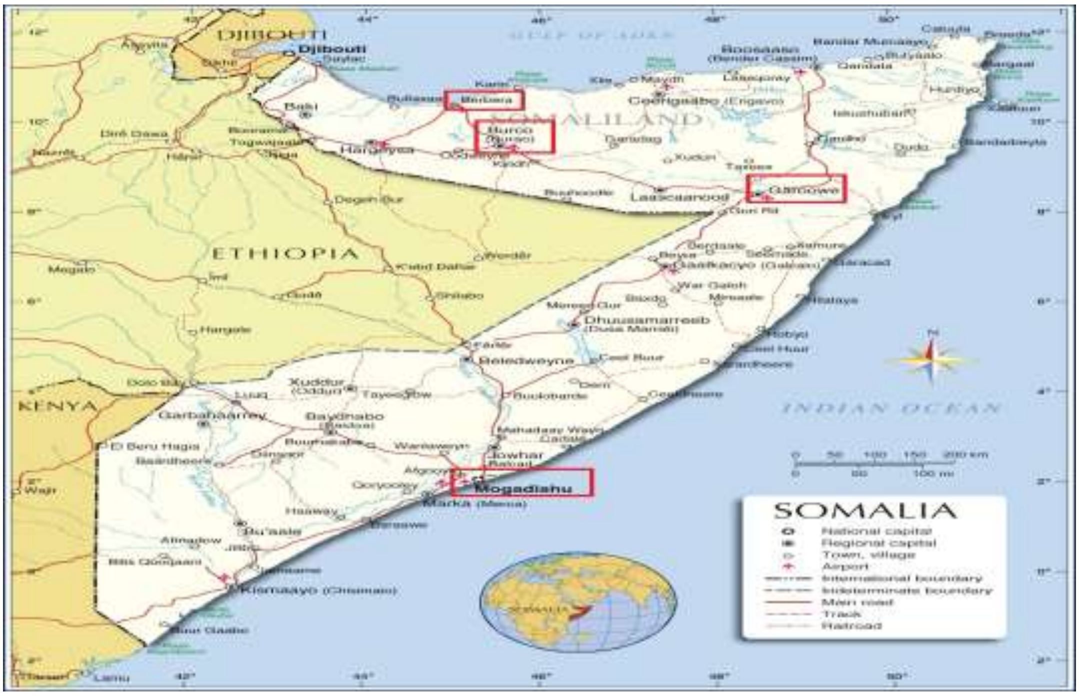
In this chapter we will discuss the methodologies followed started from the study areas, datas and models used to predict rainfall.

3.1. Study Area

Somalia is a country located in the eastern part of the Africa continent. In the west, the country is bordered by Ethiopia, Djibouti to the Northweastern, the Gulf of Aden to the North and the Indian Ocean to the east, and Kenya in the southwest. It is estimated that 16.8 million people live in the country(UNFPA, 2022). The coastline of Somalia is the longest in Africa. 637,700 km² of land area and 3,333 km of coastline make up Somalia's surface area (Worldatlas). This analysis focuses specifically on these four cities in Somalia.

Figure 3

Locations Of Study Areas In The Political Map Of Somalia



3.1.1. Mogadishu

Mogadishu, Somalia's capital city, is home to the most inhabitants.It is situated close to the Indian Ocean, with coordinates of latitude 02°02′21″ North and longitude 45°20′31″ East. Because of the river Shabele, which has its origins in the highlands of Ethiopia, the majority of Mogadishu's neighbors are agriculturally dependent in some form. Mogadishu occupies the most southern position on the coast that is traversed by the equator. Mogadishu has a climate that is tropical and semiarid at the same time. In 1990, the Mogadishu Water Supply Project was still in the process of being completed and expanded, despite having been planned for decades prior. In the vast majority of African countries, including Somalia, the primary method of obtaining water is through the use of boreholes. The altitude is 9 meters in Mogadishu.

3.1.2. Garowe

The city of Garowe in Somalia's north-eastern corner has a population of over 200,000. Its coordinates are 8 degrees 24 minutes north latitude and 48 degrees 28 minutes east longitude. Currently, Garowe is suffering intense heat. The weather is mostly sunny, and dry. It rises between 100 and 500 meters above sea level and is flanked by dry lowlands on all sides. Livestock is essential to the Garowe economy. The NugalWater Company is in charge of managing the city of Garowe's water supply at the moment. The company distributes water through pipelines that are connected to individual homes in the city.

3.1.3. Burao

Burao, the second-largest city in Somaliland, is home to Somaliland's most major livestock market and Somalia in General. It has a population of about 450,000. Boreholes drilled across the city are the primary source of Burao's drinkable water. Burao's economy is mainly dependent on the livestock, which creates jobs and generates income.It's one of the worst drought-stricken regions of Somalia. The elevation is about 1,037 ft.

3.1.4. Berbera

Berbera is the city in Somalia that has the highest yearly temperatures, with a maximum temperature of 46.7 ℃ (Weatherbase). The distribution of water in the coastal city of Berbera, located in the north-eastern region of Somalia, has deteriorated to the point where it is no longer providing enough water of a sufficient quality. The

Dubar Spring, which is situated at the base of the hills, is Berbera's principal water source. It is positioned at the lowest altitude among the other four cities (3m).

3.2. Data

Data from two different sources are used in this study.

3.2.1. Actual (Measured) Data

Climate data is scarce in Sub-Saharan Africa. Most of Somalia's meteorological stations were destroyed when the country's central government fell. Few of meteorological stations are maintained by the Somalia Water and Land Information Management of the Food and Agriculture Organization (FAOSWALIM). In this analysis, precipitation data from 2009 to 2017 was utilized. There were monthly precipitation measurements from 2009 to 2017 supplied by the Somalia Water and Land Information Management(SWALIM). The automatic measurement of rainfall is performed by a rain gauge. Measurement data is automatically transmitted or recorded at this station.

3.2.2. Satellite Data

In this particular study, the second category of data that is studied is setallite. ERA 5, MERRA 2, CHIRPS, and CFS were the four satellite-based products that were utilized in this study. In regions of the world where there is a deficiency of observational weather and climate data, such as Africa, reanalysis products are regularly utilized in their position. Satellites have the ability to monitor enormous extended of land in real time and at a high resolution. In the tropics, where convective storms play a significant role in the generation of incredibly diverse patterns of rainfall, they are particularly well-suited for the prediction of rainfall (Smith, D. F et al., 2005). These data not only fill in the data gaps between ground-based radar stations and rain gauges, but they also provide information on when, where, and how much precipitation falls all over the world.

1. ERA5. Reanalysis of the global climate by the ECMWF's fifth generation of atmospheric reanalysis, beginning in January 1979 and continuing up to the present day.Between the surface and an altitude of 80 kilometers, there are 137 levels of resolution for the atmosphere, and the data cover the entire earth on a grid that is 24 kilometers in width (0.25 x 0.25). On an hourly basis, a large number of variables relating to the atmosphere, ocean, and land surface are computed (K. Venkatesh, Srinivas and Preethi, 2020). The European Center for Medium-Range Weather Forecasts (ECMWF) is responsible for the development of ERA-final, which is intended to take the role of ERA-interim and a number of other reanalysis products (such as ERA-15 and ERA-40) (ECMWF). Additional validation is provided by taking the data from 1981–2018 and averaging it to 0.25 degrees.

2. MERRA-2 (Modern-Era Retrospective Analysis For Research And Applications). It is possible to find data dating all the way back to 1980. As a result of developments in data assimilation technology, the MERRA-2 dataset was developed in order to serve as a replacement for the original MERRA dataset. All of these features are in addition to its regular GPS-Radio, which may also be found in the MERRA-2, which is a more recent model. The spatial resolution of MERRA is equivalent to that of others (approximately 50 km in the latitudinal direction).

3. (CFS). As the oceans, land, and atmosphere all interact with one another, this system attempts to predict global climate change. The National Centers for Environmental Prediction (NCEP) oversee the work of hundreds of scientists on the model, which delivers hourly data with a horizontal precision of 12 degrees (approximately 56 km). The most current scientific technique is used by CFS to integrate observations from a variety of data sources, including surface observations, high-altitude balloon observations, aircraft observations, and satellite observations (National Centers for Environmental Information).

4. CHIRPS. An infrared precipitation product developed to study agricultural drought and global environmental change over land is the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) (Funket et al., 2015). Since 1981, CHIRPS has been producing grid-based rainfall data series for the purposes of seasonal dryness trend research and monitoring. These data series are derived from CHPclim, our in-house climatology, as well as data from our in-situ weather stations (Abdulkadir gure, 2021; Ogallo, Linda Ajuang, et al., 2018).

Table 4

Description Of Four Satellite Data Products

Product name	Data type	Projection	Horizontal coverage	Computation Resolution (Scale):	Temporal coverage	Temporal resolution
ERA5	gridded	Regular latitude-longitude grid	global	~24km(0.25^{0}x0.2	1979 to present	hourly
MERRA2	gridded	Regular latitude-longitude grid	global	~50km(0.5^{0}x0.62	1980 to 2021	Daily
CFS				gridded	Regular latitude-longitude grid	global
CHIRPS	gridded	Regular latitude-longitude grid	50°S-50°N, 0° – 360°E	$\sim 4800\text{m}(\frac{1}{20})^0$	1981 to present	Daily

3.3. Accuracy of the Satellite Products

Africa, where the majority of its economy is based on rain-fed agriculture due to global climate change, needs accurate rainfall projections more than ever. Agricultural resources in eastern Africa are vulnerable to climate change, and accurate rainfall data is essential for monitoring agricultural resources in this region. Africa's ground-based measurements are insufficient because of geographical and temporal inconsistencies (Schreck and Semazzi, 2004). Accordingly, there are numerous free satellite-based and numerical model outputs that may be validated before being used.

RMSE typically ranges between 20% and 25% when comparing hourly global data estimates derived by satellite visible-channel observations with ground-based, single-site or regional network measurements (Schmetz, 1989; Hay, 1993; Noia et al., 1993; Bayer et al., 1996). The RMSE as a whole is composed of three major subgroups: Both of the assumptions used to simplify the models that convert satellite data to earthly data are included in group (1). Hydrometeor observations include inherent imperfections that fall into Group 2, while the mismatch between instantaneous pixels stretched in space and single point measurements integrated in time falls into Group 3. Group 3 includes both of these issues. There appears to be a general underestimating of data derived from satellites in dry seasons, which could be due to an overestimation of the depth of precipitation in these conditions.

Another batch of satellite data was generated and an approach for correcting satellite data was used to increase the accuracy of this one in order to fix the problem. We used this formula to remove the error.

$(Y_N = Yo - [(a-1)X + b)]$……………………………………Eq. 1

where Y_N is the adjusted product value.

Yo is the product's value before correction, A is its slope, and B is its Equation of Coefficient. In Excel, we made a scatter plot of the data and add an equation to the chart to determine A and B. There are two types of numbers in an equation: "B" (the coefficient of the equation) and "A" (the slope of the line in the graph).

Statistical analysis was utilized to compare the satellite products that had been downloaded. CHIRPS, CFS, ERA5, and MERRA 2 with the measured one were all tested to see if there was a correlation, and then the four products were compared to see if there was a correlation between them. Contrary to the observed data from the CFS, MERRA 2 ERA 5 and CHIRPS satellite products accurately describe precipitation's temporal and spatial distribution, compared to the observed data (Rainfall varies between cities). Precipitation patterns in the four cities are described in both geographic and temporal terms. In Garowe, two product perform better than the others. Since ERA 5's R squared is higher than Chirp’s R squared, this suggests that ERA 5 is superior and more closely matches the observed data., on the other hand ERA 5, has lower RMSE and MAE than Chirps in most cities. Furthermore, only ERA 5 provides access to all other data, such as wind speed, temperature, and so on. In this analysis, ERA 5 was shown to be the best product with measurable data based on comparisons with the other goods.

Forecasting models employ temperature and wind speed as their primary climate inputs. As the Earth's average surface temperature rises, more water is evaporated, resulting in greater precipitation around the world. Increasing precipitation across the country is expected as temperatures climb. As the boundary layer is destabilized by greater evaporation, deep convection occurs, resulting in an increase in precipitation. As a result of the increasing wind speed, precipitation levels are rising significantly faster than evaporation levels do. Climate and wind speed have the greatest impact on precipitation.

3.4. Empirical Models

One sort of computer modeling is known as empirical modeling, and it different from mathematical modeling that it is not based on mathematically defined interactions between systems but rather on facts taken from the real world. An empirical model is one that draws on data from the past in order to construct (or "train") a statistical link for the goal of making forecasts about the future state of the climate. The greatest issue with empirical methods is that they are only valid for the input values for which they were built (Andrew Robertson and Frederic Vitart,2019).

3.4.1. Artificial Neural Networks (ANN)

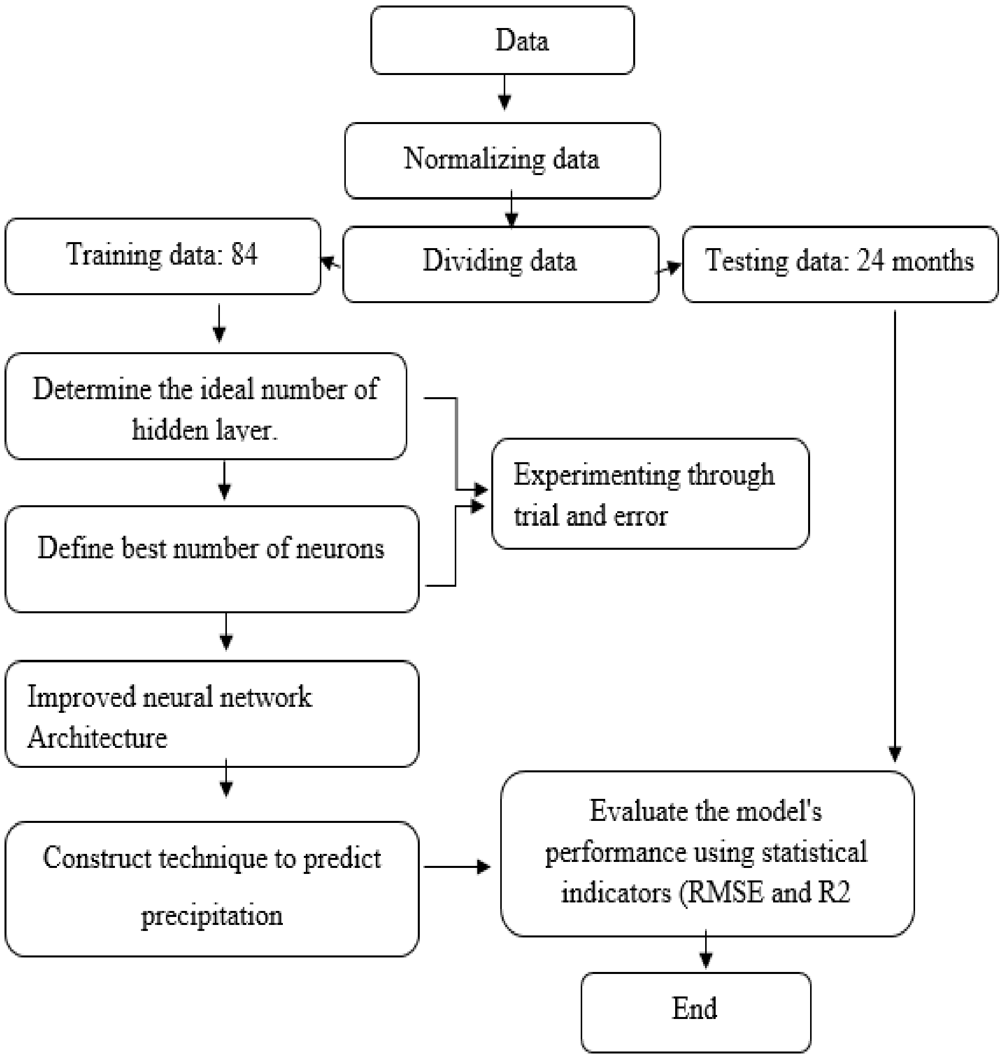
Artificial neural networks (ANN) are now the model that are utilized by the most people in order to solve nonlinear functions and define complicated systems (Kassem et al. 2022; Iravanian et al., 2022). The approach known as ANN makes use of input elements, the structure of the neural model, as well as learning in order to forecast data. The gap between the estimated and actual values can be narrowed by the application of a variety of learning strategies (Ghritlahre et al. 2020). The FFNN, CFNN, and ENN models have been used to make forecasts for the precipitation that will fall in the four cities. The month (M), the maximum temperature (Tmax), the minimal temperature (Tmin), the average temperature (Ta), and the maximum wind speed (Wmax) were the variables that were used to feed information into the model. The monthly precipitation of Era5 used as the output variable for the models that were constructed. In order to train the models, a 84-month data set was utilized, and the trained models were then used to make predictions and analyze the real-world data. In order to guarantee that the scales were consistent throughout the dataset, the variables, inputs, and outputs were all standardized to the interval [-1, 1]. Back-propagation serves as the conceptual underpinning for the training algorithm. In order to achieve better performance, a variety of network architectures were developed, each featuring a different number of hidden layers and neurons. In order to estimate the number of hidden layers and neurons, we used approaches that involved trial and error. In addition, the hidden layer and the output layer were each tested with a function that was a combination of the logistic and tangent sigmoid. There were different experiments between 10,000 and 100,000 performed. The MSE approach is utilized in order to perform an efficiency analysis on the training algorithm. All of these procedures are completed using MATLAB 2021a together with the data on the precipitation that was gathered.

3.4.1.1. Feed-Forward Neural Network (FFNN)

The FFNN is the ANN that sees the most widespread application. There are three components: the input, the hidden, and the output. It could be one or more of the hidden layers that exist between the variables that are independent and those that are dependent. The backpropagation method is utilized in the training procedure for the FFNN. The method of trial and error is used to determine everything from weights to buried layers to neuronal connections (weights, hidden layers, and neurons). The MSE metric is utilized in order to determine how effective the training algorithm is. Kassem and Gokcekus provide an explanation of the mechanism behind the proposed model (2021). (2021). The process of developing FFNN is illustrated in Figure 4.

Figure 4

FFNN Flowchart

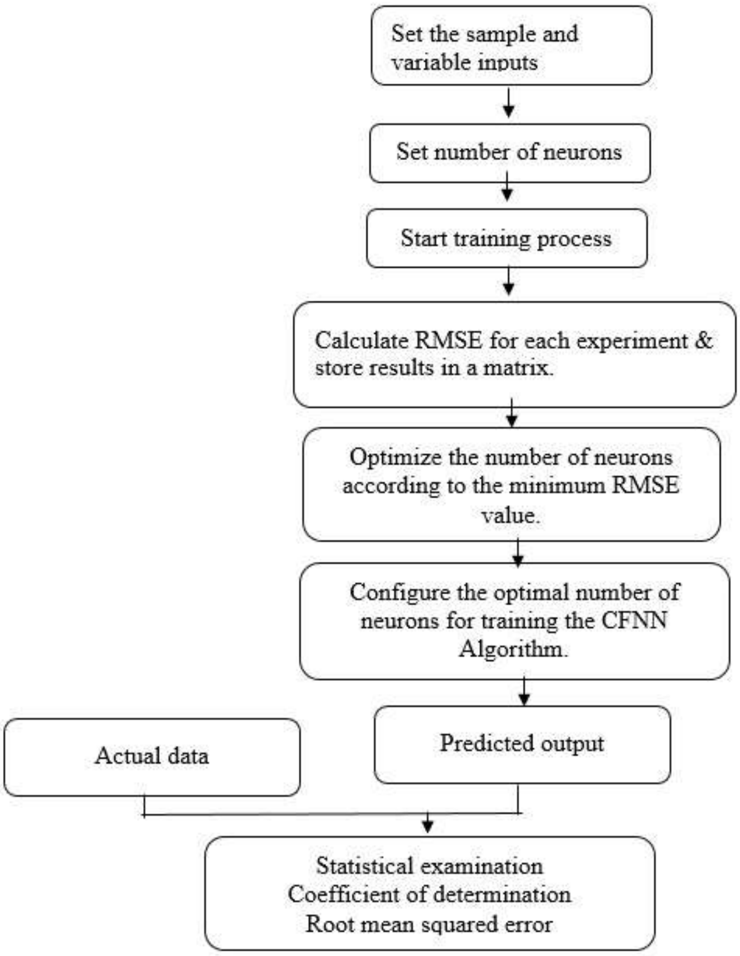


3.4.1.2. Cascade Forward Neural Network (CFNN)

A CFNN architecture consists of an input layer, one or more hidden layers, and an output layer. Weights from the input typically reside in the first layer of the neural network. Each succeeding layer incorporates the weights of the preceding layer's input and previous layer weights (Hedayat et al. 2009; Mohammadi et al.,2021). There are inherent biases at every level. The final layer is called the output layer. Weight and bias values for each layer need to be established and the MSE is used to measure the efficiency of the training method. The provided approach for the framework is explained in Kassem and Gokcekus (2021). The development of CFNN in this study is seen in Figure 5.

Figure 5

CFNN Flowchart

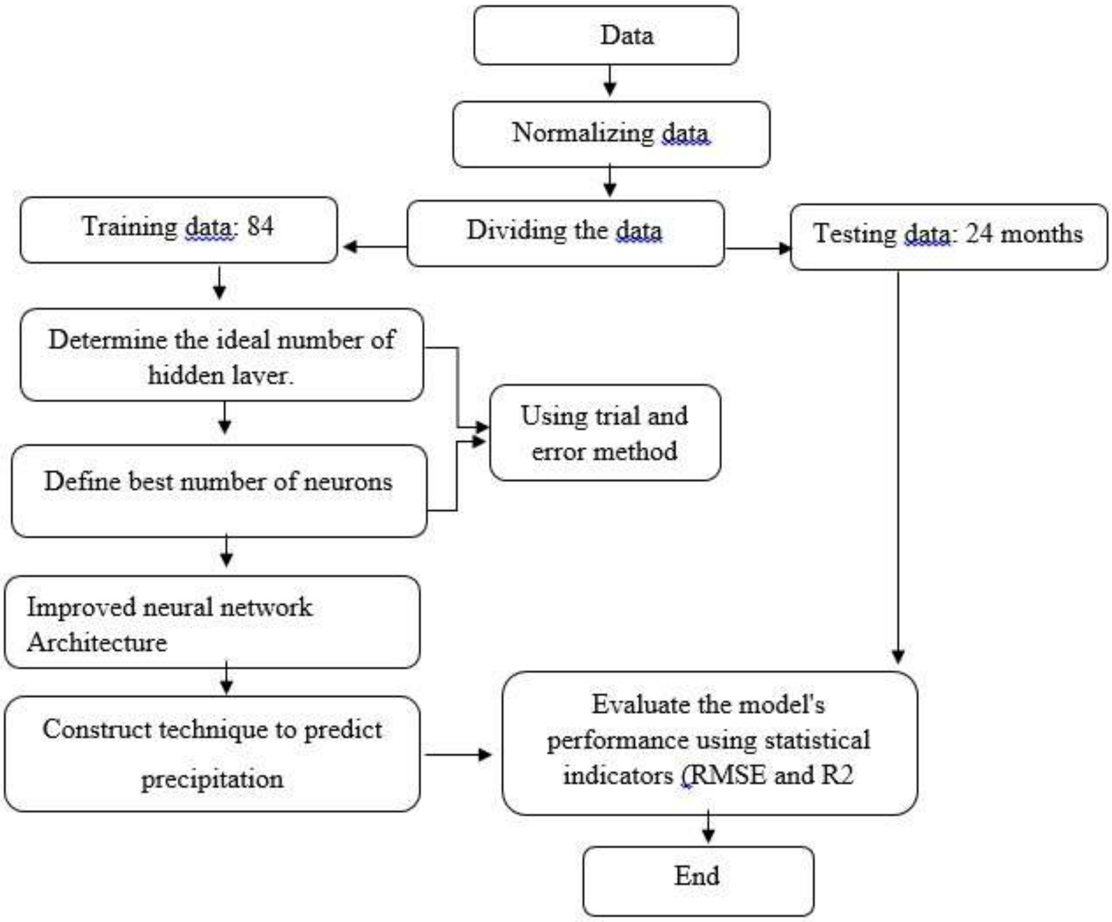


3.4.1.3. Elman Neural Network (ENN)

Neural networks that receive feedback are known as Elman Neural Networks (ENNs). This technique has four layers: the input, the hidden, the context, and the output layers (Kumar et al. 2022). The input layer is responsible for signal transmission. The output layer, on the other hand, only has a linear weight effect. A detailed explanation of the ENN model by Kumar et al. Describes the background layer's distinction between ENN and back propagation neural networks. Figure 6 shows how the ENN has evolved in this study.

Figure 6

ENN flowchart



Relationship between Precipitation, Temperature and Wind Speed.

Temperature and Rainfall:

According to the findings of Rebetz,(1996) cooler summers have a greater propensity to experience an increase in the total amount as well as the frequency of the occurrence of precipitation. Locations at lower elevations experience a unique winter climate compared to those at higher elevations. Warmer winters at lower altitudes lead to conditions that are wetter and snowier than those found higher up (only a small part of winter precipitation falls in the form of snow).

Dr. Tinyiko Nkuna and his colleague John Odiyo found in their study, "The relationship between temperature and rainfall variability in the Levubu sub-catchment, South Africa," that a rise or fall in temperature can have significant indirect and direct hydrological effects by altering the amount of water that evaporates and the amount of water that stays in the soil. For example, as temperatures rise, soil moisture, moisture storage capacity, and soil quality will degrade, reducing the availability of vital nutrients to plants.

Air Temperature and Wind Speed

Evaporation losses depend greatly on the temperature and wind speed of the air. Throughout the year, Somalia gets high average air temperatures. Temperatures have risen in several locations, according to locals. December through March are the hottest months in southern Somalia. The temperature continues to rise. In southern Somalia, the months of July and August are the coolest. The northern regions such as Awdal see its hottest weather in June and September. Open-surface reservoir evaporation losses necessitate further analysis. When the country's Gu and Deyr precipitation seasons maximum between April and November, wind speeds are at their lowest. Evaporation losses are accelerated by higher wind speeds and warmer temperatures (Oduor and Gadain, 2007).

Precipitation and Wind Speed

Larissa Back and Christopher Bretherton (2005), states that Evaporation is destabilized by higher winds and can lead to deep convection, according to a study published in the journal Geophysical Research Letters. Nevertheless, the intricacy of this argument's quantification is surprising. Convergence loops occur when precipitation increases are higher than the changes in evaporation that occur as wind speeds increase. Numerous feedback methods were tested using MSE budgets from the ERA-40 and NCEP–NCAR analyses to find the best one. A continual buildup of damp static energy in the boundary layer or column does not need to be vented by deep convection because the low-level horizontal advection in ERA-40 is comparable to evaporation (but not in NCEP–NCAR). As a result, the research was deemed to be fruitless.. (Larissa Back and Christopher Bretherton, 2005).

CHAPTER IV

Discussion

This chapter will discuss the characteristics of measured and satellite datas before and after the correction

4.1. Characteristics of Measured (Actual) Data

As a result of differences in network scope management and the technologies included into the various types of sensors used, the temporal accumulation of precipitation data is not the same in all areas of the world. Today's digital data recorders are capable of gathering the great majority of the available rainfall data. The majority of hydrological research cannot function without the utilization of gauge data. There isn't a single sensor or recording device that doesn't have its own unique maximum time limit for keeping data. The sites of four gauges that recorded monthly precipitation from 2009 to 2017 are listed in Table5, along with other fundamental information about each of the gauges. All of the data from the rain gauges were carefully examined, and any errors or discrepancies that were found were corrected.

Table 5.

Rain Gauges Location And Basic Details For The Research Region.

Location	Data period	latitude	longitude	Monthly precipitation ranges (mm)
Berbera	2009-2017	10°26′08″N	045°00′59″E	0-151.5
Burao	2009-2017	09°31′40.4″N	45°32′04.2″E	0-138
Garowe	2009-2017	8°24′N	48°28′E	0-139.5
Mogadishu	2009-2017	02°02′N	45°20′E	0-160

4.2. Characteristics of Satellite Data

4.2.1. *Era 5*

ERA5, the successor to ERA-interim and the final product in a series of reanalysis products that also includes ERA-15 and ERA-40, was recently made available by the European Center for Medium-Range Weather Forecasts (ECMWF)

(ECMWF). Additional validation is provided by taking the data from 1981–2018 and averaging it to 0.25 degrees. Before the change, the ERA5 in Berbera was already satisfactory. In particular for the months of January 2010 and June 2017, it was too near to the actual data, while January 2009 was the best fit for the model. The accuracy of Garowe and Burao was significantly worse than that of Berbera and Mogadishu. In order to rectify this scenario, a new satellite data collection has been constructed, and a fundamental method for improving the accuracy of satellite data has been applied. Both of these steps have been taken in order to increase the correctness of the satellite data. After making the necessary adjustments, there was not a discernible gap between the R squared values obtained from the CHIRPS, the ERA-5, and the ERA-5 in Burao, Garowe, or Mogadishu. When it came to measuring the intensity of rainfall, ERA-5 performed far better than CHIRPS.

Figure 7

Comparison Between Era 5 And Actual Data For Berbera City

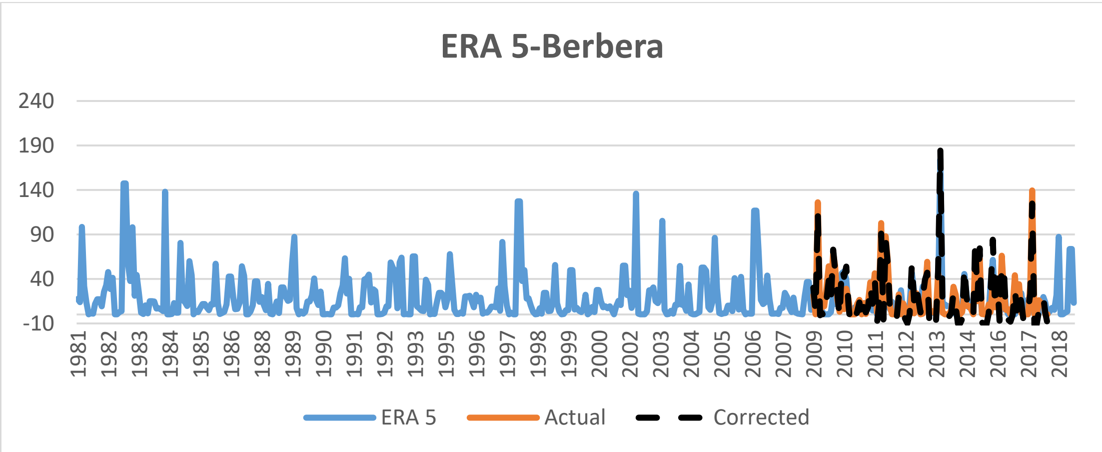


Figure 8

Comparison Between Era 5 And Actual Data For Burao City

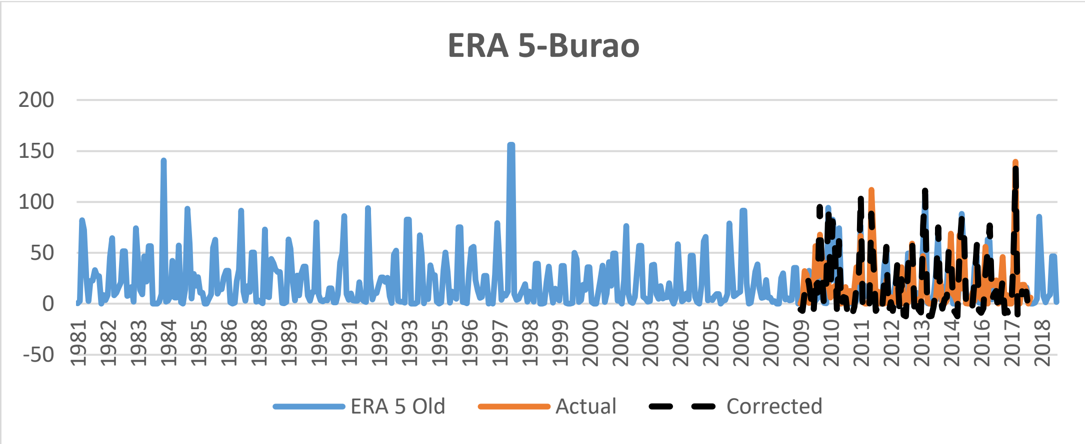


Figure 9

Comparison Between Era 5 And Actual Data For Garowe City

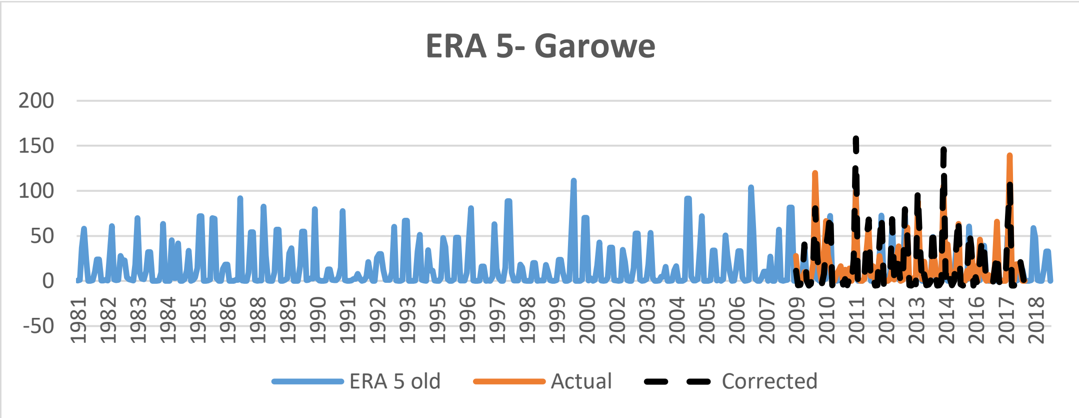
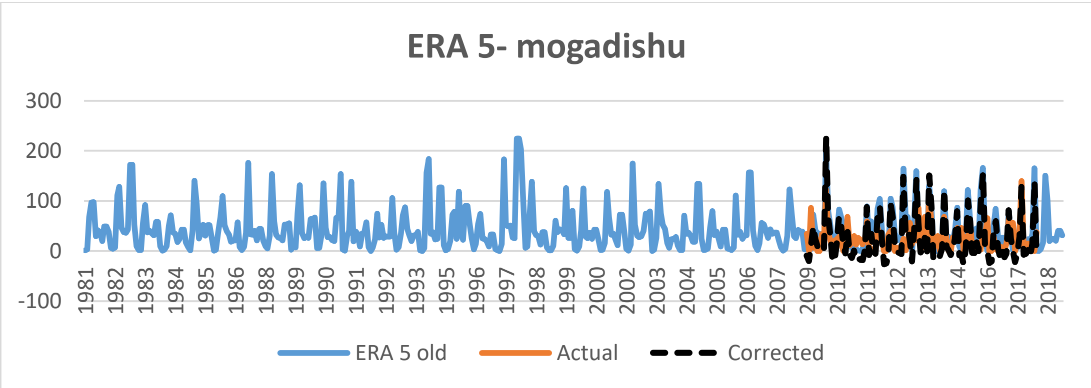


Figure 10

Comparison Between Era 5 And Actual Data For Mogadishu City



The graphs located above use actual (measured) data in conjunction with the improved ERA 5 model to make a comparison of the monthly ERA 5 precipitation in the cities of Berbera, Burao, Garowe, and Mogadishu.

4.2.2 *Chirps*

CHIRPS is shorthand for "Chipping In and Out." To track seasonal dryness trends and measure in-situ station data, CHIRPS combines our in-house climatology, CHPclim, as well as satellite images with a 0.05° resolution and in-situ station data to create an extensive series of gridded rainfall data ranging from 1981 to the present. In Garowe, CHIRPS was outstanding before the modification. It was most accurate for the months of February 2009 and June and July 2010 compared to the actual data. Berbera and Burao have worse accuracy than Garowe. The CHIRPS dataset, after normalization, shows a greater bias in Berbera. At a monthly time step, the RMSE showed a similar R squared pattern to the ERA-5 in Mogadishu, indicating that it outperformed the latter. Point evaluation is significantly different from grid evaluation, according to the results of CHIRPS. Arid and semiarid regions benefit from CHIRPS more than rain-soaked areas. When the monsoons migrate, favorable performance zones are shifted.

Figure 11

Comparison Between Chirps And Actual Data For Berbera City

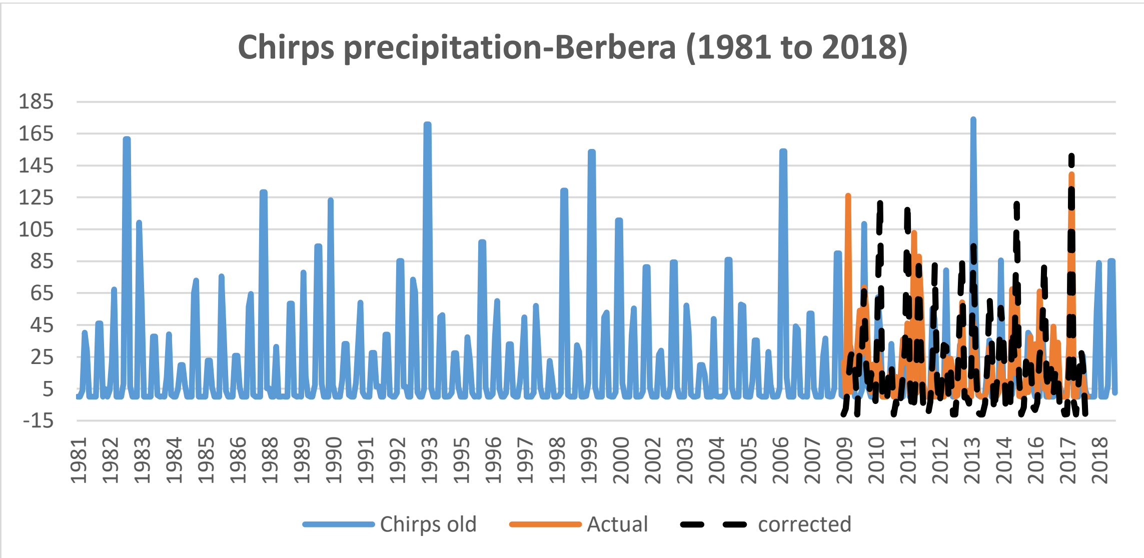


Figure 12

Comparison Between Chirps And Actual Data For Burao City

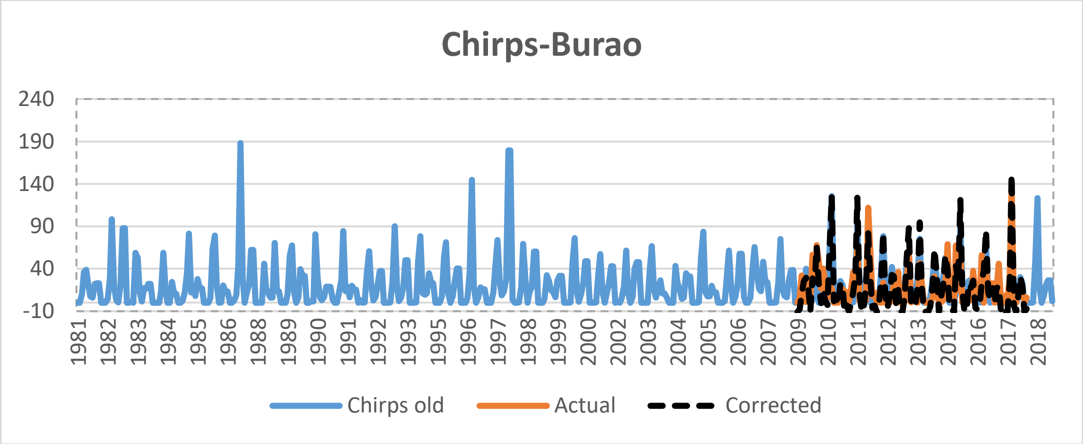


Figure 13

Comparison Between Chirps And Actual Data For Garowe City

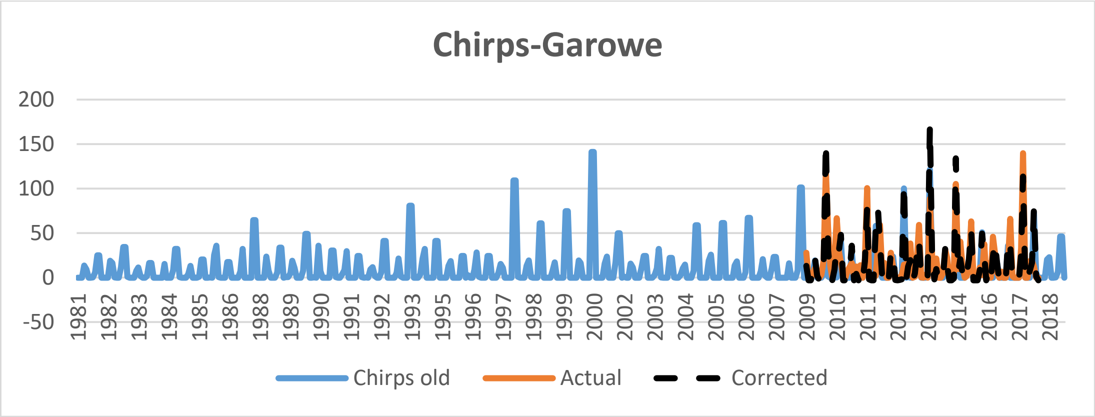
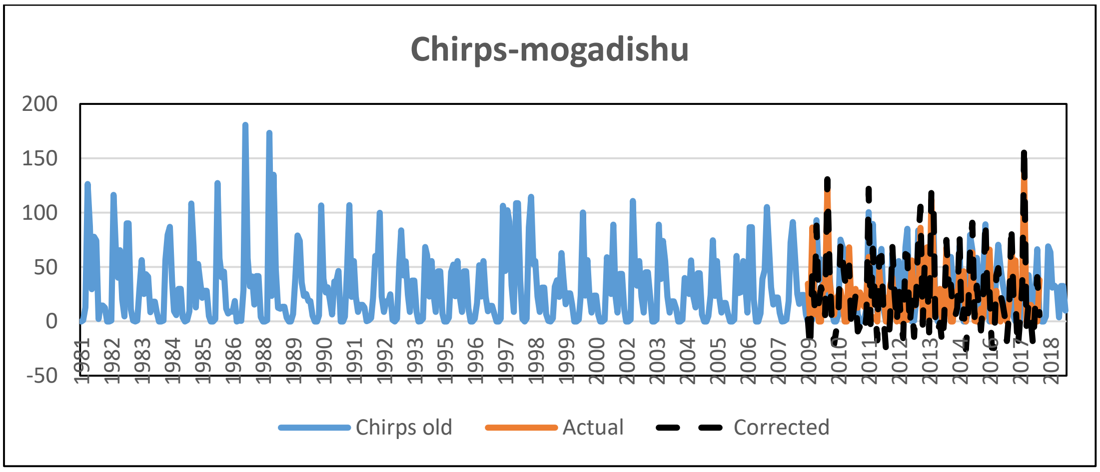


Figure 14

Comparison Between Chirps And Actual Data For Mogadishu City



The figures that are given above show the monthly CHIRPS precipitation for the cities of Berbera, Burao, Garowe, and Mogadishu using actual (measured) data as well as the corrected version of CHIRPS.

4.2.3 *Cfs*

Data from a number of sources, including surface observations, balloon observations, aircraft and satellite observations, are included in CFS. The most recent scientific approach is used. CFS was less accurate than data collected in Berbera compared to ERA 5 and CHIRPS. However, it was very close to other regions' measured data (June 2010). The CFS data from all other cities showed major discrepancies from the actual numbers. The CFS retains the same level of accuracy following correction. Excellent in Berbera due to high R squared, but not so good in the other towns. A zero CFS R squared was recorded in some cities.

Figure 15

Comparison Between Cfs And Actual Data For Berbera City

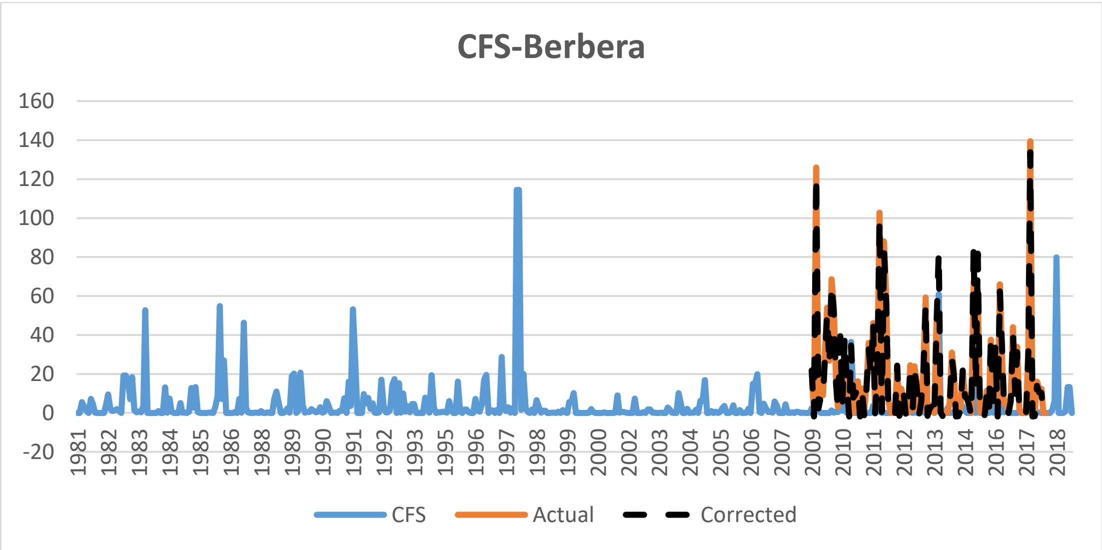


Figure 16

Comparison Between Cfs And Actual Data For Burao City

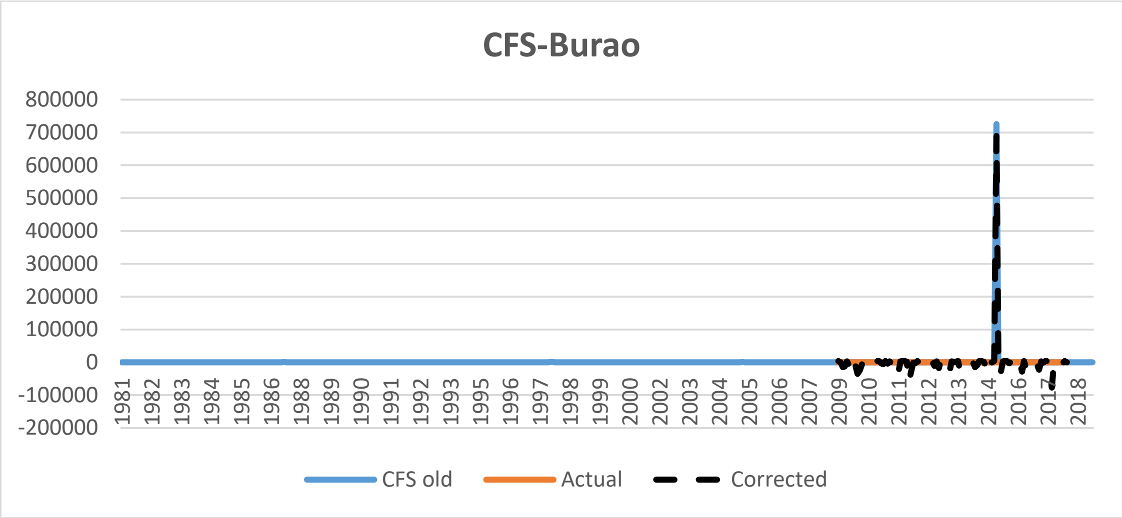


Figure 17

Comparison Between Cfs And Actual Data For Garowe City

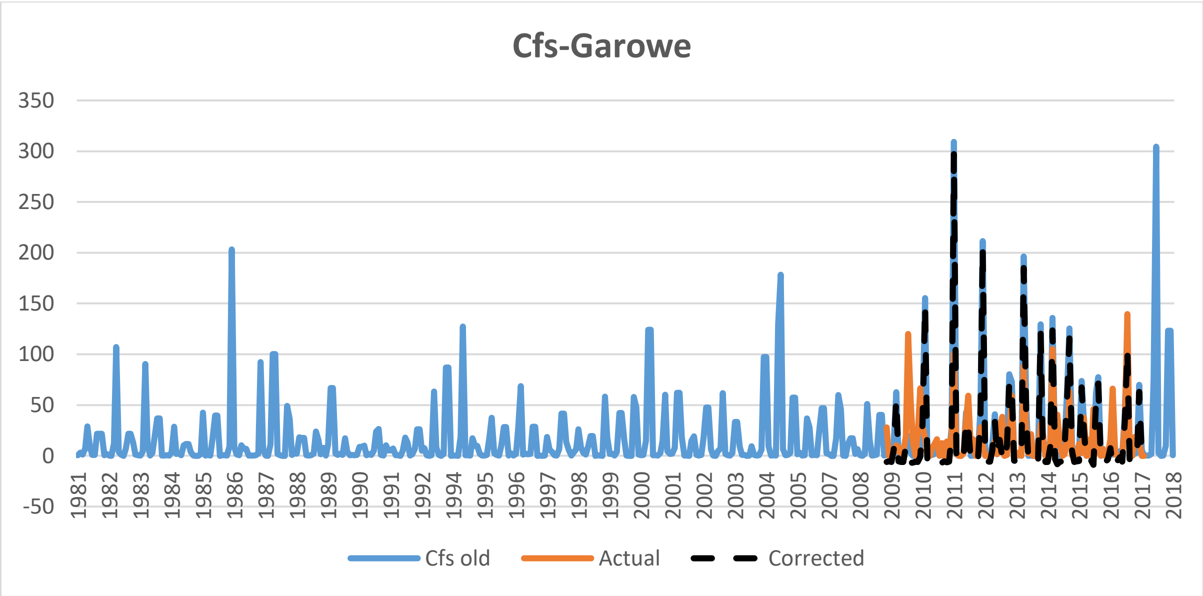
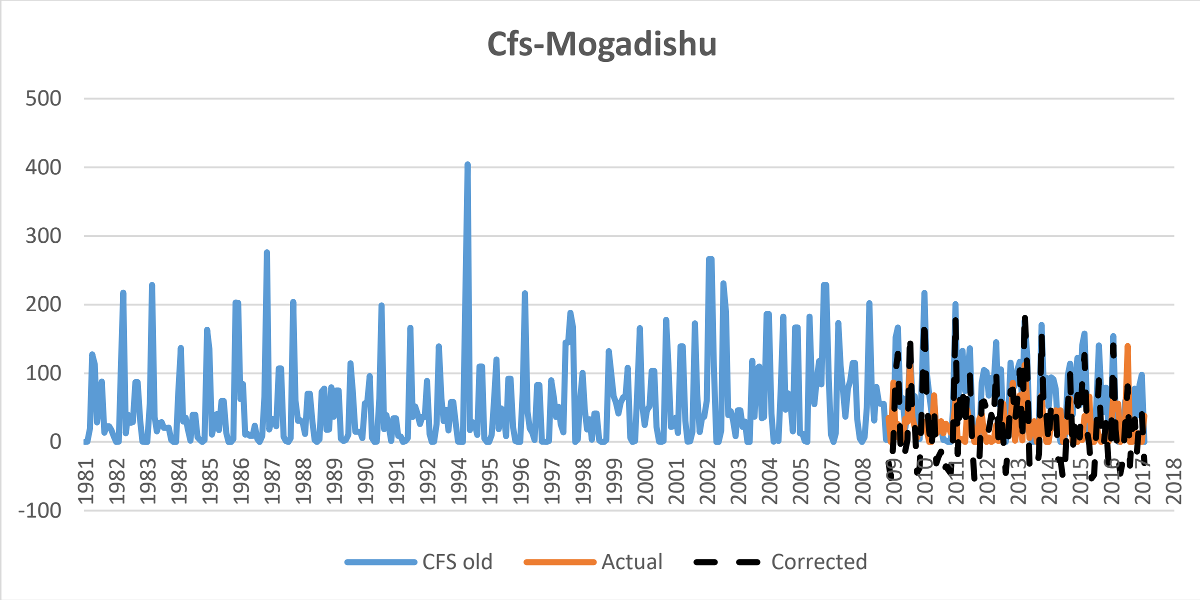


Figure 18

Comparison Between Cfs And Actual Data For Mogadishu City



The figures that are given above show the monthly CFS precipitation for the cities of Berbera, Burao, Garowe, and Mogadishu using actual (measured) data as well as the corrected version of CFS.

4.2.4 *Merra 2*

As a result of advancements in assimilation technology that make it possible to incorporate observations of contemporary high spectrum irradiance and microwaves, The MERRA and GPS-Radio datasets were retired in favor of this one. The GEOS and GSI data assimilation models are both included in MERRA-2. the spatial resolution of MERRA or a comparable one (approximately 50 km in the latitudinal direction). In the course of this research, this precipitation product was found to be the least accurate. Although the precision of all of the other towns was insufficient, the position that is closest to the target is in the city of Berbera, where the R squared of Merra 2 value was 0.74. Merra 2 (R sq= 1.4474E-07) was Garowe's lowest point on the planet.

Figure 19

Comparison Between Merra 2 And Actual Data For Berbera City

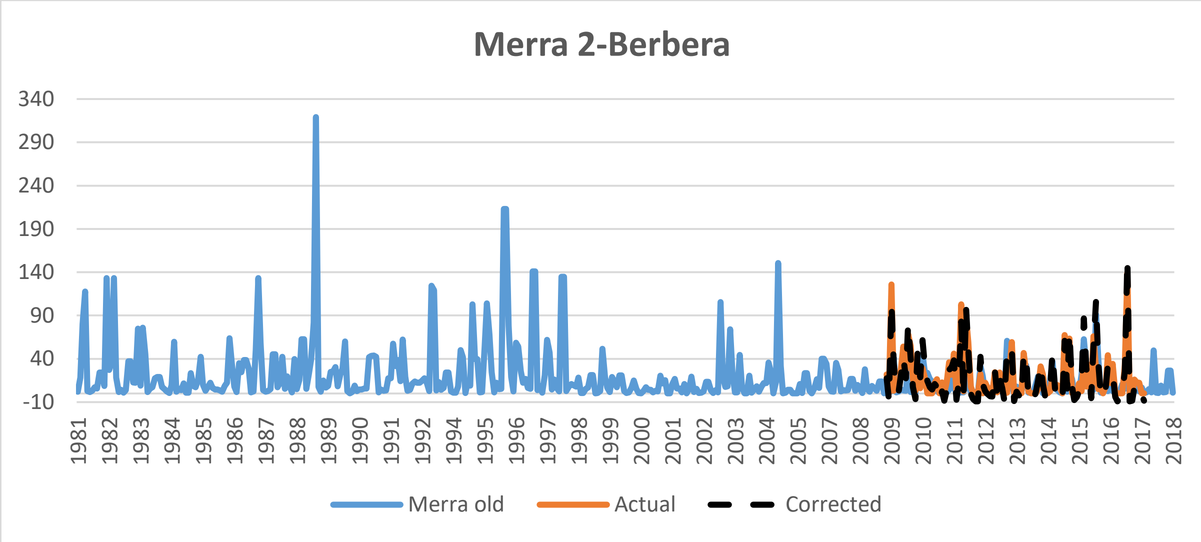


Figure 20

Comparison Between Merra 2 And Actual Data For Burao City

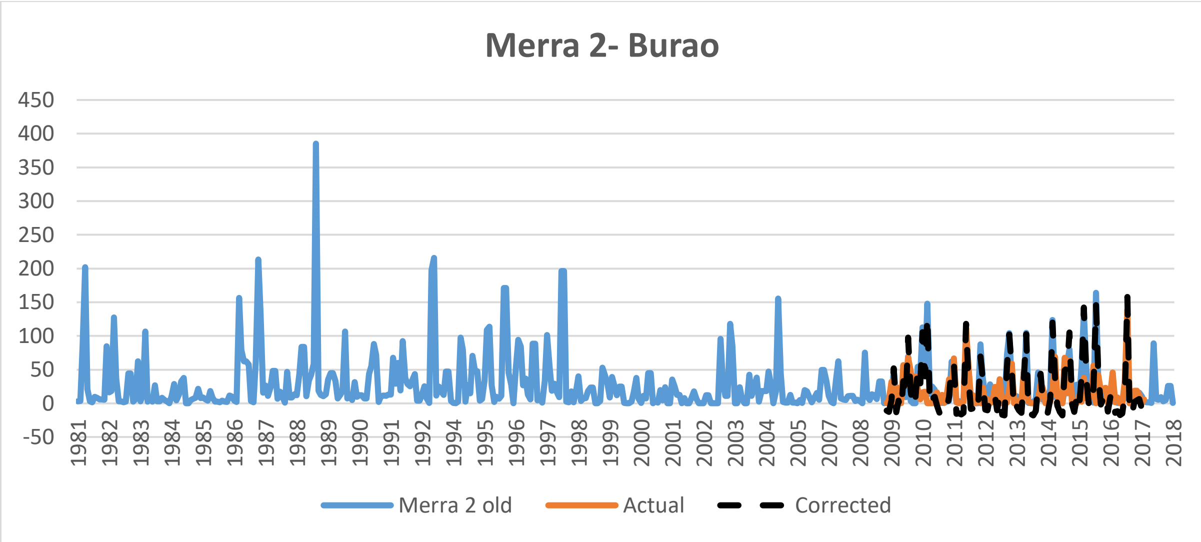


Figure 21

Comparison Between Merra 2 And Actual Data For Garowe City

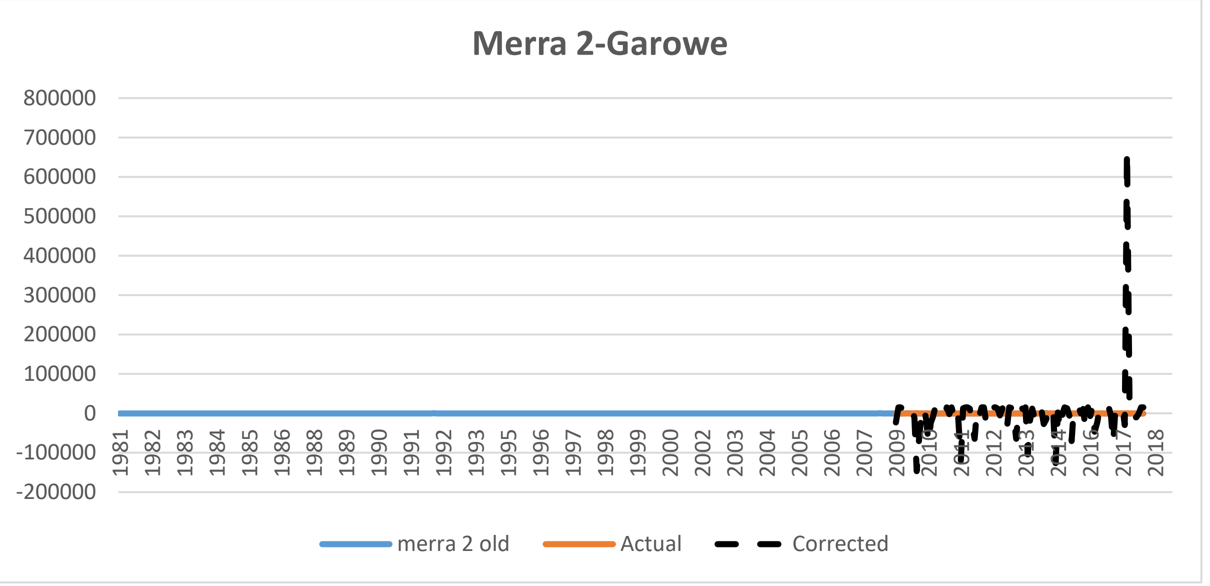
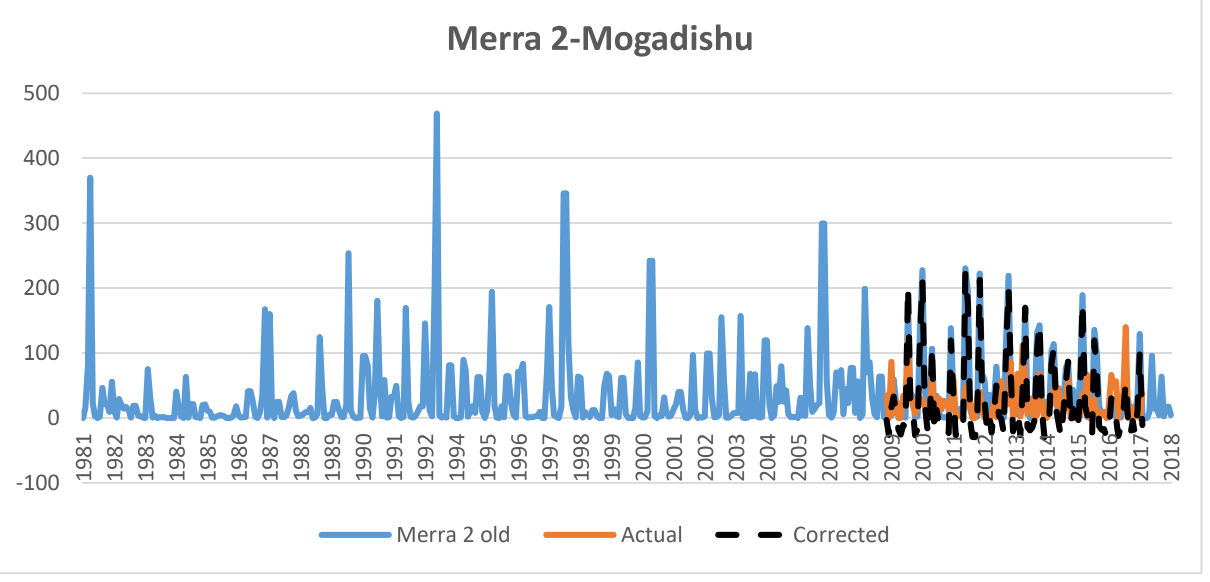


Figure 22

Comparison Between Merra 2 And Actual Data For Mogadishu City



The figures that are given above show the monthly MERRA 2 precipitation for the cities of Berbera, Burao, Garowe, and Mogadishu using actual (measured) data as well as the corrected version of MERRA 2.

CHAPTER V

Results and Conclusion

This chapter will discuss results after training and testing the data using Matlab 2021a

5.1. Training

These models were trained and tested using data acquired over a nine-year period from four different Somali cities around the country. One set of the data is used for training, while the other set is used for testing. Researchers turned to neural networks and neuro-fuzzy systems in order to attain this goal. The precipitation data from 2009-2015 were utilized in the training process for the data from 2016-2017. The MATLAB software, version 2021a, was utilized in Berbera, Burao, Garowe, and Mogadishu for the purposes of data collection, data training, and data testing.

Table 6.

R Squared, RMSE And MSE Of Trained Data For Berbera City

Model	Hiden Layer	Number of Neuron	Function	R2 Training	RMSE	MSE
FFNN	5	28	tansig	0.5884	0.2231	0.020193
Cascade	4	11	logsig	0.60418	0.2536	0.054390
Elman	2	5	logsig	0.551272	0.220888	0.0023832

In table 6, the calculation of Berbera's mean square error was accomplished through the usage of FFNN, Cascade, and Elman Neural Networks. The table makes it quite easy to observe that the best result that Elman has obtained for Berbera is 0.0023832.

Table 7.

R Squared, RMSE And MSE Of Trained Data For Burao City

Model	Hiden Layer	Number of Neuron	Function	R2 Training	RMSE	MSE
FFNN	3	19	logsig	0.43212	0.03673	5.3156e-07
Cascade	4	10	tansig	0.48391	0.053534	2.873e-05
Elman	3	11	logsig	0.013228	0.040524	5.8731e-04

Table 7 illustrates the mean square error that was calculated for Burao by utilizing FFNN, Cascade, and Elman Neural Networks. According to the data presented in the table, the best possible FFNN result for Burao is 5.3156e-07.

Table 8.

R Squared, RMSE And MSE Of Trained Data For Garowe City

Model	Hiden Layer	Number of Neuron	Function	R2 Training	RMSE	MSE
FFNN	4	28	logsig	0.441246	0.23127	0.021120
Cascade	2	6	ogsig	0.567888	0.218968	0.0016201
Elman	2	14	tansig	0.27109	0.258405	0.037133

The mean square error computed for Garowe using FFNN, Cascade, and Elman Neural Networks is depicted in Table 8. The table illustrates that the optimal result reached for Garowe in Cascade is 0.0016201.

Table 9.

R Squared, RMSE And MSE Of Trained Data For Mogadishu City

Model	Hiden Layer	Number of Neuron	Function	R2 Training	RMSE	MSE
FFNN	2	14	tansig	0.268225	0.43312	0.003210
Cascade	2	14	logsig	0.232185	0.53210	0.001002
Elman	4	28	tansig	0.167227	0.290322	0.001817

The mean square error calculated for Mogadishu using FFNN, Cascade, and Elman Neural Networks is displayed in Table 9. The table illustrates that the optimal result for Mogadishu in Elman is equal to 0.001002.

5.2. Testing

In this part of the study, we're going to have a look at the results of our testing of the concept in four different cities. After comparing the Actual and predicted data for the four cities, The Cascade Neural Network produced the best results. In

Mogadishu city the Cascade's R squared and RMSE were 0.668 and 0.232 respectively. In the cities of Garowe and Berbera the R squared and RMSE were 0.751, 0.361 and 0.593, 0.226 respectively. The Cascade NN was at best in Burao city with RMSE of 0.0005074 and Rsquared of 0.566. Cascade Neural Network is more accurate than other NN models when it comes to predicting rainfall.

Figure 23

Comparison Between Actual, Era5 And Predicted Data For Berbera City

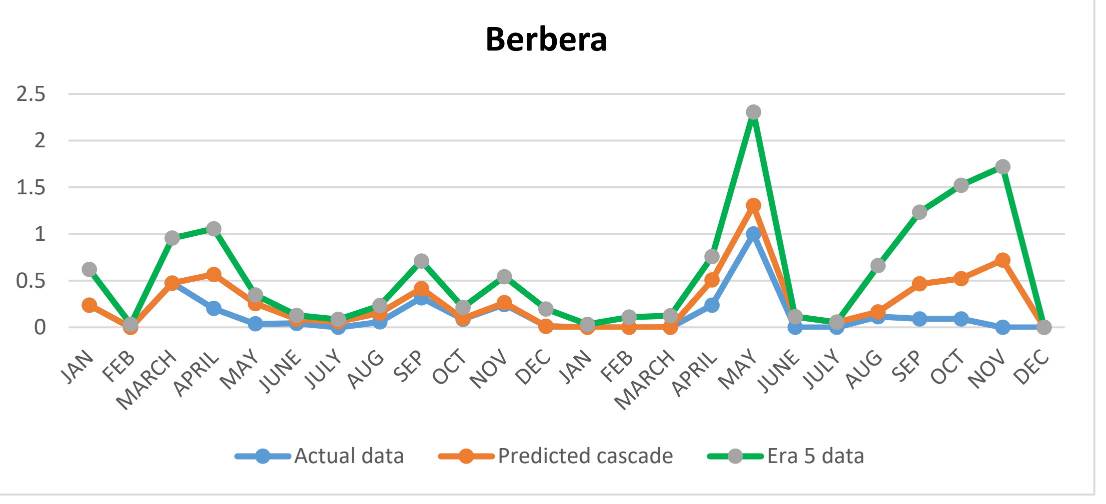
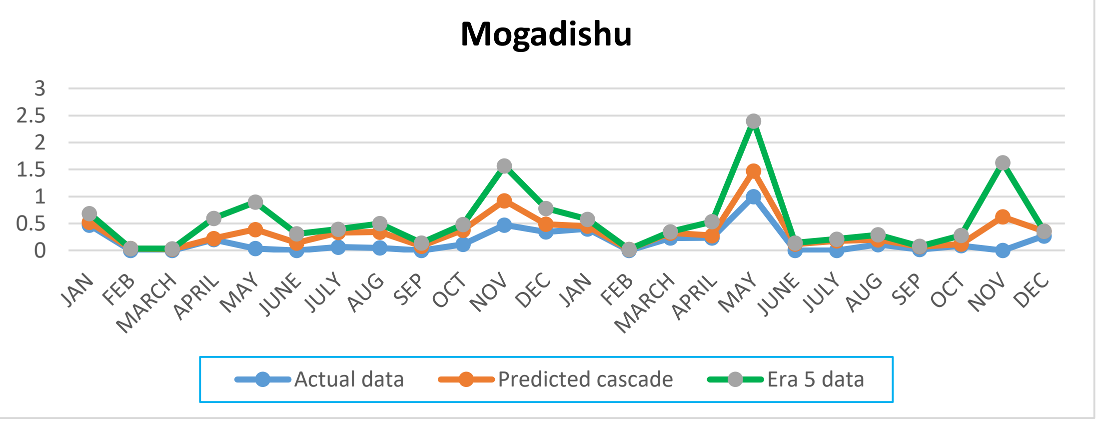


Figure 23. shows a comparison between actual and predicted data for Berbera. In the graph, the actual and forecasted data are shown to have a strong correlation.

Figure 24

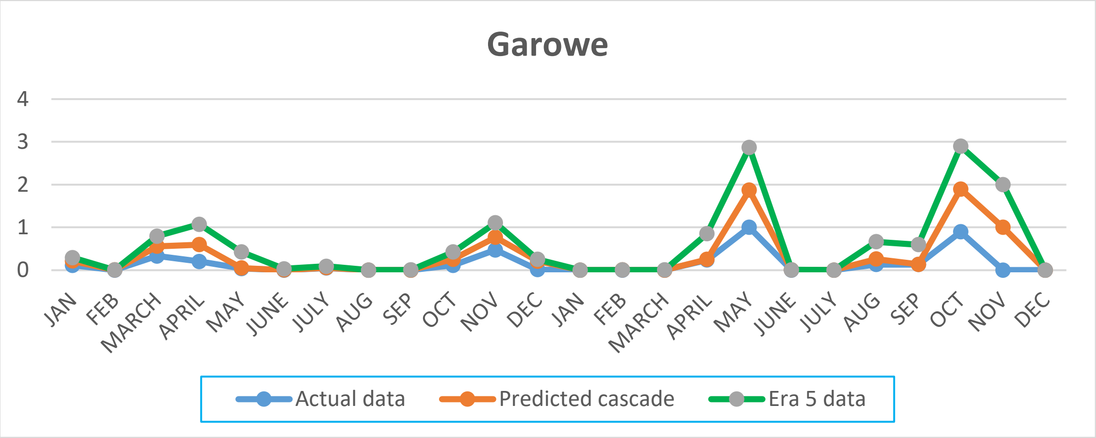
Comparison Between Actual, Era5 And Predicted Data For Mogadishu City



The graph that compares the actual and Era 5 data to the predicted data for the city of Mogadishu is shown in figure 24, which can be found above. The graph illustrates that there is a stronger correlation between the actual, Era 5 and the predictions made by Cascade NN in different way in the case of Berbera. The correlation is good between the months of June-Oct in 2017.

Figure 25

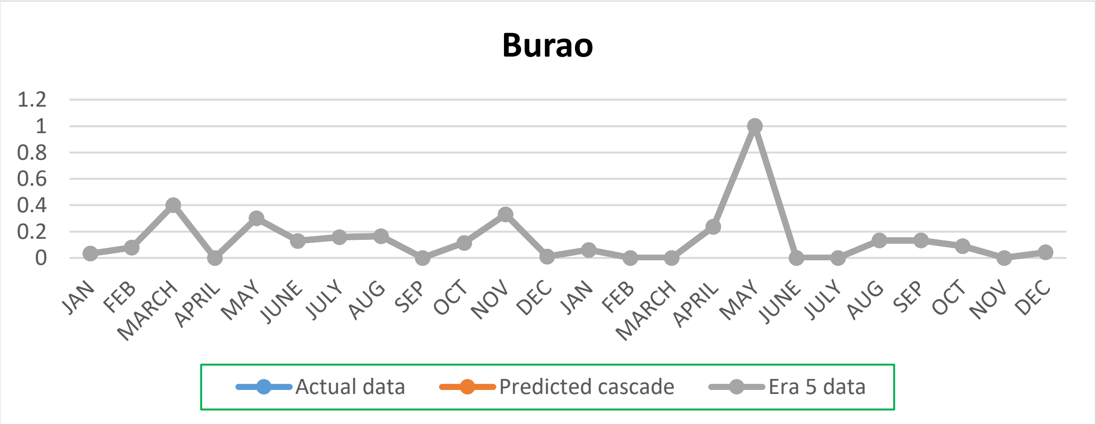
Comparison Between Actual, Era5 And Predicted Data For Garowe City



The graph that compares the actual and Era 5 data to the predicted data for the city of Garowe is shown in figure 25, which can be found above. The graph illustrates that there is a stronger correlation between the actual, Era 5 and the predictions made by Cascade NN in similar way in the case of Mogadishu. The correlation is good between the months of June-Sep in 2016 and between Dec 2016-March 2017.

Figure 26

Comparison Between Actual, Era5 And Predicted Data For Burao City



The graph that compares the actual and Era 5 data to the predicted data for the city of Burao is shown in figure 26, which can be found above. The graph illustrates that there is a strongest correlation between the actual, Era 5 and the predictions made by Cascade NN in different way in the case of other cities. The correlation is best for all month.

Conclusion

The inability to effectively estimate rainfall can have a negative impact on many aspects of water management, including agricultural production, flooding, drought, and long-term water resource management (Emmanuel Gbenga Dada, et al., 2021). As a result of the shifting climatic circumstances, temperatures are rising, and changes in the pattern of rainfall are taking place. Temperature changes, which can also lead to the occurrence of flooding and landslides, have an effect on both agriculture and industry. If people are going to keep living, they have to figure out how to keep this natural phenomenon under control. Water is essential to the survival of humans, and there is no other substance that can serve in its stead.

According to the information presented on this page, the accuracy of precipitation forecasts can be improved by utilizing one of four distinct neural network models. In the course of our inquiry, each of these models was utilized. The results obtained by the Cascade Neural Network model were superior to those obtained by the other three models. As a direct consequence of this, a Cascade Neural Network is the method of choice for forecasting the upcoming precipitation.

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Appendices

Appendix A

Monthly Era 5 for Berbera City

Year	T avg	T mini	T max	Ws max	Not corrected Era 5 rainfall	corrected Era 5 rainfall
2009	23.986861	23.07029	23.98686129	4.10337096	21.7682	29.97474
2009	24.364675	23.398511	24.364675	3.66020714	14.8984	3.2604
2009	25.338819	24.512003	25.33881935	3.21927419	12.0702	115.13
2009	27.378146	26.579413	27.37814667	3.29546333	8.1198	-0.7873
2009	30.019887	28.996174	30.0198871	2.3643	3.8179	1.46496
2009	32.346153	30.93233	32.34615333	4.04938666	0.0052	-3.4401
2009	32.409722	30.477716	32.40972258	8.34022258	0.0583	15.82033
2009	32.308845	30.867403	32.30884516	6.00669354	0.3031	37.8213
2009	31.075083	29.721603	31.07508333	3.12383666	2.7629	15.52094
2009	28.552629	27.371019	28.55262903	2.82202580	21.9989	72.89851
2009	26.553743	25.407773	26.55374333	3.12347666	11.8129	50.05934
2009	25.635219	24.647506	25.63521935	3.78482903	20.6372	24.11018
2010	24.488487	23.357284	24.4884871	4.00718387	5.8344	-3.0727
2010	24.797846	23.9034	24.79784643	3.44035714	46.3739	53.30602
2010	26.032667	25.092261	26.03266774	2.21201290	48.3553	42.1791
2010	28.31834	27.41136	28.31834	2.84240333	39.2075	53.78614
2010	30.703816	29.87291	30.70381613	2.30319354	6.0684	10.17859
2010	32.62662	31.228193	32.62662	6.31104666	0.0007	-11.6373
2010	31.560574	29.687077	31.56057419	9.33459032	3.2079	-8.4301
2010	31.746435	30.106316	31.74643548	7.47196451	7.9896	-3.6484
2010	31.343476	30.063783	31.34347667	3.0326	3.5705	2.67404
2010	29.029232	27.78649	29.02923226	2.65204838	10.38784	13.58773
2010	26.925293	25.76165	26.92529333	3.06686	4.7118	-6.9262
2010	24.606277	23.460871	24.60627742	3.48759677	8.6207	8.45248
2011	23.913651	22.826732	23.91365161	4.14919354	13.2279	2.190698

Table (Continued).

2011	24.159735	23.153371	24.15973571	3.13188928	6.9965	8.1027
2011	25.162961	24.066629	25.16296129	3.08735161	11.6872	32.82
2011	27.31452	26.379783	27.31452	3.12465333	4.3329	12.17532
2011	30.312335	29.275797	30.31233548	2.33133548	11.0443	41.362027
2011	32.44087	31.09758	32.44087	5.20570333	0	-9.99946
2011	32.221480	30.534571	32.22148065	7.69517096	0.6407	9.9396
2011	31.598190	29.843539	31.59819032	5.48095161	8.9901	90.93094
2011	31.256046	29.978927	31.25604667	3.05511666	3.7144	-5.73888
2011	28.267848	26.931516	28.26784839	2.50189677	15.1342	83.6026
2011	27.08917	25.958543	27.08917	2.68950333	13.8897	56.05043
2011	24.908467	23.6912	24.90846774	3.34580322	5.714	1.3584
2012	24.215367	23.075006	24.21536774	3.19692258	14.0747	2.4367
2012	24.28165	23.182154	24.28165	3.61868928	9.7465	-1.8915
2012	25.044003	23.901148	25.04400323	2.99857419	5.6524	-5.9856
2012	27.29651	26.47769	27.29651	3.31183	11.464	20.21672
2012	29.383667	28.20059	29.38366774	2.46695161	27.1885	15.5505
2012	32.308913	30.75086	32.30891333	5.98203666	0	-0.35028
2012	32.209896	30.47031	32.20989677	8.29913548	0.8156	-4.81442
2012	32.332980	30.975768	32.33298065	5.53426129	1.5589	-10.0791
2012	31.567893	30.175123	31.56789333	3.69219	12.099	0.461
2012	27.750732	26.451629	27.75073226	2.50272258	46.979	57.64335
2012	26.325003	25.04779	26.32500333	3.19932333	25.1169	14.75332
2012	25.235719	24.114039	25.23571935	3.11494516	21.3358	31.545
2013	24.651345	23.547545	24.65134516	3.75170322	12.9408	15.77657
2013	24.488889	23.383404	24.48888929	3.63496071	13.9363	2.2983
2013	25.766683	24.87311	25.76668387	3.50846774	31.3068	20.5791
2013	27.885256	26.965423	27.88525667	2.72764333	29.7505	39.14043
2013	30.603938	29.429145	30.60393871	1.80598709	4.5161	46.85889
2013	32.321746	30.70079	32.32174667	7.35421333	0	-11.27388
2013	32.005132	30.024555	32.00513226	10.0181032	1.7571	-6.33073
2013	31.380496	29.97431	31.38049677	5.17877096	3.3951	-5.14788
2013	31.49376	30.26859	31.49376	1.81256666	0.3697	-11.2683

Table (Continued).

2013	29.513745	28.298661	29.51374516	2.25884193	18.2246	49.18864
2013	26.567603	25.40307	26.56760333	2.73458666	174.3813	184.77256
2013	24.737716	23.334261	24.73771613	2.83151935	12.3866	2.5692
2014	24.078351	22.962868	24.07835161	4.00722258	11.3824	-0.2556
2014	24.416575	23.484529	24.416575	3.70268571	9.5357	-2.1023
2014	25.464771	24.586281	25.46477097	3.34499354	9.2799	-2.3581
2014	27.647593	26.78056	27.64759333	3.18801333	8.6713	1.67583
2014	30.072032	29.217039	30.07203226	2.44922903	7.6568	24.2381
2014	31.75541	30.237367	31.75541	5.32799	0.0358	8.4244
2014	32.163809	30.559887	32.16380968	7.91752258	1.2098	-10.4282
2014	31.8308	30.436465	31.8308	5.7089	1.8845	-9.7535
2014	31.842856	30.723913	31.84285667	3.03241333	3.9616	-5.12756
2014	28.336267	26.894745	28.33626774	1.87870322	45.5889	53.0672
2014	26.748466	25.54871	26.74846667	3.1277	22.2784	19.37928
2014	24.983338	23.815213	24.98333871	3.40791612	7.9303	5.03118
2015	24.151877	22.851365	24.15187742	3.18186774	7.2523	1.0761
2015	24.226332	23.176239	24.22633214	3.32475	8.53	-3.108
2015	25.522848	24.490977	25.52284839	3.25687419	33.3049	83.11215
2015	27.382816	26.363043	27.38281667	2.86476333	15.4467	17.28114
2015	30.068538	29.002926	30.06853871	2.15216774	28.2128	74.19679
2015	32.058456	30.727287	32.05845667	4.44162333	2.473	-8.80088
2015	32.377967	30.650355	32.37796774	7.76254516	0.0031	-11.6349
2015	32.493006	30.876119	32.49300645	6.87919032	0.4549	-11.1831
2015	31.599806	30.30167	31.59980667	2.15899	1.9334	0.76385
2015	29.032703	27.737103	29.03270323	2.93955806	34.5702	25.48104
2015	27.019556	25.67519	27.01955667	2.57683	61.472	84.06128
2015	25.571516	24.523955	25.57151613	3.57823548	12.5023	8.1467
2016	24.924464	23.958397	24.92446452	3.76919677	22.1904	40.5923
2016	24.711385	23.581693	24.71138571	3.68561785	4.447	-7.191
2016	26.197041	25.299277	26.19704194	3.28904838	5.3234	53.7652
2016	27.74555	26.994593	27.74555	2.84564333	40.9616	54.99406
2016	30.782664	29.683626	30.78266452	2.4791	7.8411	0.84563

Table (Continued).

2016	32.556023	30.885813	32.55602333	7.01460333	0.1095	-6.0667
2016	32.023477	30.361713	32.02347742	7.83656451	3.572	-8.066
2016	31.620480	29.984968	31.62048065	6.65072903	3.7266	-0.629
2016	32.045316	30.742387	32.04531667	3.37358333	0.016	28.4312
2016	29.483264	28.325223	29.48326452	2.96306774	5.2022	4.4878
2016	26.741313	25.75775	26.74131333	3.12585666	6.8563	26.1685
2016	25.152941	24.081255	25.15294194	2.44229354	23.915	13.64245
2017	24.469119	23.306387	24.46911935	2.63106129	4.3447	-7.2933
2017	24.823235	23.839618	24.82323571	3.90755	14.949	3.311
2017	25.792	24.91129	25.792	3.17524516	16.8157	5.1777
2017	27.636583	26.720957	27.63658333	3.01715	4.3502	22.7521
2017	30.554377	29.661171	30.55437742	2.50284193	9.1735	124.52235
2017	32.68395	31.15691	32.68395	6.55919333	0.0046	-11.6334
2017	32.463183	30.71351	32.46318387	8.93860967	0.2142	-11.4238
2017	32.458606	30.986797	32.45860645	6.73109677	1.1344	4.0612
2017	31.514526	30.347347	31.51452667	2.90819333	12.5386	12.27935
2017	29.101951	27.759958	29.10195161	2.69928709	19.5137	19.25445
2017	26.547663	25.374297	26.54766333	3.05965333	13.6337	1.9957
2017	24.621980	23.423387	24.62198065	3.36979032	0.8429	-10.7951

Appendix B

Ethics Letter

TO THE INSTITUTE OF GRADUATE STUDIES

REFERENCE: ABDIFATAH MOHAMOUD YUSUF (20206191)

We would like to inform you that the above candidate is one of our postgraduate students in Civil Engineering Department. He is taking thesis under our supervision on the thesis entailed: **CORRECTING AND MODELLING MONTHLY RAINFALL BASED ON CLIMATE PARAMETERS: CASE STUDY SOMALIA.** Since the researcher was not collected primary data from humans, animals, plants, or earth, this project does not need to go through the ethics committee.

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

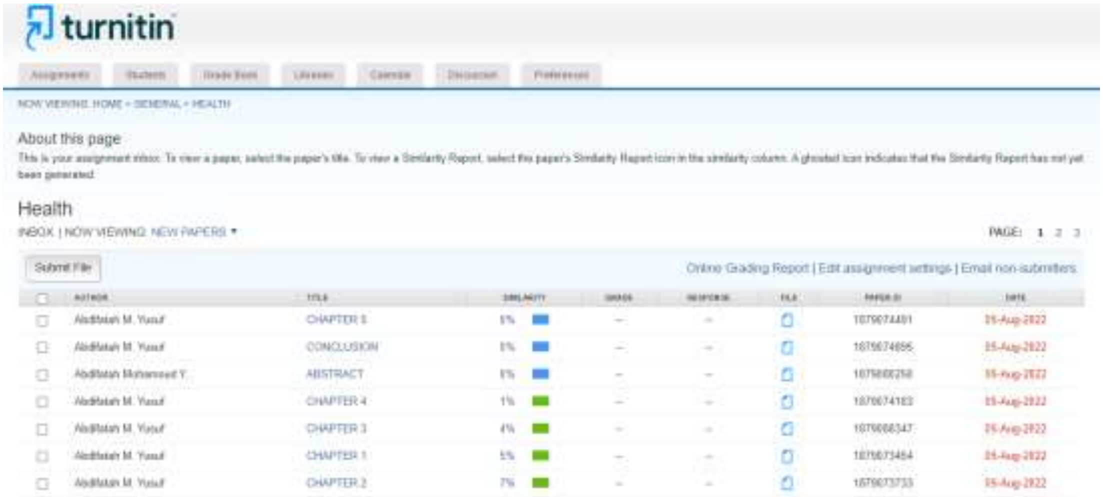
Thank you very much indeed.

Best Regards,

Prof. Dr. Hüseyin Gökçekuş
Dean of Faculty of Civil and Environmental.
Engineering, Near East Boulevard, ZIP: 99138
Nicosia/TRNC, North Cyprus
Mersin 10-Turkey
Email: huseyin.gokcekus@neu.edu.tr

Appendix C

Turnitin Similarity Report



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