**PREDICTION OF DROUGHT IN THE CONTEXT OF CLIMATE VARIABILITY AT CHEMBA DISTRICT IN DODOMA REGION**

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**BSc. Geographical Information Systems and Remote Sensing**

**Dissertation**

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# PREDICTION OF DROUGHT IN THE CONTEXT OF CLIMATE VARIABILITY AT CHEMBA DISTRICT IN DODOMA REGION

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A Dissertation Submitted to the Department of Geospatial Sciences and Technology in Partially Fulfilment of the Requirements for the Award of Bachelor of Science in Geographical information systems and remote sensing (BSc. GIS & RS) of the Ardhi University.

## CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance by the Ardhi University dissertation titled "**Prediction of Drought in the context of climate variability at Chemba District in Dodoma Region**" in partial fulfillment of the requirements for the award of degree of Bachelor of Science in Geographical Information Systems and Remote Sensing.

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| Dr. JOSEPH HAYOLA | Mr. JOSEPH MAZIKU |
| (Supervisor ) | (Supervisor) |
| Date………………… | Date………………… |

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I, NKWAE JUMA S, declare that the contents of this dissertation are the result of my own investigation and research to the best of my knowledge, and that where it is based on the work of others, credit has been given. I also declare that this dissertation has never been presented and will never be presented as part of a candidate's application for a diploma, degree, or other qualification.

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**NKWAE, JUMA S**

25499/T.2020

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# DEDICATION

*This work is dedicated to my dear family (Shaban family) for their support, encouragement, and well-wishes that enabled me get to this point today, which for me represents a higher degree of intellectual performance. My mother, Mwanaidi Saidi Ntandu, for her unwavering love, care, encouragement, financial, spiritual, and moral support, which she continues to provide without delegating the contributions of my beloved wife and my daughters.*

*In the name of Almighty God, I salute all of my Shaban relatives, sisters, brothers and friends, as well as my Islamic members, hostel members, classmates and others from GM and GI in general for their moral and spiritual support while I was attending class.*

# ABSTRACT

Droughts are increasingly impacting societies as they gradually develop over several years, causing significant harm to agriculture. Drought occurrence depends on various factors, including climate conditions like rainfall and temperature. Consequently, GIS and remote sensing-based studies offer great potential for monitoring and mapping drought compared to traditional methods. This study emphasizes the significance of Geographical Information System (GIS) and remote sensing in the assessing drought variability.

This study emphasizes the significance of Geographical Information System (GIS), remote sensing and Cellular Automata (CA) and Artificial Neural Networks (ANNs).

Three Parameters are using in the prediction of drought are Normalized Difference Vegetation Index (NDVI), Normalized Difference water Index (NDWI) and land surface temperature (LST). The combined approach of GIS, remote sensing, CA Markov and Artificial Neural Network reveals that the 30% will experience very high drought, 23.5% will experience high drought, 46.5% will experience moderate drought. The results obtained can be helpful for drought management plans and will help in revealing true drought situation in the area.

## TABLE OF CONTENTS

## LIST OF FIGURES

## LIST OF TABLES

## LIST OF ABBREVIATIONS

| | |
|---|---|
| GIS | Geographic Information System |
| NDVI | Normalized Difference Vegetation Index |
| LST | Land Surface Temperature |
| USGS | United State Geological Survey |
| MODIS | Moderate Resolution Imaging Spectrometer |
| ANN | Artificial Neural Network |
| NDWI | Normalized Difference Water Index |
| NIR | Near Infrared |
| GM | Geomatics |
| GI | Geoinformatics |

# CHAPTER ONE

# INTRODUCTION

## 1.1. Background of the study

One of the most remarkable matters facing the world now is climate variability, which is expected to alter climatic pattern and increase the frequency of extreme weather occurrence (Nam, 2015).

Drought is among the usual climate extreme events that influencing various parts of the world, especially in African countries. It is the most familiar dangerous calamity that affects socioeconomic activities and ecosystem directly or indirectly. Drought leads to different effects like desertification and land degradation, shortage of food, malnutrition, famine, crop failure, mass migration and death. It is also among constituent that enlarge the number of poverty and hunger in different regions especially in Africa (Haile, 2019). Recent studies revealed that there are numerous factors contributed to the occurrence and intensity of drought events which are low precipitation over an extended period of time, excessive water demand. Deforestation and soil degradation, atmospheric condition such as temperature and irregularity of climate which leads to the shift of intensity and frequency. According to Onyutha (2017), the drought frequency, intensity and duration vary from one region to another and the losses induced also vary depending on the drought intensity and duration.

Drought assessment and disaster management centers around the world need timely information to predict future droughts in order to properly plan and warn the public in advance. The African Continent is likely to face extreme and widespread droughts in the future. Numerous studies have been conducted in southern Africa to analyses historical droughts (Michael, 2005).

Vegetation distribution and changes may reflect the long-term effects of drought in the region. Traditional methods of assessing the extent of vegetation coverage and its changes do not provide better time resolution because the assessment is time consuming. Satellite data sensors play a better role in monitoring the relationship between climate and vegetation changes (Wilhite, 2021).

The satellite can cross the survey area in a few days and repeat the survey in the same area at specified time intervals. Integration with results from other datasets (spatial and non-spatial formats) from remote sensing technology has great potential for drought monitoring and assessment (Price, 1990). Remote sensing and GIS play important roles in drought detection, assessment, and management because they provide up-to date information on a spatial and temporal scale (Belal, 2012). Various drought indices are used to predict the drought situation in the area. These include meteorological, soil, satellite-based indices for instance normalized different vegetation index (NDVI) and normalized Difference Vegetation Index (NDWI). The vegetation index-based method is a means of monitoring drought based on the fact that the physiological adaptive characteristics of vegetation change with soil moisture and can be recorded by sensors in the form of spectral characteristics of the vegetation canopy. The Normalized Difference Vegetation Index (NDVI), derived from infrared and near-infrared channels, and widely recognized as one of the most effective indicators of vegetation activity. NDVI's are commonly used to evaluate photosynthesis at the global and regional levels due to their outstanding capabilities with strong vegetation signals and spectral contrast. It is also widely used to depict changes in vegetation coverage to some extent and to monitor and assess vegetation dryness. NDVI is one of the most basic scientific principles-based indicators. NDVI is a well-distributed composite index used to determine the importance of drought conditions (Fernandez, 1995), The Normalized Difference Water Index (NDWI) is a remote sensing index that is commonly used to assess the presence and extent of water bodies or vegetation water content (To minimize problems associated with area targeting, we recommend using in expensive satellite images that are available on a regular basis to help identify the occurrence, duration, and extent of the drought. By providing up-to-date information on the degree and severity of drought, the rating system can limit the impact of drought-related losses. In general, drought can be monitored by either ground observation or remote sensing. Soil observations are a direct and accurate method for monitoring droughts, but it is relatively slow to obtain sufficient information to monitor the entire region. It also costs a lot because it takes a lot of work to get the information you need compared to remote sensing (Dutta, 2018).

## 1.2. Problem statement

Due to global climate variability, the frequency and intensity of droughts have increased, posing a significant threat to water resources in the Chemba District. This has led to a decline in water availability for agricultural and domestic purposes, causing adverse effects on both water quality and the surrounding ecosystem. Moreover, Chemba district predicting the future drought by looking the symptoms happening during and before agriculture activities like appearing of insects and local beliefs which is not giving the correct drought condition of the future and cause the dangerous to the agriculture activities.

By using GIS and remote sensing this research will help people in the society to predict the future drought and offer early warning capabilities, improved water resource management and enhanced agricultural planning,

### 1.3. Objectives

#### 1.3.1 Main objective

To predict drought condition in the context of climate variability at Chemba District in Dodoma Region.

#### 1.3.2. Specific objectives

i. To identify the criteria used to predict drought in the Chemba district.
ii. To identify the spatial extent of drought condition in the Chemba district.
iii. To predict drought condition for the year 2024 in the Chemba District.

### 1.4 Research questions

i. What are the key factors and indicators commonly used to assess drought in Chemba district?
ii How does the severity of drought vary across Chemba district?
iii What is the drought condition of 2024 in Chemba district?

### 1.5 Significance of the Research

The research will useful in

a) Risk Reduction; Drought prediction allows for proactive risk reduction measures, which can help mitigate the social, economic, and environmental impacts of drought. By being prepared, communities and stakeholders can reduce the severity of drought-related problems.
b) Resource Optimization; Drought prediction enables the efficient allocation and management of resources, including water, finances, and manpower. This optimization ensures that resources are used effectively, particularly in regions prone to water scarcity.
c) Environmental Stewardship; Predicting drought helps in the conservation and preservation of natural ecosystems. It allows for more sustainable management of

water resources, reducing the ecological impacts of drought and supporting biodiversity.

### 1.6 Beneficiaries of the Research

Expected users of this research results will include;

a) Farmers and Agriculture; Drought prediction helps farmers make informed decisions about crop planting, irrigation, and resource management, reducing crop losses and ensuring food security.
b) Government Agencies**;** National and regional governments can allocate resources effectively for disaster response and relief efforts, helping communities cope with the impacts of drought.
c) Emergency Services and Relief Organizations**;** Early warnings from drought prediction enable these organizations to plan and coordinate disaster response efforts, ensuring timely support and relief for affected communities during drought conditions.

# CHAPTER TWO
# LITERATURE REVIEW

## 2.1. Definition of drought

Frequent and prolonged droughts in the semi-arid areas of Tanzania are an expected phenomenon under current and future climate change and climate variability (Madaha, 2012; Mkonda and He, 2018; Haile et al., 2019). Under higher emission scenarios, 50–70% of the semi-arid areas of Chemba District in Dodoma, Tanzania, are projected to experience high-temperature-induced maize and bean yield decreases due to increased evaporative demands of the land surface and reduced duration of crop growth (Thornton et al., 2009). By 2050, climate change and variability in Tanzania is projected to negatively affect yields for maize, sorghum, and rice by 3.6, 8.9, and 28.6%, respectively (Rowhani et al., 2011). Drought, food insecurity, and pest and diseases are identified as among the most serious threats to local livelihoods in the central and northern semi-arid areas of Tanzania. The three later can be influenced by the former, which greatly impact on crop production (Temu et al., 2011).

According to Rahman (2016), drought is a complex, natural recurring phenomenon of dry weather and inadequate rainfall and that time people are not having scientifically information to predict the future drought. This occur when the rate of evaporation and transpiration exceeds the amount of precipitation in a region for a period of time. Meteorological droughts are short but recurring natural disasters caused by lack of precipitation.

### 2.1.1 Conceptual and Operational definitions of drought

Conceptual definitions, formulated in general terms, help people understand the concepts of drought. For example, drought is protracted period of deficient precipitation resulting in extensive damage to crops, further resulting in loss of yield. Conceptual definitions may also be important in establishing drought policy (Siburian, 2018).

An operational definition of drought helps people to identify the beginning, end and degree of severity of a drought.

## 2.2. Types of droughts

According to Eslamian (2017), there are four types of droughts there are four types of droughts which are Meteorological drought, Agricultural Drought, Hydrological Drought and Socio-economic drought.

### 2.2.1 A Meteorological drought

Meteorological drought is normally defined through the degree of drought (in comparison to the "normal" or average amount) and the duration of the dry period. The definition of meteorological drought is considered region-specific due to the fact that the atmospheric situations that cause lack of precipitation vary broadly from region to region. For instance, some definitions of meteorological drought specify the duration of a drought based on the number of days that precipitation falls below a certain threshold.

### 2.2.2 Agricultural Drought

The definition of agricultural drought should be able to account for the various levels of susceptibility that plants exhibit from early development to maturity. When plants are planted, a lack of topsoil moisture can hinder germination, lower plant populations per hectare, and lower final yields. Even if the subsoil is lacking at this early stage, the subsoil will be filled during the growth phase or by rainfall if the topsoil moisture is sufficient for the initial growth needs.

### 2.2.3 Hydrological Drought

Hydrological drought is correlated with the effects of precipitation periods (including snowfall) on surface or underground water supply (for instance reservoir, stream, lake water levels, and groundwater). Hydrological drought frequency and severity are often defined at the level of water or river basins. All droughts are due to lack of rainfall, but hydrologists are more concerned about how that shortage affects the hydrological system. Hydrological droughts are normally out of phase or delay the incident of meteorological and agricultural droughts. It takes time for shortages of precipitation to appear in the components of the hydrological system, such as stream flow, soil moisture, groundwater, and reservoir water levels. As a result, these effects are out of phase with the effects of other economic sectors.

### 2.2.4 Socio-economic drought

The supply and demand for some economic products are combined with the characteristics of a meteorological, hydrological, and agricultural drought in the socioeconomic definition of a drought. In contrast to the aforementioned types of droughts, this one depends on supply and demand dynamics in time and space to identify or categorize the drought. Numerous economic commodities, including water, feed, cereals, fish, and electricity, are weather-dependent. Natural climate variations cause water resources to be adequate in some years while being insufficient to meet the demands of both the environment and people in others. When resources are in short supply due to weather-related water limitations, there is a socioeconomic drought.

## 2.3. Indicators of drought

According to World Meteorological Organization (2016), drought monitoring is usually performed on a regular basis at critical times based on the interpretation of some indicators. To quantitatively measure the severity of a drought, the measured parameters are given specific limits or thresholds that do not adversely affect the economy. Several physical indicators of drought monitoring are possible, including Temperature, rainfall or effective soil moisture, the availability of surface water, and the depth of the groundwater. Vegetation coverage and composition, crop and feed production, livestock health, and pest epidemics are common biological or agricultural indicators. The availability of food and feed, changes in land usage, livelihood shifts, and emigration of people and cattle are all examples of indicators that have an impact on the environment.

## 2.4 Impacts of drought

The impacts from droughts are commonly classified as direct or indirect. Reduced crop, range land, and forest productivity, increased fire hazard, reduced water levels, increased livestock and wildlife mortality rate and damage to wildlife and fish habitat are few examples of direct impacts (Panagoulia & Dimou, 1998). The consequences of these impacts illustrate indirect impacts. For example, a reduction in crop, range land and forest productivity may result in reduced income for farmers and agribusiness, increase prices of food and timber, unemployment, reduced government tax revenues because of decreased expenditures, increased crime, and migration (Wilhite, 2021).

Also, the drought impacts are classified as social, economic and environmental.

### 2.4.1 Economic impacts

This involves losing money by individuals, families, businesses and government. Example, low crop yield means farmers lose a lot of money, farm workers have to pay cuts and some may even have to be laid off. Business and industries that manufacture farm products and equipment lose money because farmers won't have money to buy from them.

### 2.4.2 Environmental impacts

Plants, animals, climate, soils, rocks and many others are all affected by drought conditions. Some biotic and abiotic factors recover when the droughts are over, but others never recover again.

### 2.4.3 Social impacts

The social implications of drought are perhaps the most felt, as they directly involve with us and our families. Healthy has a direct link to the water supply of any settlement. Clean and adequate water for drinking and sanitation help to prevent and manage the society from disease.

## 2.5 Satellite based drought indices

Drought indicators assimilate information on rainfall, stored soil moisture or water supply but do not express much local spatial detail. Also, drought indices calculated at one location is only valid for single location. (Katongo, 2020) Thus, a major drawback of climate-based drought indicators is their lack of spatial detail as well as they are dependent on data collected at weather stations which sometimes are sparsely distributed affecting the reliability of the drought indices (Brown and Reed et al. 2002). Satellite derived drought indicators calculated from satellite-derived surface parameters have been widely used to study droughts. Normalized Difference Vegetation Index (NDVI), Normalized difference vegetation index (NDWI), Land Surface Temperature (LST) are some of the extensively used vegetation indices.

### 2.5.1 Normalized Difference Vegetation Index (NDVI)

Tucker first suggested NDVI in 1979 as an index of vegetation health and density (P. Thenkabail et al., 2014). NDVI is a standardized index allowing generating an image displaying greenness (relative biomass). This index takes advantage of contrast of the characteristics of two bands from a multispectral raster dataset – the chlorophyll pigment absorptions in the red band and high reflectively of plant materials in the near-infrared (NIR) band. An NDVI is often used worldwide to monitor drought, monitor and predict agriculture production, assist in predicting hazardous fire zones, and map desert encroachment. The NDVI is preferred for global vegetation monitoring because it helps compensate for changing illumination conditions, surface slope, aspect and other extraneous factors. The differential reflection in red and infrared (IR) bands enables to monitor density and intensity of green vegetation growth using the spectral reflectively of solar radiations. Green leaves commonly show better reflection in the near-infrared wavelength range than in visible wavelength range. When leaves are water stressed, diseased or dead, they become more yellow and reflect significantly less in the near- infrared range, while the difference is most zero for rock and bare soil. The NDVI process creates a single-band dataset than mainly represents greenery. The negative values represent clouds, water and snow and value near zero represents rock and bare soil.

NDVI is defined as

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2,1)$$

Whereby;

NDVI is Normalized Difference Vegetation Index

NIR is Near Infrared band of electromagnetic spectrum

RED is red band of electromagnetic spectrum.

This means that a healthy plant will reflect more NIR and less than visible light. Healthy plant will absorb most of the visible light falling on it for photosynthesis activities. Thus, when you have high value of NDVI you have a healthier vegetation.

**2.5.2 Land Surface temperature**

Land surface temperature (LST) refers to the temperature of the Earth's surface, specifically the temperature of the ground or other materials that make up the Earth's surface (Li & Duan, 2017).

It plays a crucial role in various environmental processes and has significant implications for climate studies, ecosystem dynamics, urban planning, and agriculture, among other fields (Li & Duan, 2017).

Measuring land surface temperature typically involves remote sensing techniques using satellite-based sensors. (Hulley et al., 2019) These sensors capture the emitted thermal infrared radiation from the Earth's surface, allowing the estimation of LST. The thermal infrared band is particularly useful for LST measurement since it corresponds to the wavelengths at which the Earth's surface emits the most energy. The following are steps on how to calculate the land surface temperature (Yu et al., 2017).

i. Digital Numbers (DN) converted to spectral radiance

(Lk)= ML*QCAL +AL ………………………………………………(2.2)

ii. Convert the spectral radiance (Lk) to brightness temperature in Celsius

TB=K2 /In (K1/Lk +1) - 273.153………………………………………(2.3)

iii. Calculate the NDVI of the study area and obtain its maximum and minimum values

iv. Calculate the proportional of vegetation

$PV = Square\ ((NDVI - NDVImin)/\ (NDVImax - NDVImin))$…..(2.4)

v. Calculate the land Surface Emissivity (E)

E = 0.004 x PV + 0.986…………………………………………………….(2.5)

vi. Calculate the land surface temperature (LST)

LST= (BT/1) + W * (BT / 14380) * In(E), W = 10.8 ……………………..(2.6)

LST is influenced by several factors, including solar radiation, atmospheric conditions, land cover type, and land-use changes. Urban areas tend to have higher LST due to the urban heat island effect, where built-up surfaces absorb and re-emit more heat compared to natural vegetated areas (Yu et al., 2017).

Table 2.1; showing k value for Landsat 8

| | |
|---|---|
| K1_CONSTANT_BAND_10 | 774.8853 |
| K2_CONSTANT_BAND_10 | 1321.0789 |

**2.5.3 Normalized Difference Water Index (NDWI)**

The Normalized Difference Water Index (NDWI) is a remote sensing index that is commonly used to assess the presence and extent of water bodies or vegetation water content (Gao, 1996). It is derived from satellite or aerial imagery, particularly those captured in the near-infrared and short-wave infrared bands. The formula for calculating NDWI is as follows:

$$NDWI = \frac{(NIR-SWIR)}{(NIR+SWIR)} \quad \text{……………………………..(2.7)}$$

The concept behind NDWI is based on the fact that water bodies tend to have high reflectance in the near-infrared region and low reflectance in the green region, while vegetation generally exhibits the opposite pattern (McFEETERS, 1996). By calculating the normalized difference between these two spectral bands, NDWI emphasizes the presence of water. The resulting NDWI values range from -1 to 1, with higher values indicating a higher likelihood of water presence. Negative values usually represent non-water features like bare soil or urban areas, while values close to zero indicate a mix of water and other features.

## 2.6. Role of remote sensing in drought assessment

The assessment is often difficult to obtain over large and remote areas. The remote sensing is useful for drought assessment to obtain the data information that is difficult to collect by traditional methods such as field survey and sampling questionnaires (Chopra, 2006). The possible predictions and monitoring of drought disaster requires rapid and continuous data and information generation or gathering. Since disasters that cause huge social and economic disruptions normally affect large areas or territories and are linked to global changes (Katongo, 2020). It is not possible to effectively collect continuous data on them using conventional methods.

Remote sensing tool offer excellent possibilities of collecting continuous data. The remote sensing techniques can be used to monitor the current situation before, during or after disaster (UNDRR,2021). They can be used to provide baseline data against which future changes can be compared while the GIS used as a tool to provide suitable framework for integrating and analyzing many types of data sources required for drought monitoring. The development and advancement in remote sensing technology to address issue like drought detection, prediction, monitoring and assessment have been dealt with very successfully and helped in formulation of plans to deal with this slow onset disaster (Alahacoon & Edirisinghe, 2022).

## 2.7 Artificial Neural Network and CA Markov model

Artificial Neural Networks (ANNs) are a class of machine learning models inspired by the structure and function of biological neurons in the human brain. ANNs are widely used for various tasks, including prediction and classification, due to their ability to learn complex patterns and relationships in data. When it comes to predicting of drought, ANNs can be applied to capture the intricate interactions between various environmental factors that influence drought, such as vegetation cover, temperature, and precipitation conditions.

Several studies have used different types of ANNs to predict drought using satellite data, such as Landsat, MODIS, LST, humidity and Sentinel. In recent years, some of the advanced techniques based on geospatial data with the good spatial and temporal resolution has been used to forecast the drought conditions include the use of Artificial Neural Network (ANN) (Abarghouei et al. 2013; Masinde 2014).

Cellular Automata (CA) is a spatial dynamics model extensively utilized in the examination of land use transformations. It is a well-liked simulation model that treats time and location separately, with interactions occurring locally.

This method finds widespread application in various geographical domains, particularly in forecasting urban development and changes in land use. (Sabree Ali et al., 2020).

## 2.8 Prediction of future drought and validation of results

Prediction of future drought using CA-ANN is conducted to predict the drought of the years to come by using several data sources like LST, Air temperature, NDWI, NDVI, soil moisture, humidity where by the one input used to predict the future drought with the other parameters according to the study.

Validation made by using several years' data to predict the data in raster format that were used and checking its kappa location, kappa histogram and accuracy of prediction where by the percentage of prediction acceptable should at least 50% (Abarghouei et al. 2013; Masinde 2014).

## CHAPTER THREE

## METHODOLOGY

### 3.1. Overview

This chapter outlines the method used to achieve the objectives of this study. The initial step was the selection of the data to be used in the study. Landsat 8 images Satellite data was used to calculate Normalized difference Vegetation Index (NDVI) normalized difference water index (NDWI)and land surface temperature (LST).

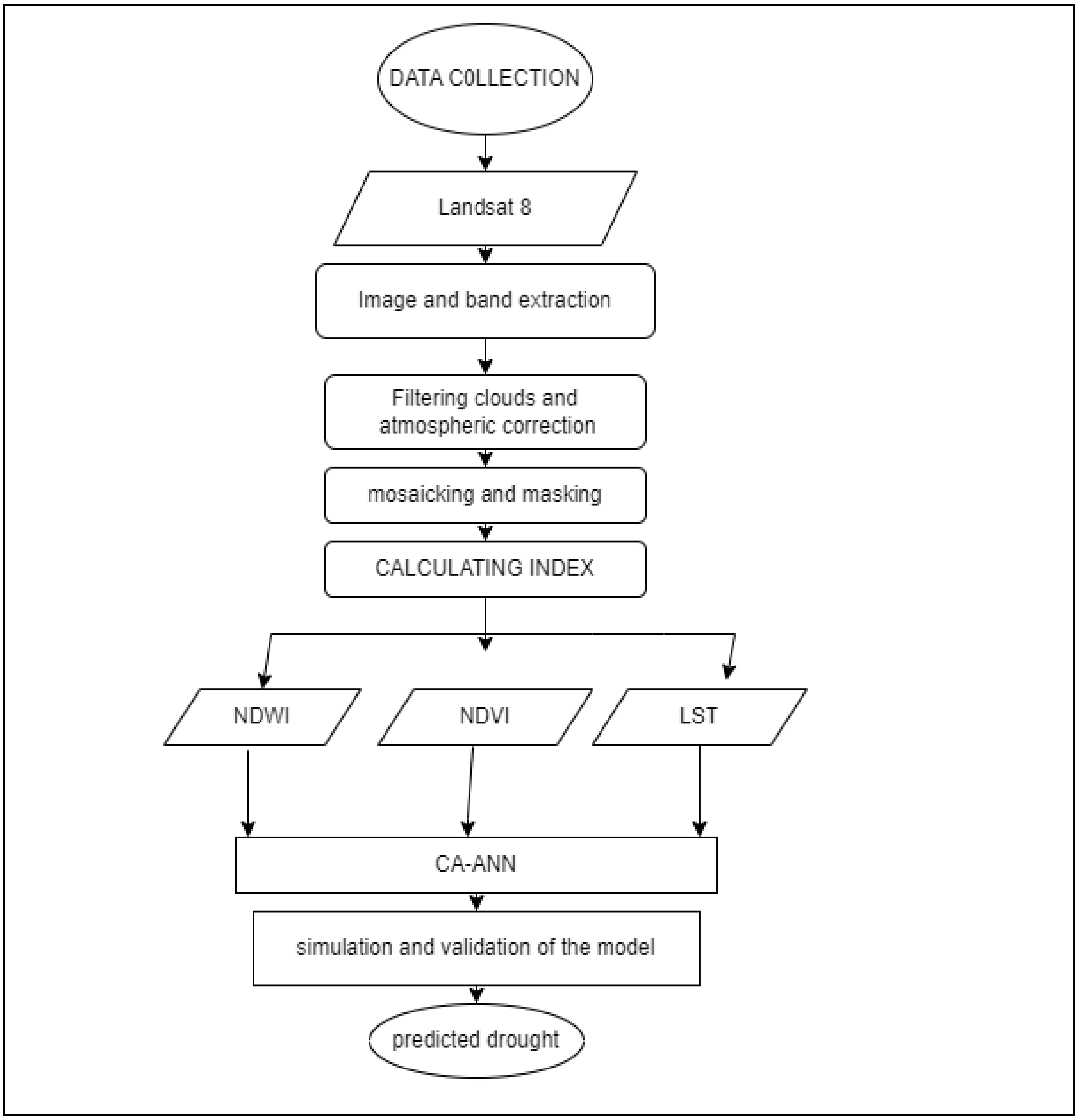


Figure 3.1: Methodology Workflow

### 3.2. Location and accessibility

This study was conducted in Chemba district which is lies between WGS 84-UTM Eastings 750000-85000 and Northings 9350000-9500000 in Dodoma region in Tanzania. A total landmass of 7,653 square kilometers is covered by the district. Kondoa district borders Chemba district to the North, Manyara region to the East, Chamwino district to the south and Singida region to the west. According to the 2022 Tanzania National Census, Chemba district has a population of 535,711 people.

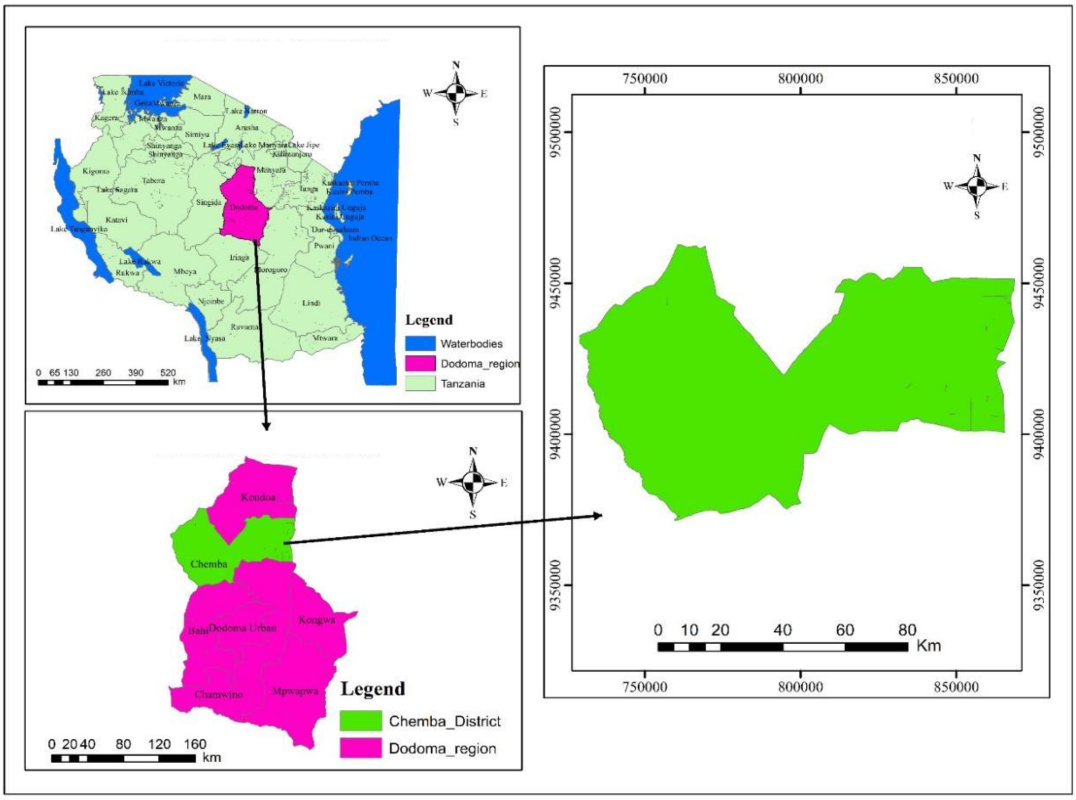


Figure 3.2: Location of the study area and other districts at Dodoma region

### 3.3. Data sources and types

Table 3-1 shows the types of data that are using in the research which Landsat OLI images.

Table 3-1: Characteristics of research data

| DATA | ACQUISTI-ON DATE | FORMAT | SOURCE | USE |
|---|---|---|---|---|
| Landsat 8 OLI image | 2009, 2014 and 2019 | TIFF | (https://glovis.usgs.gov/app) | For calculation of NDVI, LST and NDWI |
| Administrative boundaries | | shapefile | DIVA-GIS (https://www.diva-gis.og) | For extracting the study area |

#### 3.3.1 Remote sensing data

Landsat 8 satellite images were employed in this study as remote sensing data. The USGS National Center for Earth Resources Observation and Science (http://glovis.usgs.gov/) provided these satellite images encompassing the months of 2009,2014 and 2019 with a spatial resolution of 30m.

### 3.4 Pre – processing

Pre-processing involving image pre-processing, atmospheric corrections, which using in the doing pre-processing for the aim of getting different outputs using in the research.

#### 3.4.1 Image pre – processing

In this process, the data was prepared for analysis. The Landsat 8 images which has 9 OLI bands and 2 TIRS bands, four OLI bands were used (blue, green, red and near-infrared bands). The process involved atmospheric corrections which converts DN value to the surface reflectance, mosaicking, projection and clipping the study area.

#### 3.4.1.1 Atmospheric corrections

This process removes the scattering an absorption effects from the atmosphere to obtain surface reflectance characterization of surface properties. Where the dark object subtraction (DOS) technique was added.

#### 3.4.1.2 Mosaicking and masking

Different Landsat image scenes of the area of study are mosaicked together in order to accomplish the area of interest and then masking using Chemba District shapefile to get

### 3.4.2 Extraction of indices

The corrected images were then used to compute various indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Land Surface Temperature (LST).

$$NDVI = \frac{NIR-RED}{NIR-ED}$$ (P. Thenkabail et al., 2014)

$$NDWI= \frac{(NIR-SWIR)}{(NIR+SWIR)}$$ (Gao, 1996)

i. Digital Numbers (DN) converted to spectral radiance

(Lk)= ML*QCAL +AL

ii. Convert the spectral radiance (Lk) to brightness temperature in Celsius

TB=K2 /In (K1/Lk +1) - 273.153

iii. Calculate the NDVI of the study area and obtain its maximum and minimum values

i. Calculate the proportional of vegetation

$$PV = Square\ ((NDVI - NDVImin)/\ (NDVImax - NDVImin))$$

v. Calculate the land Surface Emissivity (E)

E = 0.004 x PV + 0.986

vi. Calculate the land surface temperature (LST)

LST= (BT/1) + W * (BT / 14380) * In(E), W = 10.8 (Hulley et al., 2019).

### 3.5 Validation of the predicted drought

The CA-ANN model was first used to predict the drought for 2019 to ensure the acceptance of prediction result in table 3.2 With the help of the QGIS-MOLUSCE Plugin software, a comparison of the predicted and the estimated maps was established using different kappa parameters. The comparison showed excellent results as all the kappa parameters like kappa location, kappa Histogram and overall kappa. Percentage of accuracy this is used to show the accuracy of prediction by taking predicted map of 2019 with the NDWI of 2019.

Table 3.2: CA- ANN model validation for predicted drought

| **Kappa statistics** | **Kappa location** | **Kappa histogram** | **Overall kappa** | **Percentage of accuracy** |
|---|---|---|---|---|
| **Drought 2024** | Value from -1 to 1 | Value from -1 to 1 | Value from -1 to 1 | Value in percentage % |

#### 3.5.1 Kappa location

This used to assess how well two methods agree on classifying items into categories. The coefficients range from -1 to 1, 1 represent perfect agreement, 0 indicating agreement equivalent chance and negative values indicating agreement less than chance (Abarghouei et al. 2013; Masinde 2014).

#### 3.5.2 Percentage of accuracy

This is used to show how the accuracy of the prediction by comparing to raster datasets of the predicted and one which is available and checking the percentage of accuracy to be more than 50%. This accuracy acceptable and giving chance to predict the drought of 2024.

### 3.6 Prediction of future drought

MOLUSCE plugin tool in the QGIS software for this study was used to predict the 2024 drought distribution by using CA, ANN model. The input module for this study contains dependent variable NDWI distribution and independent variables NDVI and LST. NDWI of 2009, 2014 and 2019 were used to predict 2024 drought map. All the images are converted in the 30 m × 30 m spatial resolution using standardization approach before performing prediction analysis. The CA-ANN model was used to predict drought in the modelling methods stage setting the maximum iteration at 1000. Transition potentials prompt the probability of future drought change using a neural network and include detailing of the descriptive power of driver variables. Predicted drought maps were generated (Abarghouei et al. 2013; Masinde 2014).

# CHAPTER FOUR

# RESULTS, ANALYSIS AND DISCUSSION

## 4.0 Overview

This chapter presents the results, analysis, and discussion of research conducted, providing insights into the achievements of the research objectives. The outputs of the entire study are described here in, utilizing maps to present a comprehensive overview.

## 4.1. Remote sensing indices

The indices derived from the satellite images are discussed which are NDVI, LST and NDWI.

### 4.1.1 Normalized Difference Vegetation Index (NDVI)

The NDVI derived (see Figure 4. 1) shows it ranges between -0.26 to 0.58, -0.155 to 0.73 and -0.15 to 0.59 respectively this shows the condition of vegetation varies from one year to another. NDVI shows that the part of southern of the chemba district having low vegetation cover. This can have a significant influence on plant development in general, resulting in crop failure or poorer crop yield in agricultural regions. Early detection of plant water stress can help to avoid such outcomes.

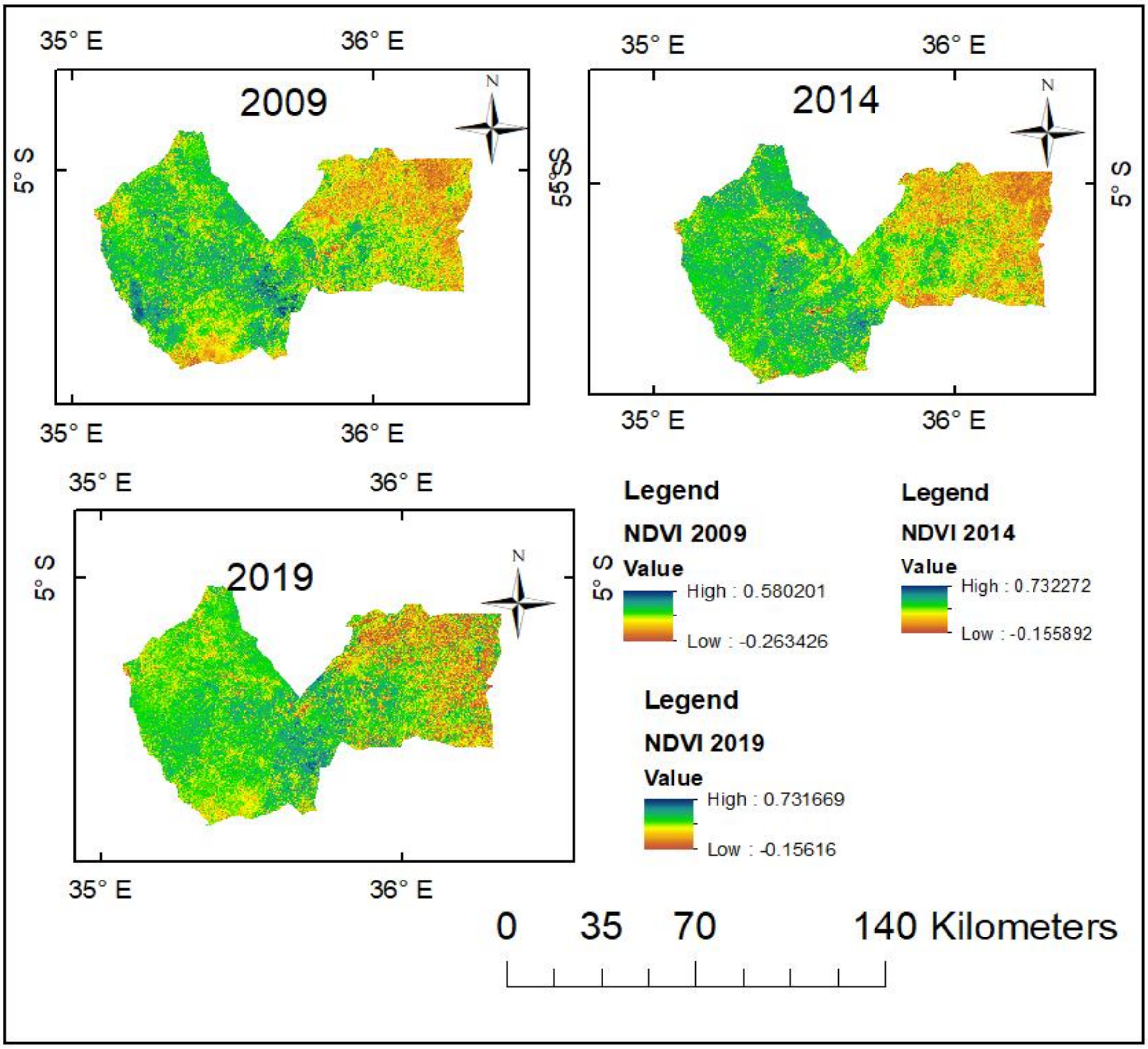


Figure 4.1: A map showing NDVI of 2009, 2014 and 2019

### 4.1.2 Normalized Difference Water Index (NDWI)

The Normalized Difference Water Index (NDWI) has been shown to be highly linked to plant water content. Consequently, the NDWI serves as a reliable indicator of plant water stress. (see Figure 4. 2). Also, water index of the chemba is varies from one year to another which ranges for 2009,2014 and 2019 is -0,8 to 0.54, -0.46 to 0.46 and -0.7 to 0.718 respectively.

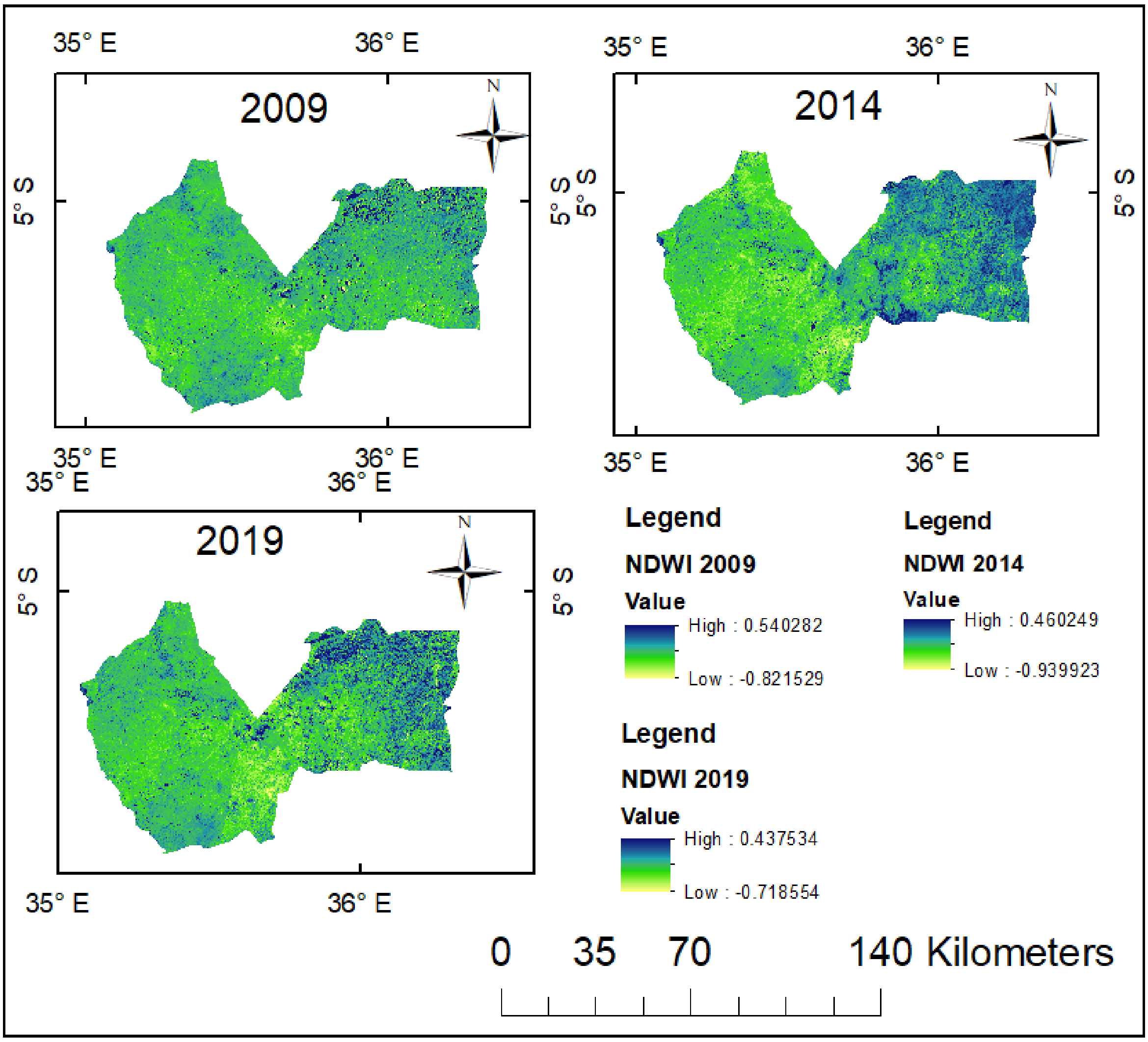


Figure 4.2: NDWI map of 2009, 2014 AND 2019

### 4.1.3 Land Surface Temperature (LST)

Land Surface Temperature (LST) refers to the temperature of the Earth's surface as measured from space or aerial platforms. It plays a crucial role in understanding the thermal behavior of land surfaces and has various applications in environmental studies, urban planning, agriculture, and climate research (Moran et al., 1994). See Figure 4.3. Land surfaces temperature and has various applications in environmental studies, urban planning, agriculture, and climate research (Moran et al., 1994).

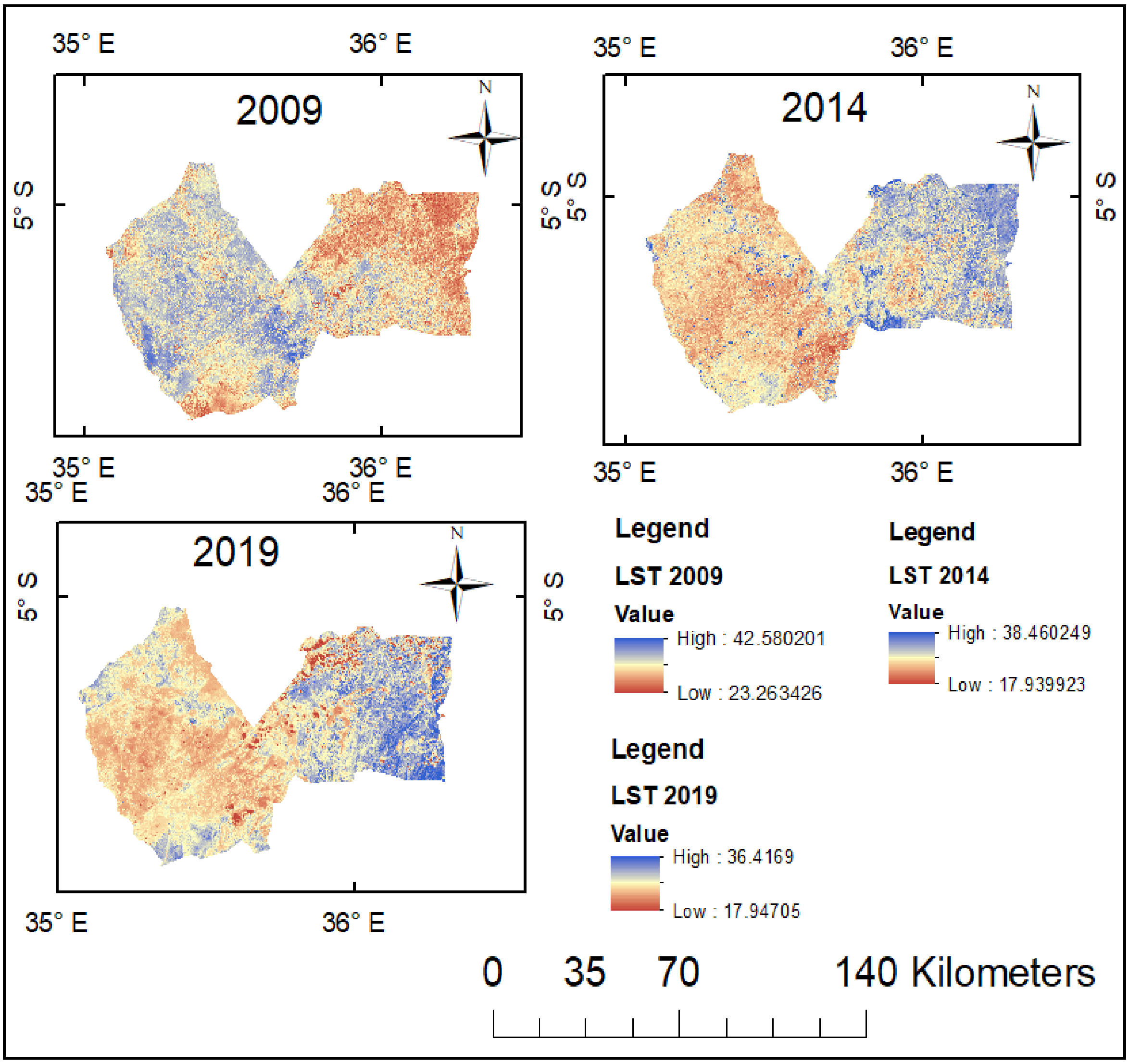


Figure 4.3: LST map of 2009, 2014 AND 2019

## 4.2 Validation of the predicted drought

The CA-ANN model was first used to predict the drought for 2019 to ensure the acceptance of prediction result. With the help of the QGIS-MOLUSCE Plugin software, a comparison of the predicted and the estimated maps was established using different kappa parameters. The comparison showed excellent results as all the kappa parameters like kappa location, kappa Histogram and overall kappa. Percentage of accuracy this is used to show the accuracy of prediction by taking predicted map of 2019 with the NDWI of 2019 as shown at the figure 4.4. The results of the validation is shown on the figure 4.5 which show kappa location, kappa overall and kappa histogram and percentage of accuracy is 60.43% which is acceptable for prediction where percentage of prediction of validation should at least 50% (Abarghouei et al. 2013; Masinde 2014). So that this percentage of prediction were used to know that the prediction of drought will give the good results. Figure 4.4 shows the two maps one is predicted NDWI of 2019 and another one is NDWI for checking validation of the prediction.

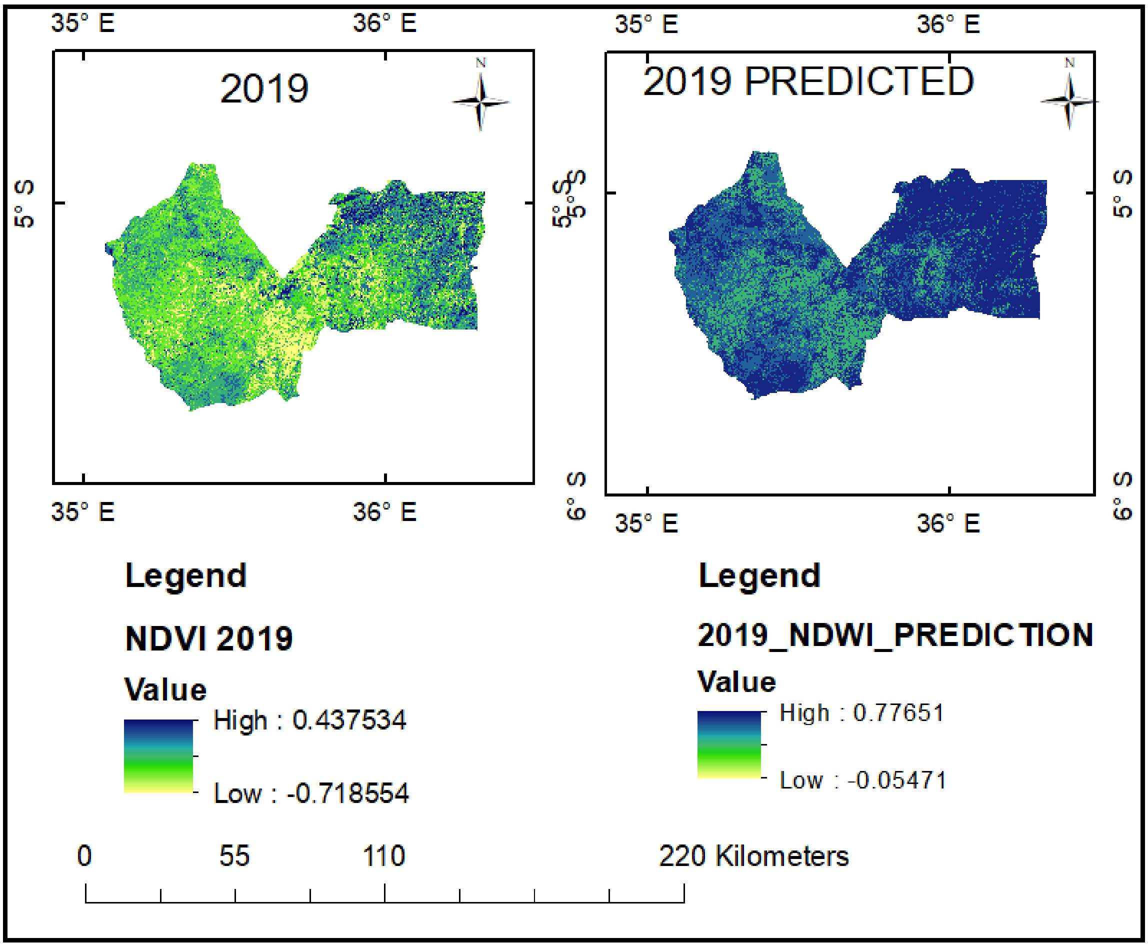


Figure 4.4: NDWI and predicted NDWI map of 2019

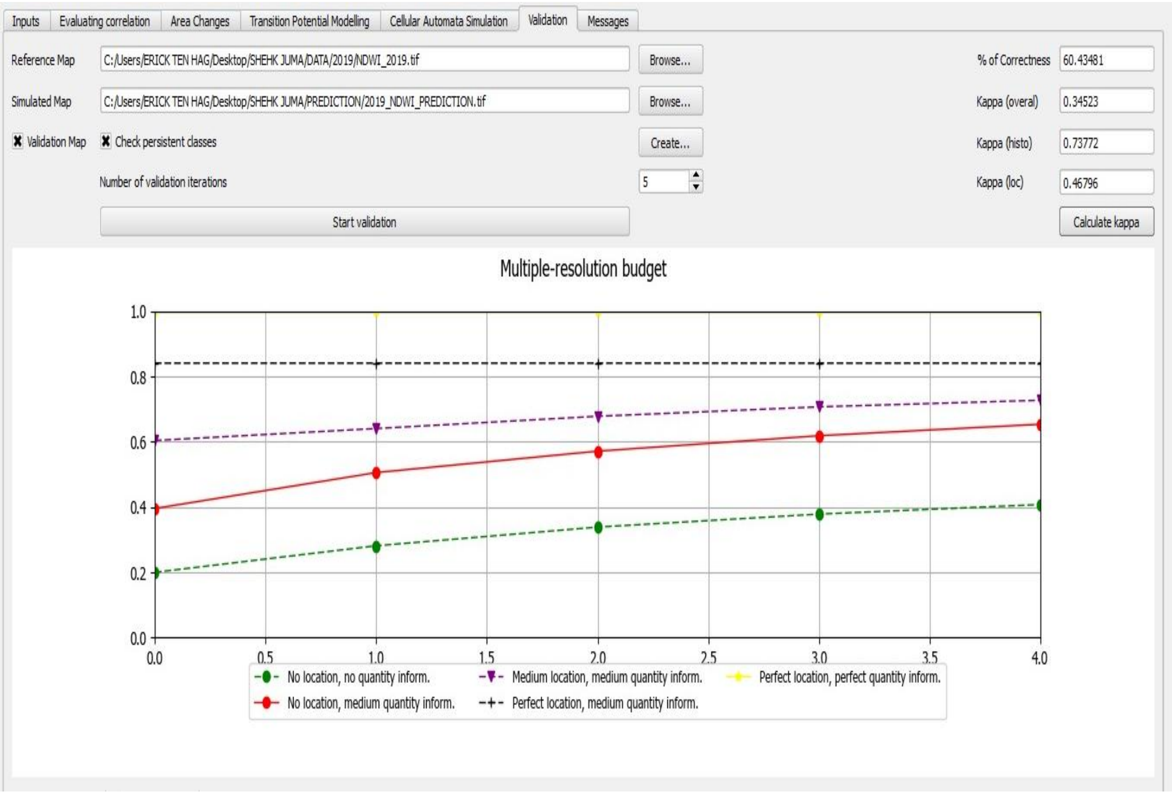


Figure 4.5: Graph of validation of prediction NDWI 2019

### 4.5. Drought Predicted map

After checking the validation, the three identified parameters of the different years 2009, 2014 and 2019 NDWI are used as input where by LST and NDVI are used as dependent parameters in a Geographic Information System (GIS). This generates 9 maps and by using CA-CNN predicted drought condition map for the year 2024 generated, figure 4.4. The predicted map is then divided into five classes representing different levels of drought. The results reveal 30% will experience very high drought, 23.5% will experience high drought, 46.5% will experience moderate drought.

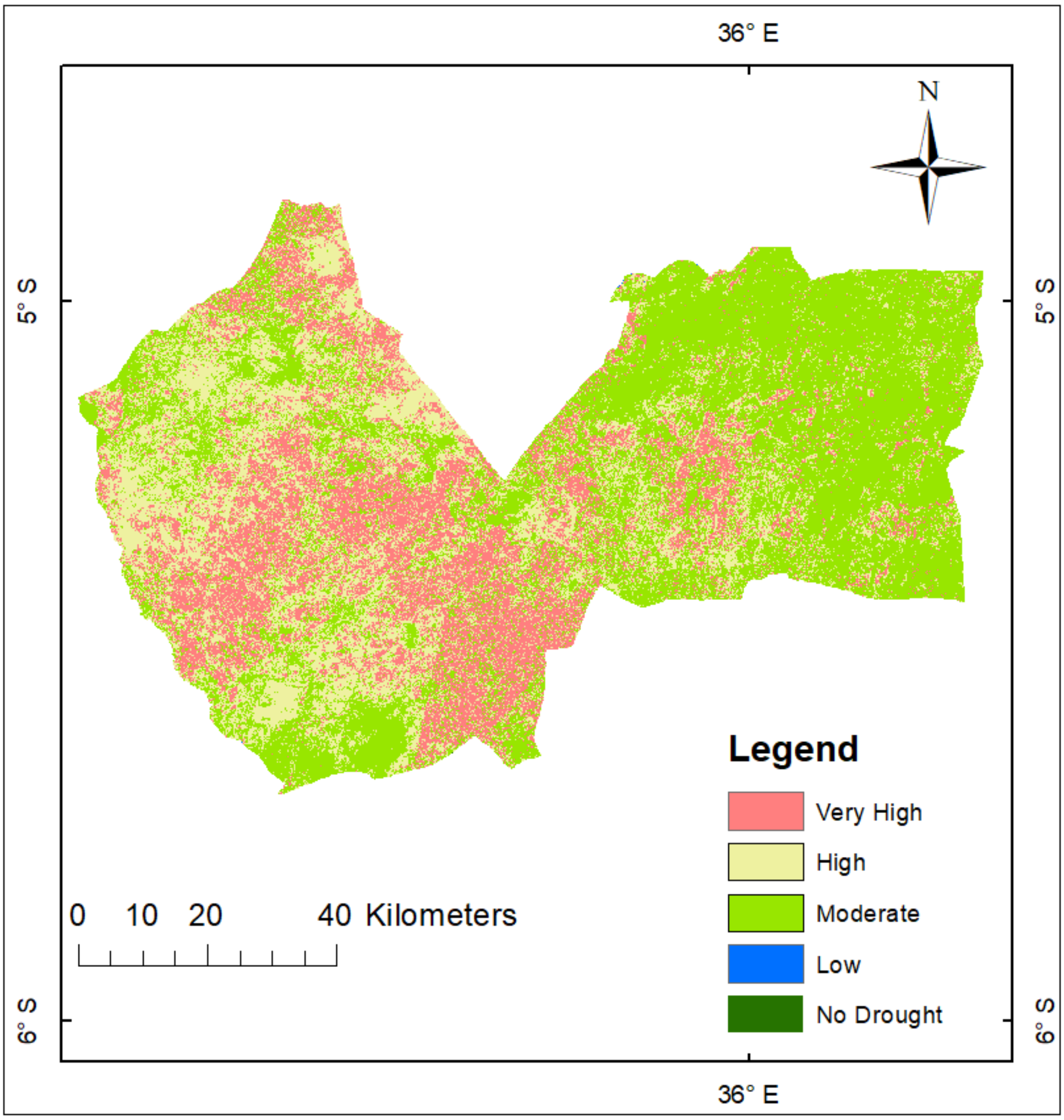


Figure 4.4: Predicted drought map of Chemba District for year 2024

# CHAPTER FIVE

# CONCLUSION AND RECOMMENDATION

## 5.1. CONCLUSION

This work has been carried out for drought prediction in Chemba District, Dodoma Region. Prediction made by CA-ANN. Findings of the study reveal that 30% will experience very high drought, 23.5% will experience high drought, 46.5% will experience moderate drought. The drought predicted according to the NDWI, NDVI and LST. However, limitations of the study include the low resolution of the dataset used and the need for ground truth verification, which is limited due to financial constraints. Therefore, an overall outcome of this study is under moderate drought and the study presents that the risk area can be predicted appropriately by integration of various data sources.

## 5.2. RECOMMENDATION

Based on the results attained, it is recommended that stakeholders to implement a community-based water conservation program. The objective is to address this challenge and promote sustainable water management especially in the affected regions. Also, more research should be conducted using different models and many data sources.

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