AN INVESTIGATION OF DRY SPELLS OCCURRENCE IN ZOMBA DISTRICT FOR AGRICULTURAL APPLICATION

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ABSTRACT

The threat of accelerating climate variability impacts on species and the future are subjects of growing scientific interest. These variabilities are causing harmful effects on agricultural production around the world including Malawi because of its low adaptive capacity. This study investigated the occurrence and impacts of dry spells on maize production in Zomba District in Malawi. Specifically, the study examines the trends in consecutive dry days (CDD) during January and February when the maize development is critical, alongside the temperature and rainfall data for planting and growth season (November to February). A dry day was defined as a day with less than 1mm of rainfall while for investigating dry spells we used the threshold of at least 7 consecutive dry days.

Quality control and cleaning was done on the data set using Jupyterlab and Microsoft excel to determine the frequency of dry spell occurrence, assessment of its impact on maize production and the development of statistical predictive models. Mann-Kendall trend analysis showed no statistically significant trends in consecutive dry days (CDD) during January and February over the study period (2009–2023) as well as in rainfall and temperature, though notable inter-annual variability exists. Correlation analysis revealed a strong, statistically significant negative relationship between January dry spells and maize yield ($r = -0.703$, $p=0.0035$), highlighting the vulnerability of crops to early-season water stress. Predictive models using logistic and linear regression suggested that temperature and rainfall patterns moderately influence the likelihood and duration of dry spells, although their predictive strength was limited. The findings underscore the importance of targeted drought monitoring and the integration of dry spell forecasting in agricultural planning. This research provides valuable insights for enhancing climate resilience, informing policy, and supporting adaptive strategies in maize-dependent farming systems in Southern Malawi.

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ACRONYMS/ABBREVIATIONS

DCCMS – Department of Climate Change and Meteorological Services

CDD – Consecutive Dry Days

UNSDG - United Nations Sustainable Development Goals

EVT - Extreme Value Theory

MLDS – Maximum Length of Dry Spell

AMDSL - Annual Maximum Length of Dry Spell

ITCZ - Inter Tropical Convergence Zone

IDE - Interactive Development Environment

ENSO – El Nino Southern Oscillation

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1. CHAPTER ONE: INTRODUCTION

1.1. Background

Most countries are on high pressure with the drastic results from the impacts of natural hazards, some of which are due to climate change and Malawi is not an exception. Malawi has been experiencing significant variations in weather patterns, ranging from severe drought conditions, extreme flood events, changes in Normalized Difference Vegetation Index (NDVI) and the occurrence of dry spells (Mkandawire, 2014). These changes have various impacts on agricultural production, affecting the people's socioeconomic livelihoods including agriculture. A dry spell is a sequence of consecutive dry days where a day is considered dry if it receives less than a specified threshold amount of rainfall, typically 1mm (DCCMS, 2024), for instance as a condition where there is no more than 2 millimeters of cumulative rainfall for more than 7, 10 or 14 consecutive days. The frequency and length of dry spells are the considered factors for determining the possibility that dry spell will occur and its impact on people especially those in remote areas. The analysis of the probability distribution of dry spell characteristics (occurrence and duration) provides useful information for agricultural and environmental planning and for the management of drought-prone areas, which have always been a concern for researchers (Di Giuseppe, Vento, Epifani, & Esposito, 2005). Dry spells affect not only in agriculture but also other sectors such as fisheries, electricity etc. The fish productivity from fresh water is likely to be stricken by longer dry spells and as well generating electricity using hydroelectric power can also be interrupted by longer dry spells. Generally, the impacts of dry spells on agriculture is pronounced during the planting period in November/December and flowering periods in January/February thereby affecting crop production (Walker & Twomlow, 2011), hence food insecurity.

Malawi has been experiencing dry spells especially in the southern region which have a great impact on agricultural production in districts like Zomba, Chiradzulu, Phalombe, Thyolo, Blantyre, Mulanje, Chikwawa and Nsanje. Most of these areas are highland places that are prone to both El nino and La nina oscillations thereby making them to significantly experience dry spells (Mwafulirwa, 1999). Severe El Nino events occurred in 1877, 1884, 1891, 1899, 1911, 1918, 1925, 1941, 1957, 1972, 1982 and 1986 and very incarnation of El Nino is accompanied by a deficient rainfall virtually everywhere in the world. The extent of rainfall deficiency varies as does the magnitude of the pressure difference leading to El Nino. One major dry spell event was reported by the Ministry of Agriculture that occurred during the 2015–2016 growing season and affected crops in many districts (Government Internal Report, 2016). Understanding characteristics such as dry spell distribution within a rainy season enhances benefits in rain fed agricultural regions and the knowledge of the dry spell characteristics and analysis can be useful for deciding a particular crop variety, supplementary irrigation water demand and drought interpretation (Malvern, et al., 2012). Therefore, through the employing of quantitative analysis and statistical modeling this study intended to identify the frequency distribution of dry spells, assess their temporal variability and investigate potential correlations with climatic indices and maize yield. By incorporating in-situ meteorological data and maize production, through trend analysis, and modelling this research sought to validate and refine its results.

Recent studies highlighted that statistical techniques have the potential in trend analysis and time series modeling when characterizing and investigating dry spell patterns and trends (Ellasy Gulule Chimimba & Bernard Minoungou, 2023). Additionally, this study was done to investigate occurrence of dry spells (length of consecutive dry days) in southern region of Malawi with a focus on Zomba district during the 2009-2023 rainy seasons, using statistical method on historical monthly rainfall data, monthly maximum and minimum data and consecutive dry days (January and February), that was derived from main synoptic stations in Zomba district to assess their impact on maize production. The findings of this study were aimed at contributing valuable insights to policymakers, agricultural

practitioners, and other stakeholders involved in dry spell risk management and adaptation planning in Malawi.

1.2. Problem statement

The southern region of Malawi faces recurrent challenges associated with dry spells particularly Zomba district, which have profound implications for agricultural productivity, food security, and rural livelihoods. These dry spells, characterized by extended periods of below-average precipitation, pose significant risks to rain-fed agriculture, particularly in a region where the majority of the population relies on subsistence farming for their livelihoods like Zomba District (Chipeta, Mwalusepo, Ali, & F. O., 2016). In addition, long dry spells led to heavy costs to the affected communities and the success or failure of the crops, particularly under rainy conditions, is highly related with the distribution of dry spells (Mkandawire, 2014).

However, there is limited research on the dry spell occurrence particularly in the context of Maize production for Zomba district despite its significance on agricultural production for the country and being prone to dry spells. Therefore, since Zomba District is highly vulnerable to dry spell occurrence and being an important agricultural region in Malawi, understanding and predicting impacts of dry spells on Maize production can inform strategies to improve crop resilience and food security. In addition, since climate change is projected to increase the frequency and duration of dry spells globally, making it essential to enhance our understanding of dry spell dynamics and how it impacts the agricultural production in Zomba District.

Hence this study was carried out to address this gap by specifically employing these statistical methods to Zomba District, to comprehensively investigate the occurrence of dry spells and its impact on agricultural production for maize crop. By integrating statistical analysis of meteorological data with maize yield of Zomba, it was possible to enhance our understanding of dry spell dynamics, identify areas of vulnerability and give evidence-based decision-making for dry spell management and agricultural planning.

1.3. Main objective and Specific objective

1.3.1. Main objectives

The main objective of this study was to do an investigation of dry spells occurrence in Zomba district for agriculture application specifically Maize production using observational data from 2009 to 2024 of temperature and precipitation (November to February) and consecutive dry days (January and February).

1.3.2. Specific objectives

- To determine the frequency of dry spells in Zomba district of Malawi during the time period of 2009-2024.
- To relate the impact of dry spells and Maize productivity.
- To develop statistical models for predicting the occurrence and duration of dry spells in the Zomba district.

1.4. Research question

1. How dry spells in vary spatially and temporally?
2. What factors influence their occurrence and intensity?
3. What is the relationship between dry spells and Maize productivity?
4. What growth stages of maize are affected by dry spells?
5. How advanced statistical methods assess impact of dry spells on maize yields?
6. Are statistical model techniques in predicting dry spells in Malawi effective?
7. What strategies mitigates the impact of dry spells on maize production?

1.5. Significance of the research

This research is significant in policy formation and decision making through the provision of a comprehensive analysis of dry spell dynamics in Malawi, thus to inform evidence-based policy and decision-making processes at the local, national, and regional levels. This research is going to enhance agricultural resilience through the insights gained from the research findings thereby contributing to the development of targeted adaptation strategies aimed at enhancing agricultural resilience to drought and climate variability.

In addition, this study is significant in supporting Sustainable Development Goals by addressing the impacts of dry spells on food security, water resources, and rural livelihoods aligns with the United Nations Sustainable Development Goals, particularly Goal 2 (Zero Hunger) and Goal 13 (Climate Action).

Fourthly, it is helpful in building capacity and collaboration through collaborative research partnerships and stakeholder engagement since this study seeks to build local capacity in climate resilience, remote sensing, and geospatial analysis, fostering knowledge exchange and innovation within Zomba district.

Finally, the study is helpful in promoting environmental sustainability by identifying environmental drivers of dry spells and their impacts on ecosystem services, thereby contributes to efforts aimed at promoting sustainable land management practices and biodiversity conservation in Malawi.

2. CHAPETER TWO: LITERATURE REVIEW

2.1. Introduction

This chapter provides a review of the literature on the dry spell occurrence and different statistical methods that other researchers employed in their various studies. The objective of this review was to uncover what was already researched thereby helping to identify key gaps in the research area under study.

2.2. Global and local context of dry spell occurrence

According to Mathugama and Peiris in 2011, proposed that dry spell is based on the length of the consecutive dry days observed although the definition of a dry spell may vary depending on the aims and methodology used in each study. They stated that minimum number of consecutive dry days required to define a dry spell has to be identified in a meaningful manner depending on the practical problem (Mathugama C. & Peiris, 2011)

An extended stretch of at least 15 days in which no day recorded more than 0.1 mm of rainfall was referred to as a "dry spell" in British rainfall records in 1919 (Douguedroit, 1987). But according to Mathugama and Peiris (2012), it was proposed that, based on the deemed practical issue, the minimum number of consecutive dry days required to constitute a dry period must be determined in a reasonable way (Mathugama S. & Peiris, 2012). These dry spells have been classified into two categories as Meteorological and Agricultural (Falkenmark & Rockstrom, 2009). The Falkenmark and Rockstrom identified meteorological dry spells as those that occur less than two times in three years due to lack of rain fall for 2 to 5 weeks, resulting in reduction of agricultural yield. On the other hand, Falkenmark and Rockstrom identified agricultural dry spells as those that occur more than two times in three years due to poor rainfall leading to low plant availability and poor water uptake capacity by plants, thereby resulting to complete crop failure.

Dry spells have profound impacts on crop growth, water availability, and food security. In Malawi, where rain fed agriculture is the primary livelihood for the majority of the population, dry spells can lead to crop failures, reduced yields, and food shortages, causing poverty and malnutrition (Tilya & Mhita, 2006). In addition, during dry spells, soil moisture levels decrease, making it difficult for crops to access water for growth and development. This can result in stunted growth, wilting, and ultimately crop loss since dry spells can lead to water shortages for irrigation, further increasing the vulnerability of agricultural systems (Hao, 2015).

A minimum of 10 consecutive dry days can create water stress in many crops, which lowers production. This is based on study findings about the impact of dry periods on soil depth and retention capacity (Kumar, 2009). Water stress can occur in less than seven days for crops with shallow roots in low water-retaining soils. In high water retention soils, deep-rooted crops may withstand considerable water stress for approximately 15 days. Furthermore, research indicates that the first 30 days of a crop's life cycle are when dry spell induce the greatest amount of water stress (Samba, 2012).

The analysis of dry spells is normally done based on two variables namely Maximum Dry Spell Length (MDSL) and Number of Dry Spell Periods (NDSP) (Samba, 2012). Already several researchers have done some work towards analyzing trends in dry spells using these variables. For example, Mkandawire (2014) analyzed historical climate data to identify trends in dry spell occurrence in different regions of Malawi. He found that dry spells are occurring but they do not have significant trends since out of the 10 stations studied and out of three threshold categories used, only one station and one category showed a significant decreasing trend. He also found that dry spells have become more frequent and prolonged in recent decades, particularly in southern and central regions, posing significant challenges to rain fed agriculture.

Despite these contributions, gaps remain in our understanding of the complex interactions between climate variability, agricultural practices, and socio-economic factors in determining vulnerability to dry spells in Malawi. Therefore, this research project seeks to advance knowledge of dry spells and inform evidence-based strategies for enhancing

agricultural resilience and food security in Malawi particularly Zomba district. Therefore, this was achieved by determining frequency of dry spell occurrence, assessing the impacts of dry spells on maize crop production, and by the development of statistical models for predicting the occurrence and duration of dry spells in the southern region of Malawi.

2.3. Statistical methods used in dry spells analysis

Time series analysis techniques such as autoregressive integrated moving average (ARIMA) models has been widely used to characterize the temporal variability of dry spells. For example, in 2017, Smith used ARIMA to characterize the temporal variability of dry spells and its models to enable the identification of trends, seasonality, and autocorrelation within dry spell data (Smith, 2017). In a study by Nnoli et el in 2020, they used the Mann-Kendall (MK) test and wavelet spectral methods in detecting the trend of dry spell occurrence in the series. Then to estimate the magnitude of the trend they used the Theil and Sen's slope estimator, and they used the inverse distance weighted interpolation technique to represent the spatial trend (Nnoli, Ahmed, Jerome, & Agele, 2020).

The study by Li Yi (2019) employed an Extreme Value Theory (EVT) to model the distribution of extreme dry spell events, thereby providing insights into their frequency and severity. He founded that by estimating the tail distribution of dry spell durations, the EVT is able to facilitate the assessment of the probability of occurrence of severe and prolonged dry spell (Li, 2019). In addition, while evaluating rainfall spells, a threshold for classifying wet and dry days is required because the frequency distribution of spell length is dependent on the threshold chosen since the rainfall time series is characterized by rainy and dry period. However, according to Mengistu in 2020 various thresholds have been employed globally based on the aspect of the spells that required to be evaluated. As a result, in 1990 Reddy used a threshold of 3mm per day, which is the lowest rainfall depth threshold value for crops to satisfy their crop water requirements during a growing season while in 2004, Cenallos et el employed a criterion of 10 mm daily rainfall for wet and dry spells (Mengistu, 2020).

Li Yi (2019) also proposed that by modeling the tail distribution using Extreme Value Theory (EVT), researchers can assess the likelihood of extreme dry spell events of varying

magnitudes and durations, even in regions with limited historical data. And one of the key advantages of EVT in dry spell analysis is its ability to provide robust estimates of the probability of extreme events which are essential for assessing the risk and impact of severe dry spells on water resources, agriculture, and ecosystems. He later concluded that by understanding the frequency and severity of extreme dry spells events, decision-makers can implement appropriate mitigation and adaptation measures to minimize their adverse effects.

A study by Jones (2018), used a Markov chain analysis which is a mathematical model that describes a sequence of events where the probability of transitioning to a future state depends only on the current state and not on the sequence of events that preceded it, thus applied to study the stochastic nature of dry spell occurrence. Through analyzing the transition probabilities between dry and wet states, he used Markov chain models to offer insights into the persistence and duration of dry spells (Jones, 2018). Then he concluded that Markov chain analysis in dry spell analysis is simple and flexible since is suitable for both, short-term and long-term assessments of dry spell and risk.

In addition, Adane et el in 2020 found out that analyzing the probability of the occurrence of dry or wet spell rainfall using the Markov chain model is essential to determine the relative chance of occurrence of a given rainfall to characterize a rainfall period as a dry or wet spell (Adane, Birtukan, Chul-Hee, & Woo-Kyun, 2020).

2.5. Impact of dry spell on crop production

According to the study by Chen and Eklundh in 2004, they proposed that the occurrence of dry spells is mostly negatively correlated with agricultural yields especially in semi-arid regions. The consensus behind was that rainfall appears to be the direct cause of year-to-year variability of crop yields since dry spells are periods characterized by significantly reduced or absent rainfall over a defined region and time period (Chen & Eklundh, 2004). Consequently, Asfaw in 2014 examined the impacts of dry spells on maize production in Malawi using crop modeling techniques and his findings indicated that prolonged dry spells during critical growth stages can lead to substantial yield losses thereby highlighting the vulnerability of maize production to climate variability.

In addition, a study by Chaim et. el in 2020 in the Burkinabe Sahel, found that growing corn poses a climate risk, particularly during the mid-season, which is the most vulnerable time of year. Therefore, they concluded that in order to minimize production losses and guarantee food security, an adaptation scenario must be established to prevent water shortfall and one option to reduce this climate risk was to analyze the distribution of dry spells during the agricultural season which would enable the determination of the best time to plant maize (Doto, Dial, Malicki, & Hamma, Statistical Study of Dry Spells and Their Impact on Rainfed Corn in the Burkinabe Sahel, 2020).

The study by Doto et. el in 2015, pointed out that six-day dry spell is enough to deplete half of the soil's water store on the most tillable soils which greatly impacted the physiology of maize and its production particularly when water stress occurs during a dry sequence lasting longer than seven days. However, they found that if the soil water content at the start of the series is identical to the water content at the field capacity, then the occurrence of dry spells lasting five to seven days will not have an impact on maize output. Then they concluded that the only supplementary option for irrigation was to concentrate on mid-season in order to replace the rain during those extended dry periods during the most vulnerable maize development stage (Doto, Dial, Hamma, Agbossou, & Lahmar, 2015). However, the statistical analysis of the agricultural season conducted in this study revealed that the sowing strategy of supplemental irrigation would emerges climate risk for rain fed maize farming since it reduces the risk of water stress during the most sensitive period of maize (mid-season), with an observed probability of about 80% for dry spells of more than security.

Furthermore, Gao et al. 2019 found that the most critical and vulnerable growth stages for maize crop in terms of dry spell occurrences are the germination and flowering. According to them the maize crop variety, planting date, and temperature all have a significant impact on the crop's first stage (germination) since many crops, including maize, achieve effective full cover at the start of blooming (Gao, Chen, Xu, & Simelton, 2019). According to Allen et al. (1998) the pollination time from tasseling to blister kernel stage > before tasseling > grain filling period is the important period for soil water stress for maize crops. And they

found that if there is no previous water stress, the pollination time is extremely important (Allen, Pereira, Raes, & Smith, 1998).

Mugalavai et al. (2012) evaluated dry spells severity throughout sensitive growth phases (germination and flowering) for maize crop in Western Kenya. With probabilities ranging from 0 to 65% and 0 to 56% for the 7 and 10 day durations, respectively. However, the germination stage dry spell severity was greatest towards the northern portion of the Lake Victoria Basin and around the lake coasts with a 5mm daily rainfall threshold. The likelihood of dry spells during the flowering stage varied from 0 to 73% and 0 to 65%, with the northern part of the Lake Victoria Basin and the area surrounding the lake features experiencing the highest severity and the microclimatic rainfall threshold having the lowest, lasting 7 to 10 days.

3. CHAPTER THREE: METHODOLOGY

3.1. Introduction

The chapter outlines the methods that were employed to carry out the study. It began by providing the description of the area of focus in terms of population, climate and its topography, followed by the materials and data collection methods used. Lastly, the chapter explained the data analysis methods that were adopted to achieve objectives of the study.

3.2. The study area

Zomba district was our area of focus in this study of investigating the occurrence of dry spells for agricultural application. It is located in the Southern Region of Malawi, bordered by Chiradzulu, Blantyre, Mulanje, Phalombe, Machinga, Balaka, and the Republic of Mozambique to the east. As shown in figure 1. The overall land area is 2,363 square kilometers, with a total population of 746,724 (Torrance, 1972). The district's main agricultural operations are the production of tobacco and cotton cash crops, as well as maize, rice, beans, and other pulses.

Zomba District in Malawi is located at about 15.3833° S latitude and 35.3333° E longitude. Being in the Southern Hemisphere, its located south of the equator adding to its subtropical climate (National Planing Commission, 2024). This latitudinal location affects the duration of daylight hours and the angle of the sun, which later affects temperature fluctuations throughout the year. The Inter Tropical Convergence Zone (ITCZ) also influences climate of Zomba District, as it does throughout Malawi (Samba, 2012). During the wet season, which runs from November to April, the ITCZ brings heavy rain and high humidity to this area, making this time to be distinguished by high temperatures and lush greenery (Mkandawire, 2014).

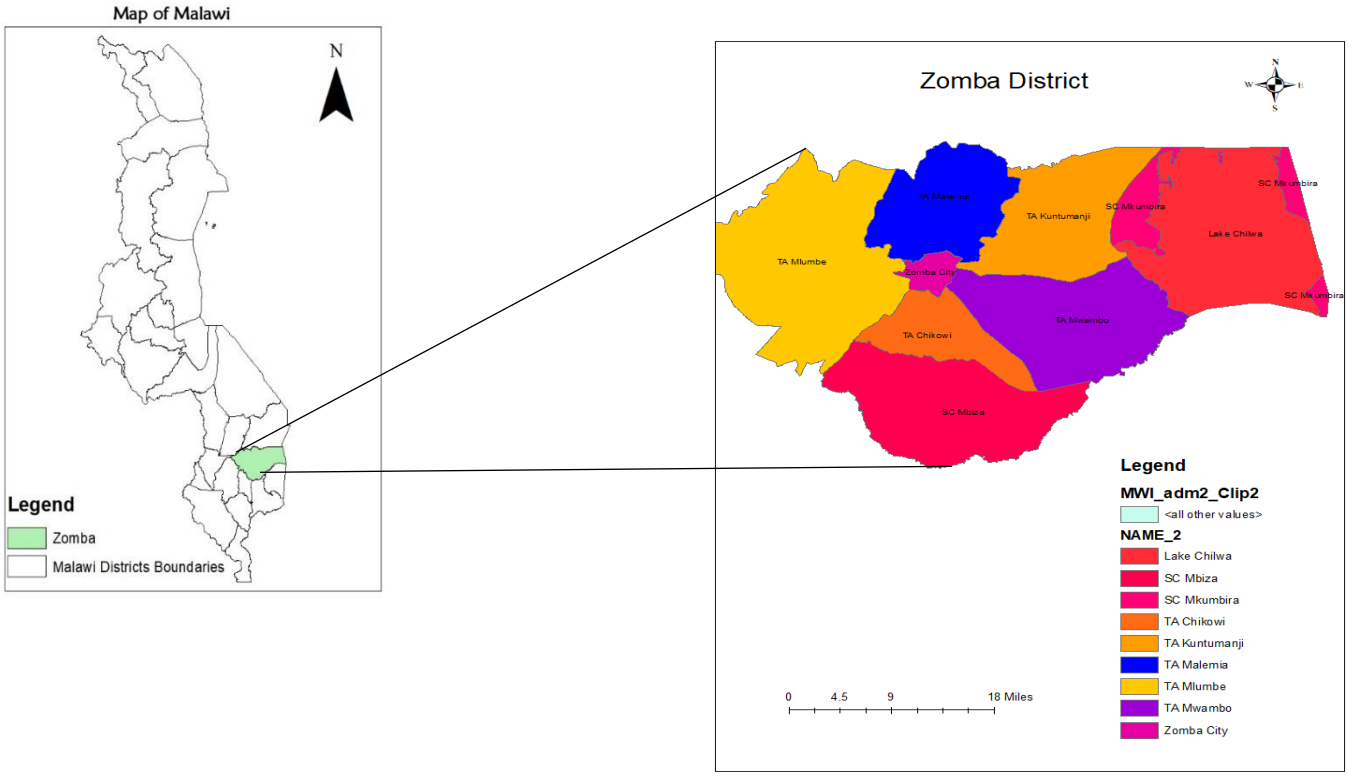


Figure 1: Map of Malawi District Boundaries and Zomba district

The systems in southern region of Malawi interact with local topography and wind patterns to determine the distribution and intensity of rainfall in the Southern region of Malawi. The timing and strength of these systems can vary from year to year, influencing the overall climate and weather patterns in the area.

3.3. Research Design

This research study used a quantitative research technique to investigate the impacts of the dry spells on agricultural productivity in the southern region of Malawi. Quantitative research design refers to a systematic approach for investigating phenomena through the collection and analysis of numerical data. This research design is used to test the hypotheses, establish patterns and make prediction.

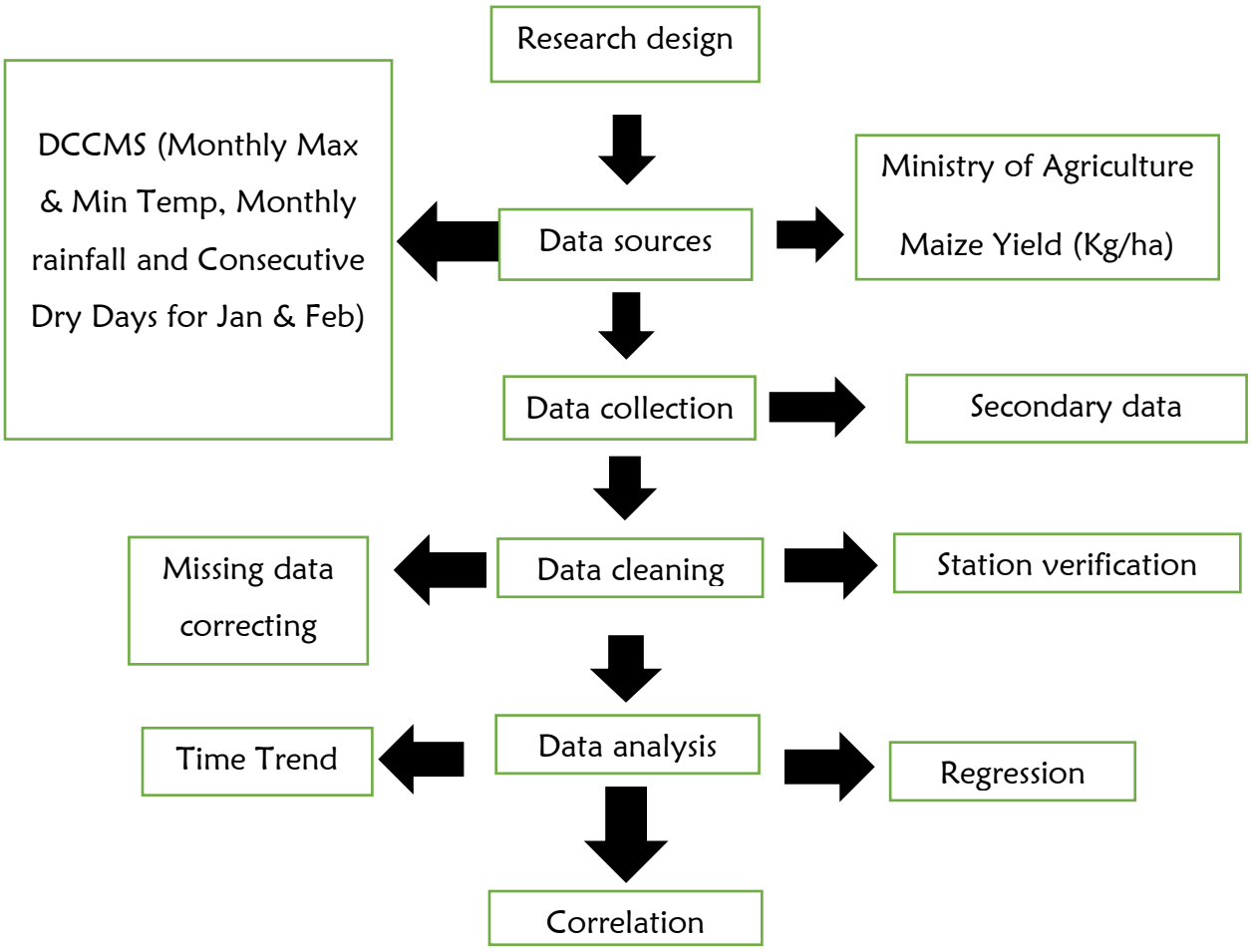


Figure 2: Methodology flow chart

3.4. Data sources

This study involved quantitative data collection of secondary data, which is the data that was collected for other purposes, thus Monthly maximum and minimum temperature data, Monthly rainfall data (November to February), and Seasonal characteristic data which contained consecutive dry days (January and February) was collected from the Department of Climate Change and Meteorological Services (DCCMS). Maize yield data was collected from the Ministry of Agriculture to provide a comprehensive understanding of the investigation of dry spell occurrence impacts on its productivity.

3.5. Data collection Methods

The Secondary data for this study was collected from DCCMS, for Zomba district both Monthly maximum and minimum temperature and Monthly rainfall data (November to February), and the seasonal characteristic data which contains CDD (January and February), rain start-end dates, Seasonal length and Annual Rainfall. This data was basically from two significant man-made weather station and automatic weather station at Makoka and Zomba agricultural weather station. Finally, the seasonal or annual Maize yield data for Zomba district was directly given by the Ministry of Agriculture office located in the district along the M3 road.

3.6. Data cleaning

3.6.1. Crop yield data

The annual crop yield (Maize) data collected from the Ministry of Agriculture for Zomba district, contained the Maize productivity from 2009 to 2023 period, this data was related with the dry spell occurrence to determine its impact on agricultural productivity with a focus on Maize crop. This data was carefully checked before manipulations were done.

3.6.2. Temperature, Precipitation and CDD Data.

The Monthly maximum and minimum temperature and Monthly rainfall data (November to February), which were being measured by Thermometer and Rain gauge respectively, was provided by the Department of Climate Change and Meteorological Services (DCCMS) for Zomba district for the 2009-2023 period. This data went two levels of quality control. Firstly, data was manually checked for anomalous records, which involved the verification of station locations, identification of repeated data and the identification of outliers. Secondly, we performed a comparative tests using neighboring stations and investigated suspicious zero values or missing rainfall data using the arithmetic mean method (Maidment, 2013). Using the formula:

$$P_x = \frac{1}{n} \sum_{i=1}^{i=n} P_i$$

Where: P_x is the missing precipitation,

n is the number of nearby stations,

P_i is precipitation at i^{th} station.

These steps were essential to ensure that the model input data is sufficiently clean (Isaaks & Srivaski, 2020). The main benefit of the spatial interpolation of rainfall data is the reduction of the uncertainties and of the sensitivity associated with the point value of a variable rainfall field (Maidment, 2013).

3.6.3. Data collection and analysis tools

The data collected in this research was analyzed using an open-source web-based interactive development environment (IDE) called Jupyterlab and the statistical software called Microsoft Excel. We used the interactive Jupyterlab notebooks for python code editing, exploring data for data visualization. Three methods were used namely Mann-Kendall trend test, correlation and Multiple regression method. The climatological data was analyzed using the Mann-Kendall trend test, the relationship between meteorological data and Maize yield was analyzed using the correlation method while the statistical model for prediction dry spell occurrence and duration was analyzed using the multiple logistic and linear regression method respectively.

3.6.4. Data analysis

3.6.4.1. Time series analysis

This involved analyzing historical dry spell data, maximum and minimum temperatures and monthly precipitation data to identify the frequency through trends in dry spell occurrence over time period from 2009-2023 in Zomba district. Therefore, we organized the temperature and precipitation data in a chronological order and applied the time series decomposition techniques to separate trends, seasonal patterns, and irregular components.

We applied the Mann-Kendall trends test which is used to perceive statistically significant decreasing or increasing trend in long term temporal data like temperature and precipitation (Kerdiles & Hoek, 2017). Mann-Kendall trend test is based on null hypothesis (H_0) and alternate hypothesis (H_1) whereby the H_0 express the existence of no trend while H_1 shows significant rising or declining trend of a particular weather variable data like precipitation data (Ampitiyawatta & Guo, 2009). It is a good method for trend test in

climatological time series analysis because it does not assume that the data is distributed according to any particular rule, for example it does not require that the data should be normally distributed, it is not effected by unavailable data and it is not affected by the length of the time series The formula used was:

Mann-Kendall Trend Test (S) $= \sum_{i=1}^{n-1} \sum_{j=k+1}^{n} \boldsymbol{sign}(\boldsymbol{x_j - x_i})$

Where: S is the Mann-Kendal's test statistics

x_j *and* x_i are the sequential data values of the time series in the years i and j

(j > i),

n is the length of the time series,

$sign(x_j - x_i)$ is the sign function.

When, $\boldsymbol{Sign\ (xi-xj)} = \begin{cases} \boldsymbol{1},\ \boldsymbol{x_j - x_i > 0} \\ \boldsymbol{0},\ \boldsymbol{x_j - x_i = 0} \\ \boldsymbol{-1},\ \boldsymbol{x_j - x_i < 0} \end{cases}$

Note that a positive S value indicates an increasing trend and a negative value indicates a decreasing trend in the data series, while Zero shows that there is neither an increasing nor decreasing trend. To compute the standardized Mann-Kendall statistic, the variance must be found using:

$$\boldsymbol{Var(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{j=1}^{p} tj(tj-1)(2tj+5)\right]}$$

Where, p is the number of tied groups in the data set.

t_j is the number of data points in the j^{th} tied group.

Upon computing variance, the standardized Mann-Kendall statistic, Z_{mk} is found using:

$$\boldsymbol{Zmk} = \begin{cases} \frac{S-1}{\sigma},\ \boldsymbol{if\ S > 0} \\ \boldsymbol{0},\ \boldsymbol{if\ S = 0} \\ \frac{S+1}{\sigma},\ \boldsymbol{if\ S < 0} \end{cases}$$

A positive Zmk value indicates an upward trend while a negative value indicates a downward trend. The null hypothesis is rejected when the test was conducted at an alpha value of 0.05. The P value is used to see whether the trend is significant or not since the P value of less than 0.05 shows that there is a significant trend either a significant increasing trend or a significant decreasing trend.

Consequently, for the distribution and frequency of dry spells over time period 2009-2023 to be visualized, we used the collected rainfall and temperature data for Zomba to calculate summary statistics such as mean and standard deviation for dry spell duration and intensity using time series scatter plots (Laudien, 2020).

3.6.4.2. Correlation analysis

This method addressed the second objective which involved assessing of the relationship between Maize yield (Kgs/ha) from 2009 to 2023 and dry spells (CDD) in January and February to find Pearson's correlation coefficients (r) and P-values. This assessment of the relationship between Maize crop yield and dry spell occurrence was done to assess the impact of dry spells on Maize productivity for Zomba district, using Jupyterlab the collected data for Maize crop yield from the Ministry of Agriculture (Privette, 1995). The calculated Pearson's correlation coefficients and P-values between Maize yield and CDD were used to know whether we have a perfect linear relationship or perfect negative relationship.

$$\mathbf{r} = \frac{\mathbf{n}(\sum \mathbf{xy}) - (\sum \mathbf{x})(\sum \mathbf{y})}{\boldsymbol{n}(\sum \boldsymbol{x2}) - (\sum \boldsymbol{x})\mathbf{2}][\boldsymbol{n}(\sum \boldsymbol{y2}) - (\sum \boldsymbol{y})\mathbf{2}}$$

The value of r ranges from -1 to +1, when r is approaching -1 it indicates that the variables have a strong negative correlation where the increase in the independent variable results to the increase in dependent variable. While when the r is approaching +1 it indicates that the variables are in positive correlation which occurs when the increase in an independent variable results to the decrease in a dependent variable (Sridhara, 2021).

We performed hypothesis tests of r to determine the significance of observed correlations by finding the p-value for correlation coefficient that was used at the confidence level of

95% (=0.05). If the p-value < 0.05 we rejected the null hypothesis which says there is no correlation between the two variables, while when the p-value > 0.05 we accepted the null hypothesis. The relationship between variables was visualized by scatter plot.

Using probabilistic methods, we estimated the likelihood of different levels of dry spell occurrence and their potential impact on agriculture through the estimation of the probability distribution of dry spell occurrence using historical data (Hao, 2015). Then we calculated Metrics such as return periods and exceedance probabilities to quantify the likelihood of different levels of dry spell severity or dry spell frequency. Then we assessed the potential impact of dry spells on agriculture by combining risk estimates with vulnerability assessments for crops and farming systems thereby helping to assess the impact of dry spells on agricultural productivity.

Exceedance probabilities is the probability that an event of similar depth and duration will be exceeded in a year. It was found using the equation where T is time:

$$\text{Exceedance Probability} = \frac{1}{T}$$

A Return period is an estimate of how long it will be between rainfall events of a given magnitude. And given the exceedance probability of an event the return period was calculated using:

$$Tr = \frac{1}{\mathbf{P(Exceedance)}}$$

3.6.4.3. Multiple Regression analysis

This method was used to develop the statistical models of the relationship between dry spell occurrence and duration with potential predictors such as mean maximum and mean minimum temperature and monthly rainfall in this case from November to February (2009-2023). These relevant predictors were chosen to fit logistic regression models and multiple linear regression that predicts dry spell occurrence and duration respectively based on these three predictors (SDNP, 2014).

- Logistic Regression

This was used to model the prediction of dry spell occurrence since the dependent variable was a binary (Yes/No) thus we used 1 if CDD > 10, else 0.

$$P(Y=1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}}$$

Where: P = Probability of a dry spell occurring.

β_1, β_2, β_3 =Coefficients of regression.

X_1 = Mean Maximum Temperature

X_2 = Mean Minimum Temperature

X_3 = Mean Monthly Rainfall

β_o = Intercept.

e = Euler's number (approximately 2.718).

- **Multiple Linear Regression**

This method was used to model the prediction of dry spell duration, thus how many consecutive dry days will be possibly experienced in the upcoming Maize planting and growing season.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

Where: P = Dry spell duration.

X_1 = Mean Maximum Temperature

X_2 = Mean Minimum Temperature

X_3 = Mean Monthly Rainfall

β_1, β_2, β_3 = Coefficients of regression.

β_o = Intercept.

ϵ = Error term.

Then the assessment of the goodness-of-fit of the models and interpretation of the coefficients was done to understand the impact of each predictor variable. This model was trained using historical weather, and we applied cross-validation techniques to tune the model hyper parameters to optimize performance (Validate). However, to evaluate model performance we employed metrics such as accuracy and precision (Matiu & Ankerst, 2017).

4. CHAPTER FOUR: RESULTS AND DISCUSSION

4.1. Introduction

This chapter cover data analysis results and discussion while corresponding to the objectives of this study. The main objective of this study was to do an investigation of dry spells occurrence in Zomba district for agriculture application specifically Maize production using observational data from 2009 to 2024 of temperature and precipitation (November to February) and consecutive dry days (January and February) to see how dry spells affected maize yield and predict future occurrence and duration of dry spells.

4.2. Trend Results for CDD (Jan and Feb), Rainfall, Temperature and Maize Yield.

4.2.1. Mann-Kendall Results for CDD in January and February.

This section gives an analysis of CDD for the month of January and February from 2009-2023 from Makoka weather station in Zomba District obtained from DCCMS. The table below show the Mann-Kendall results for monthly CDD.

Table 1: Mann-Kendall Results for CDD in January and February

Month	S	Var(S)	Std	Zmk	P-value	Interpretation	Trend
CDD January	24.0	398.0	2.6	8.85	0.249	Accept null	NST
CDD February	-7.0	397.0	1.9	-3.15	0.763	Accept null	NSTS

According to the results displayed above, there was a decreasing trend of CDD in the month of February because the value of Zmk was negative, while there was an increasing trend in the month of January since the Zmk value was positive. Regardless these findings, it was noted that there was no statistically significant trend in both months throughout the period of 2009- 2023. The graphs in figure 3 and figure 4, shows the variation of number of CDD in January and February whereby in January the CDD varied from 3 days to 12 days while in February the trend of CDD varied from 2 days to 9 days. CDD in January was shown lowest in the year 2012 and 2016 while the highest CDD was shown in 2017

followed by 2015 then 2022. While in February the CDD was observed lowest in 2020 and the highest was shown in 2010 and 2021.

Figure 3: Graph showing variation of CDD in January

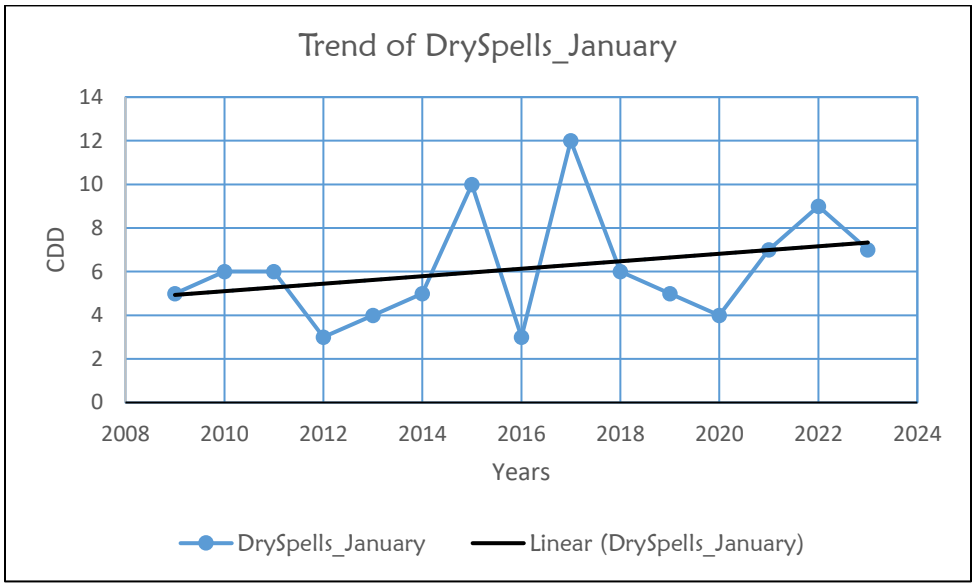
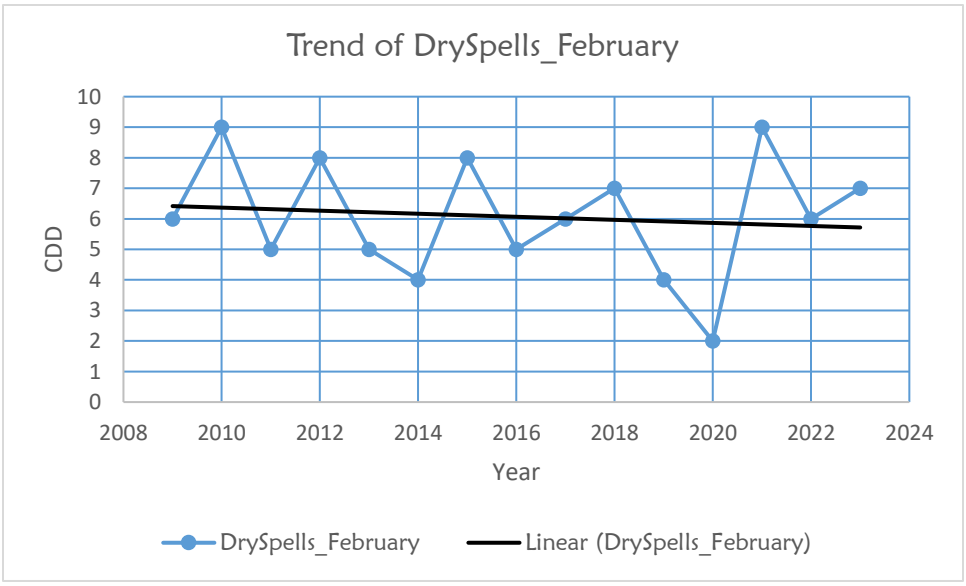


Figure 4: Graph showing variation of CDD in February



4.2.2. Mann-Kendall Results for Average Rainfall (November to February)

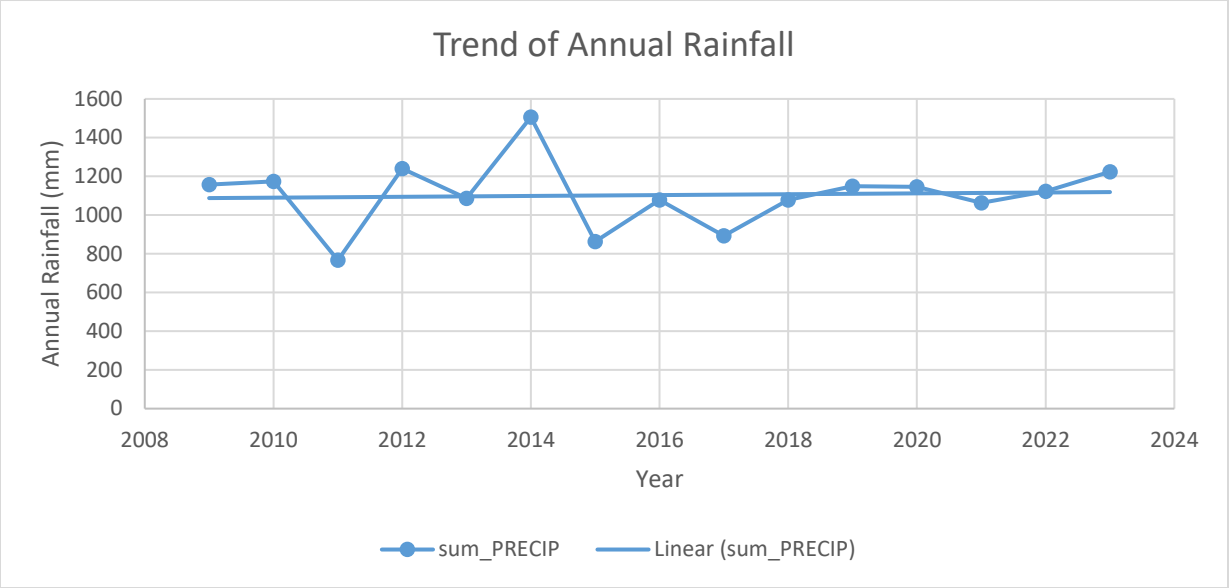
This section gives an analysis of average rainfall from the month of November to February from 2009-2023 at Makoka weather station in Zomba District obtained from DCCMS. The table below show the Mann-Kendall results for average rainfall for four months.

Table 2: Mann-Kendall Results for Average Rainfall (November to February).

Month	S	Var (S)	Std	Zmk	P-value	Interpretation	Trend
NOV	-10	314.7	170.0	-0.18	0.872	Accept null	NST
DEC	49	314.6	167.8	0.87	0.392	Accept null	NST
JAN	53	314.0	171.4	0.92	0.354	Accept null	NST
FEB	-4	284.8	170.5	-0.05	0.955	Accept null	NST
Average Rainfall	1.0	408.3	174.3	0	1.0	Accept null	NST

According to the results above, the trend of rainfall decreases in the month of November and February since the Zmk values were found negative while the rainfall trend in December and January showed an increasing trend since it resulted to a positive Zmk. The annual rainfall also showed a slight increased trend from the 2009 to 2023. Regardless all these observations there was no significant trend since the p-values are more than 0.05 under confidence level of 95% thereby accepting the null hypothesis. The graph in figure 5 below, shows the trend of annual rainfall over time whereby the variation occurred from 766.7mm in 2011 to 1506.1mm followed by 1223.2 in 2023. The annual rainfall amount has fluctuated and the trend showed a bit increase in rainfall amount. The average mean rainfall for 15 years was 1103.14mm and the standard deviation was 174.3mm.

Figure 5: Graph showing variability of Annual Rainfall (mm)



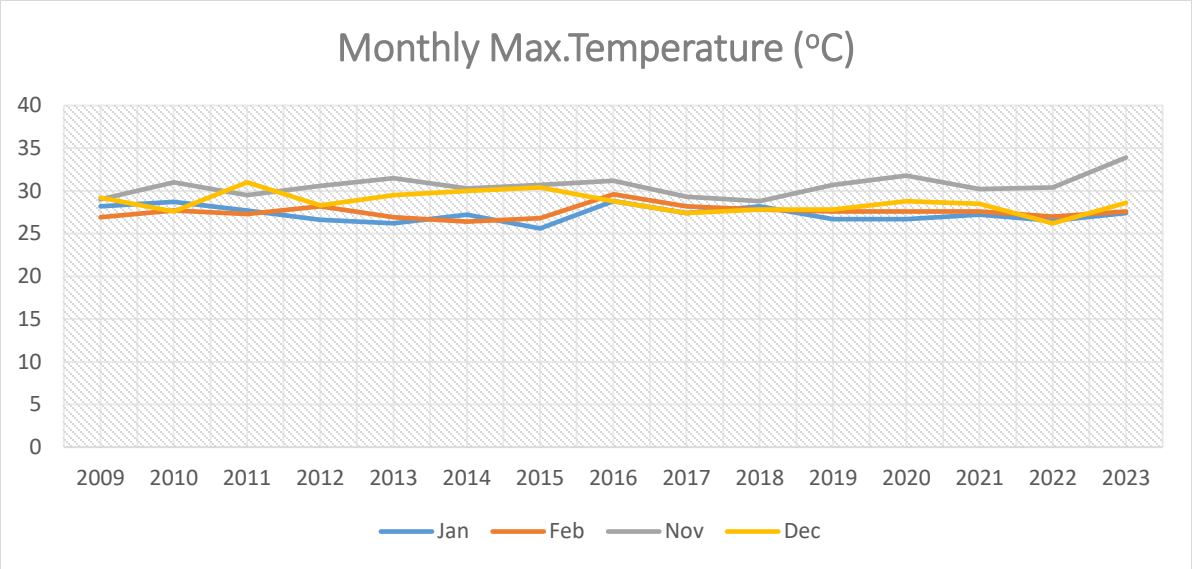
4.2.3. Mann-Kendall Results for Monthly Maximum Temperature (November to February)

Table 3: Mann-Kendall Results for Monthly Maximum Temperature

Month	S	Var(S)	Std	Zmk	P-value	Interpretation	Trend
November	20.0	407.3	1.3	14.9	0.371	Accept null	NST
December	-27.0	406.3	1.3	-20.0	0.197	Accept null	NST
January	-19.0	404.3	0.9	-20.0	0.371	Accept null	NST
February	3.0	397.6	0.8	2.5	0.920	Accept null	NST

According to the results above, there was a slight decrease trend of maximum temperature in the month of December and January since the Zmk values were found negative, while in November and February there was an increased trend in maximum temperature since it resulted to a positive Zmk value. These monthly maximum temperatures also showed a no significant trend (p-value > 0.05) throughout the period 2009-2023. The graph in figure 6, below shows the trend of Maximum Temperature throughout the period.

Figure 6: Graph showing variability of Monthly Maximum Temperature (ºC)



The graph for monthly maximum temperature showed an increase trend for January and December with the highest temperature being observed in 2016 at 28.8℃ and 2023 at 30.4℃ respectively. The lowest temperature was observed in 2015 at 25.6 in January and at 26.2 in December 2022. On the other hand, the slight decrease in trend showed in November and February was highest in 2016 and 2023 at 29.6℃ and 33.9℃ respectively. While the lowest maximum temperature in November and February was observed in 2018 at 28.8℃ and in 2013 at 29.3℃, from there the temperatures had a fluctuation. The mean value for maximum temperature was 30.6℃ and their mean standard deviation was 1.08.

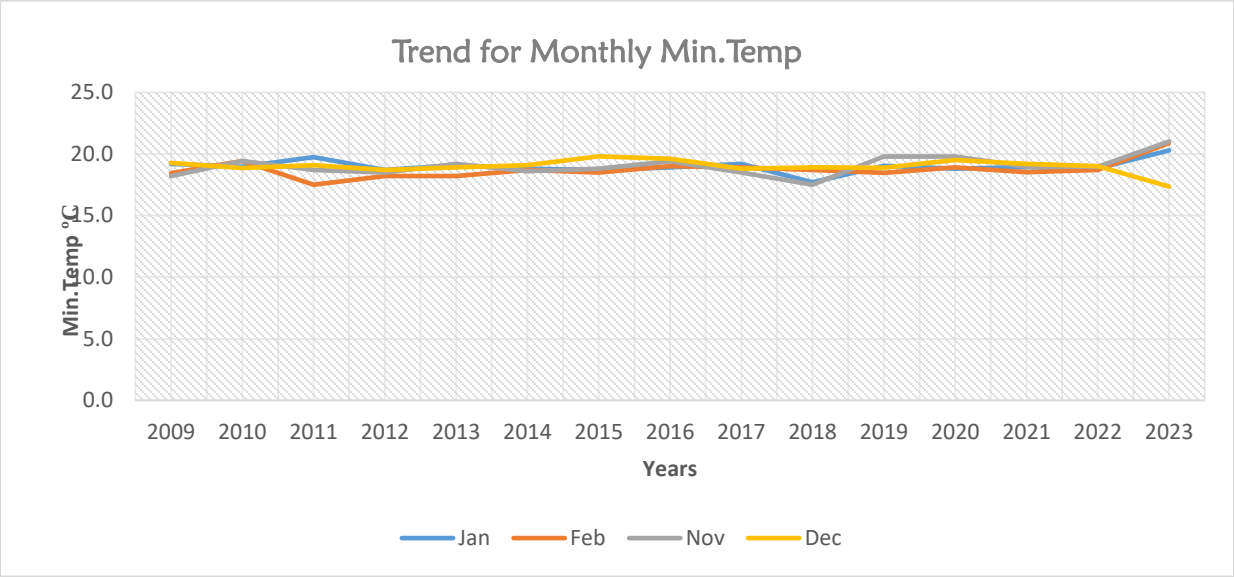
4.2.4. Mann-Kendall Results for Monthly Minimum Temperature (November to February)

Table 4: Mann-Kendall Results for Monthly Minimum Temperature

Month	S	Var(S)	Std	Zmk	P-value	Interpretation	Trend
November	33.0	404.3	0.8	40.0	0.112	Accept null	NST
December	-8.0	398.6	0.5	-14.0	0.726	Accept null	NST
January	-10.0	400.6	0.5	-18.0	0.653	Accept null	NST
February	33.0	399.0	0.7	45.7	0.109	Accept null	NST

According to the results in table 4 above, there was a slight decrease trend of minimum temperature in the month of December and January since the Zmk values were found negative, while in November and February there was slightly increased trend in minimum temperature due to positive Zmk value. These monthly maximum temperatures also showed a no significant trend (p-value > 0.05) throughout the period 2009-2023. The graph below shows the trend of Minimum Temperature throughout the period.

Figure 7: Graph showing variability of Monthly Maximum Temperature (ºC)



These findings are in line with what Mkandawire (2014) found out through analyzing historical climate data to identify trends in dry spell occurrence in different regions of Malawi. He found that dry spells are occurring but they do not have significant trends since out of the 10 stations studied in Malawi, and out of three threshold categories used only one station and one category showed a significant decreasing trend. However, this does not really differ from what was found out in our study, that almost all the weather parameters showed no significant trend. This might be due to the dynamic characteristic of the atmosphere.

4.3. Correlation Analysis Results

4.3.1. Introduction

This section highlights the impact or effects of Consecutive Dry Days on Maize yield (Kg/ha) in Zomba District. In addition, we also analyzed the relationship between the Maize yield and weather variables and provided the result in form of Pearson's correlation coefficients (r) and p-values to determine the strength and the direction of the impact of the CDD and other weather variables (Mean Max. and Mean Min. Temperature and Seasonal Rainfall) on Maize yield.

The results of the analysis of Maize annual yields and production for Zomba district from 2009 to 2024 shows a varying sequence in the amount of maize produced annually that it highly depends on the temperature and precipitation.

4.3.2. Correlation Results of Maize yield (kg/ha) and CDD in January and February

Table 5: Maize yields and CDD correlation

Weather Parameter	r	P value	Interpretation
CDD_January	-0.703	0.0035	Reject null
CDD_February	-0.367	0.1778	Accept null

The results in table 5 above, showed that correlation was strong and negative in January, meaning that as the number of CDD in January increased, the maize yield tends to decrease. The p-value < 0.05, indicated that this correlation was statistically significant and it's unlikely to be due to chance. This suggests that January dry spells have a substantial and statistically significant negative impact on maize productivity in Zomba. While for February the results showed that correlation was moderate and negative, meaning that as the number of CDD increased, the maize yield tends to slightly decrease. The p-value > 0.05, indicated that this correlation was not statistically significant thereby failing to reject the null hypothesis. The graphs below show the correlation between Maize yield and CDD in January and February.

Figure 8: Graphs showing Correlation of Maize yield and CDD (January)

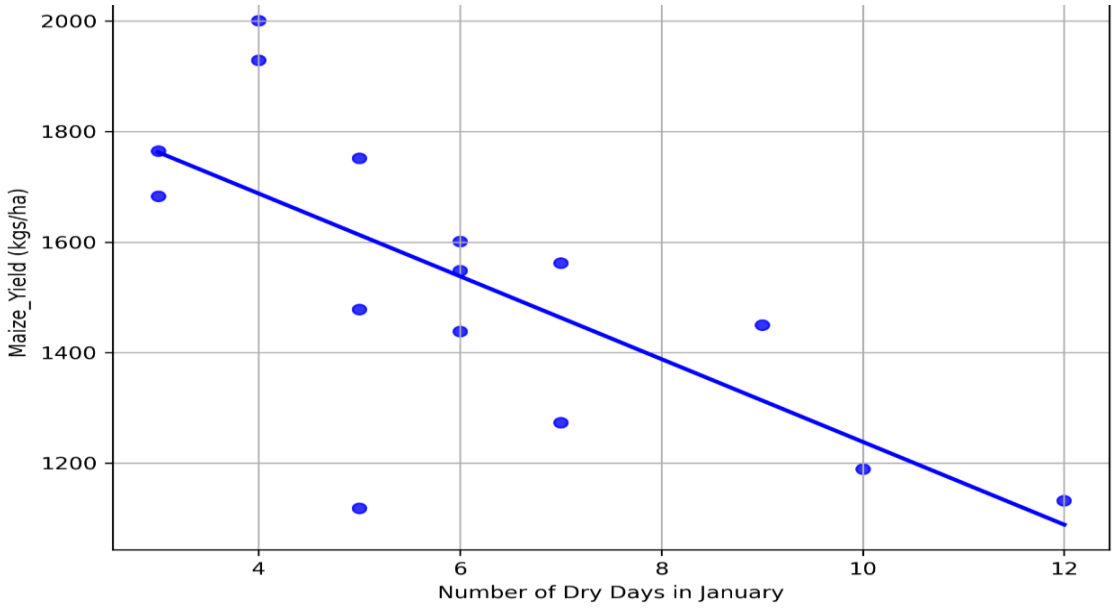
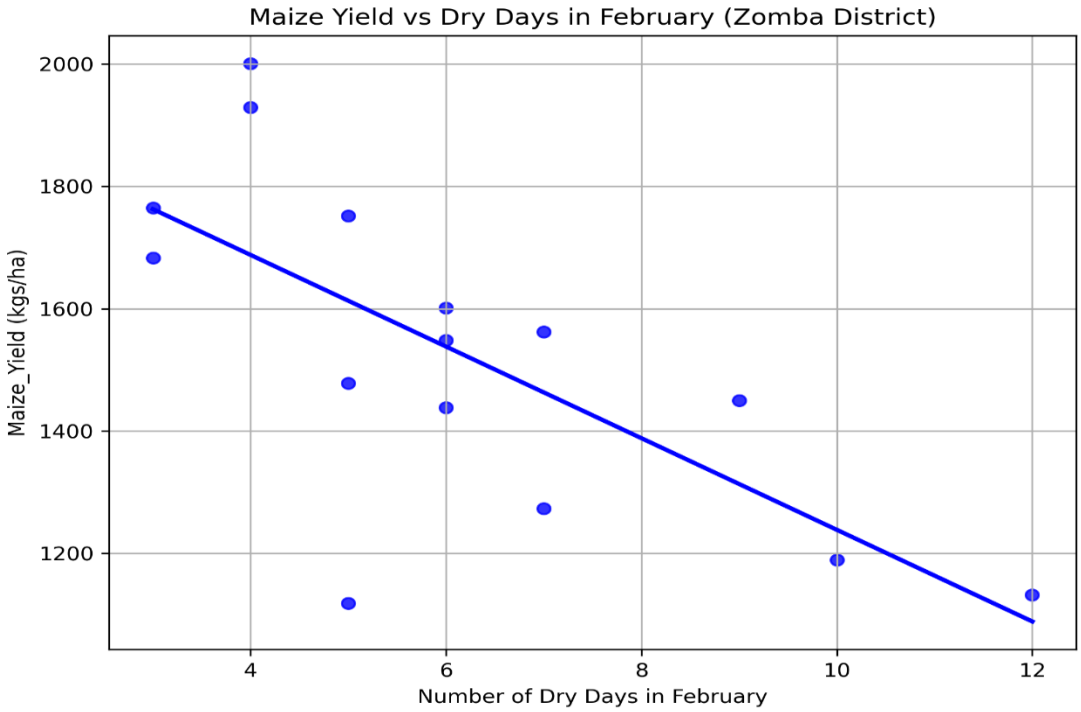


Figure 9: Graphs showing Correlation of Maize yield and CDD (February)



However, these findings suggested that prolonged dry spells during January month significantly reduce maize productivity, for example in 2015, Zomba experienced 10 CDD in January which resulted to the reduction of Maize yields from 1188 Kg/ha to 666kg/ha. This aligns with what Chen and Eklundh in 2004, proposed that the occurrence of dry spells is mostly negatively correlated with agricultural yields especially in semi-arid regions. Consequently, in February CDD showed a weaker, non-significant relationship with yield ($r = -0.367$, $p = 0.1778$), possibly indicating maize's relative resilience later in the growing season. This is so since February is the month of continual maize development in the southern region of Malawi hence CDD affects maize yields relevantly.

4.3.3. Correlation Results of Mean Maximum, Mean Minimum Temperature and Annual rainfall with Maize Yield (kgs/ha) – November to February

Table 6: Maize yields and Weather Variables Correlation

Weather Parameter	r	P value	Interpretation
Mean Max. Temp	0.226	0.4176	Accept null
Mean Min. Temp	0.037	0.8972	Accept null
Annual Rainfall	-0.029	0.9184	Accept null

According to the results in table 6 above, the r (0.226) for mean maximum temperature was found a weak positive correlation, suggesting that as maximum temperatures from November to February slightly increases, maize yield tends to increase slightly as well. Since the p-value was found greater than 0.05, it meant the result was not statistically significant, implying that there is a high probability (41.76%) that this weak correlation is due to chance, not a meaningful relationship. There's no strong evidence that higher maximum temperatures during the November–February period have a significant influence on maize yield in Zomba from 2009–2023. However, the positive trend, although weak, might still suggest a small benefit of warmth.

For Mean Minimum temperature, correlation coefficient was found 0.037, which is very close to 0, which means almost no linear relationship between minimum temperatures and

maize yield. Whether minimum temperature goes up or down during November to February, there was no effect on yield. P-value was greater than 0.05, which means not statistically significant. There's almost a 90% probability that this weak correlation is due to random chance.

For annual rainfall, correlation coefficient of -0.029 was found which is extremely close to 0, indicating no linear relationship between annual rainfall and maize yield, meaning variations in rainfall do not explain variations in yield. The p-value was found to be 0.9184, which is much greater than 0.05, meaning it's not statistically significant. This implies the observed correlation could easily be due to random chance there's no meaningful pattern in this data between rainfall and maize yield for Zomba.

Figure 10: Graph showing Correlation of Maize yield and Mean Maximum Temperature (Nov-Feb)

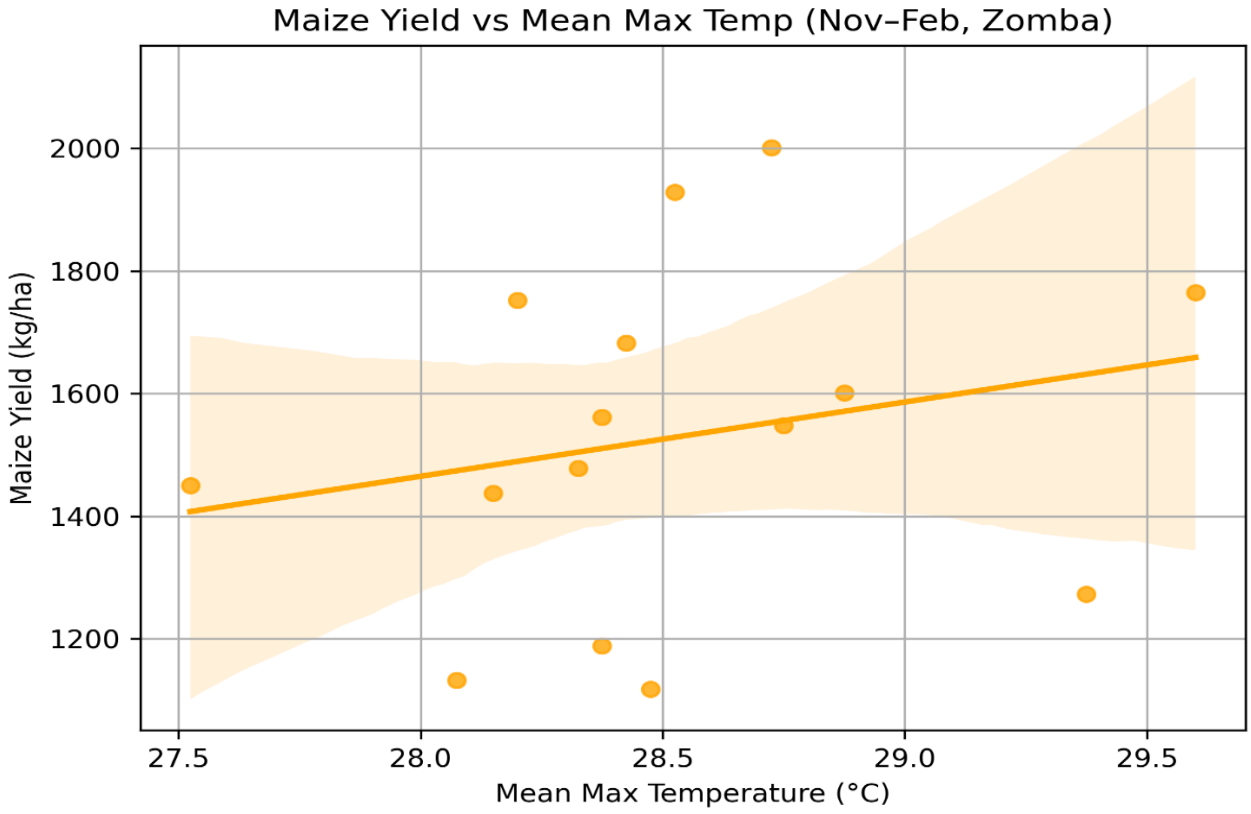


Figure 11: Graph showing Correlation of Maize yield and Mean Minimum Temperature (Nov to Feb)

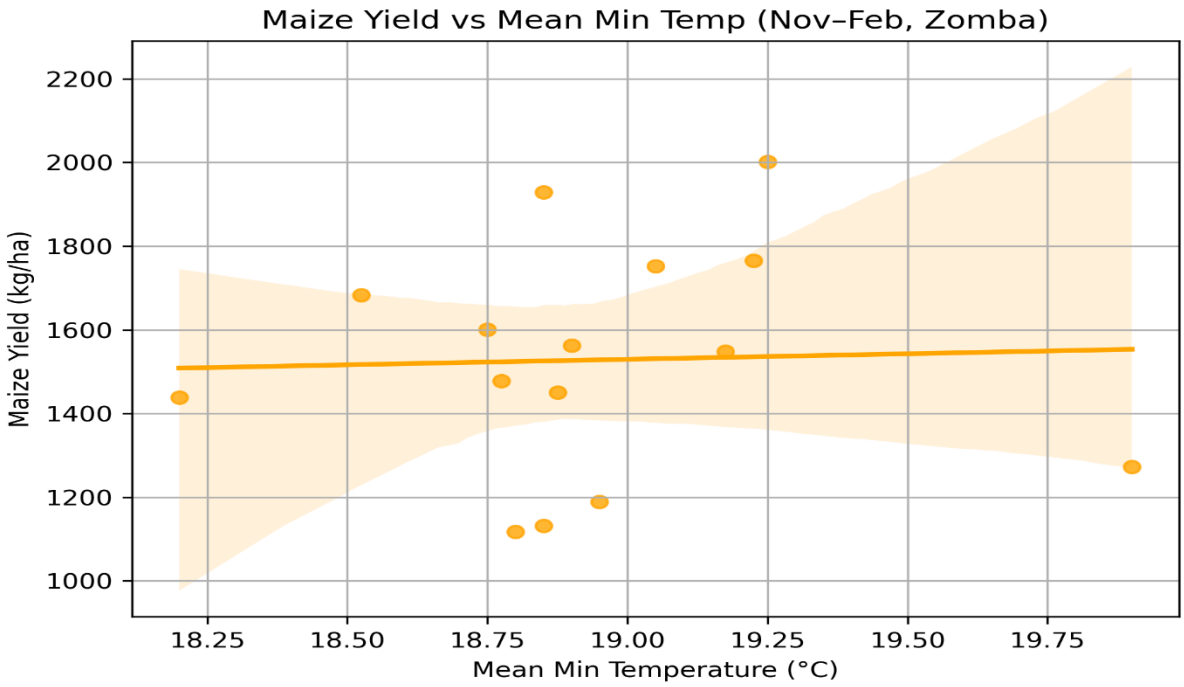
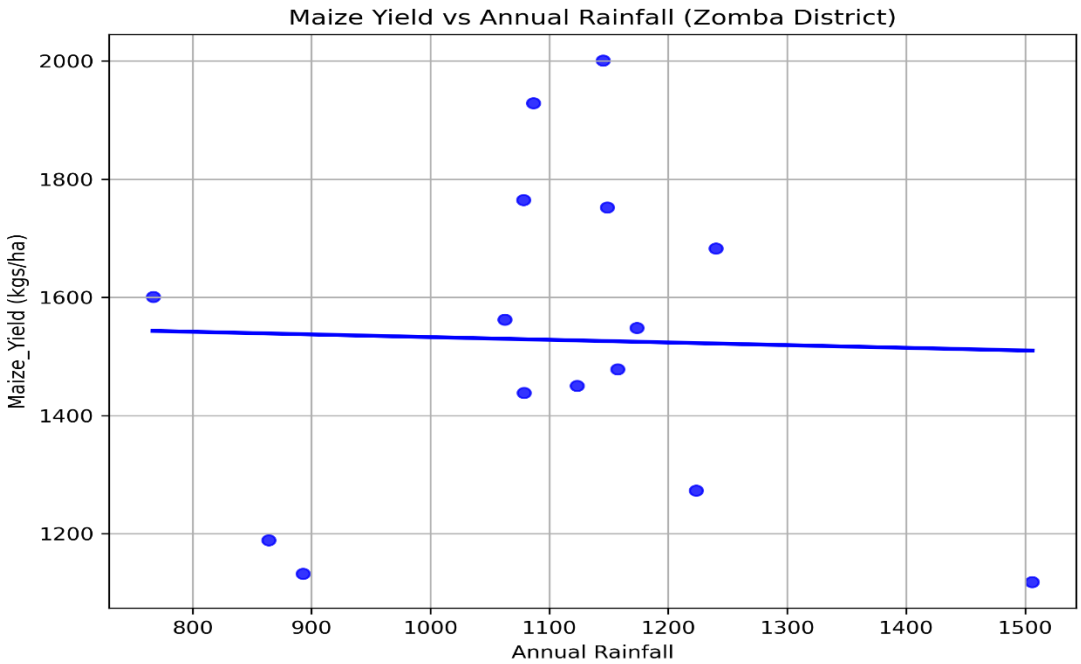


Figure 12: Graph showing Correlation of Maize yield and Annual Rainfall



Interestingly, rainfall and temperature had negligible correlations with maize yield (r values between -0.029 and 0.226), suggesting that it is not total rainfall but rather its temporal distribution especially dry spells, that critically affects crop output in Zomba district regardless of the findings of Mugalavai et al. (2012), who evaluated dry spells severity throughout sensitive growth phases (germination and flowering) for maize crop in Western Kenya and concluded that the likelihood of dry spells during the flowering stage varied from 0 to 73% and 0 to 65% (January and February), with the northern part of the Lake Victoria Basin and the area surrounding the lake features experiencing the highest severity and the microclimatic rainfall threshold having the lowest, lasting 7 to 10 days.

4.4. Multiple Regression Analysis Results

4.4.1. Introduction

This section highlights the results of the models that were developed to predict the occurrence and duration of the dry spell (CDD) in Zomba District during the planting and glowing period of maize crop. This was achieved using the multiple regression approach that used Dry Spell as the dependent variable while the independent variables or predictors were Mean Maximum and mean minimum temperature, and seasonal rainfall. Note that the data for all these predictors were taken from November to December since this is the planting and growing period for maize crop and it's when the dry spell occurrence has a great impact on the maize crop in the southern region of Malawi particularly in Zomba District. Both models were taken though a training session and were validated through cross validation.

4.4.2. Logistic Regression Results

This method was used to develop a statistical model for predicting the probability of occurrence of a dry spell using the mean maximum and mean minimum temperature and seasonal rainfall data from November to February. We used the threshold of at least 7 consecutive dry days to define the dry spell (DCCMS, 2024). The graph in figure 13, shows the 3-Dimension probability surface incorporating all three predictors used. We used 1 if CDD are greater than 1, else we used 0 to refer to no dry spell occurrence.

Figure 13: Graph showing the Logistic Regression Model

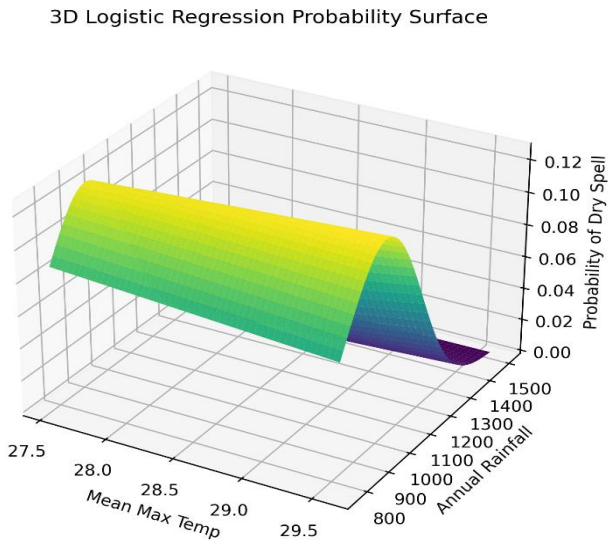


Table 7: Logistic Regression Results

	Precision	Accuracy	F1-score
0	0.00	0.00	0.00
1	0.67	0.67	0.80

Logistic Model was found as: $\log (p / (1 - p) = -0.0051-0.0979 X_1-0.0382X_2 + 0.0030X_3$

To compute the actual probability, we change the log equation to exponential equation as: $\boldsymbol{P} = \frac{\mathbf{1}}{\mathbf{1}+e^{-z}}$

Where: $Z = 0.0051-0.0979 X_1- 0.0382X_2 + 0.0030X_3$

P = Probability of a dry spell occurring.

$\beta_1, \beta_2, \beta_3$ =Coefficients of regression.

X_1 = Mean Maximum Temperature

X_2 = Mean Minimum Temperature

X_3 = Mean Monthly Rainfall

0.0051= Intercept.

Approximately 2.718 = *e* (Euler's number)

The intercept value is the baseline log-odds of a dry spell when all predictors are zero since zero rainfall and zero temperatures are not realistic. Therefore, in mean max temperature (November–February) it showed that 1°C increase, results to the decrease of log-odds of an occurring dry spell by 0.0979, thus higher maximum temperature causes slight reduction of the chance of a dry spell occurring, assuming everything is constant. While for every 1°C increase in mean minimum temperature (November–February), the log-odds decreases by 0.0382, meaning higher minimum temperatures also slightly reduce dry spell occurrence probability. Finally, for each additional mm of seasonal rainfall, the log-odds increases by 0.0030, meaning higher rainfall is associated with a slightly higher chance of a dry spell occurring which specify local seasonal dynamics in Zomba District like more rainfall overall, but less evenly distributed, since logistic regression models the log-odds, not probabilities directly. This logistic regression model yielded moderate accuracy (67%) and suggested that rainfall, rather than temperature, had a modest influence on the likelihood of dry spell occurrence in January and February.

4.4.3. Multiple Linear Regression Results

This method was used to develop a Linear statistical model for predicting the duration of a dry spell using the mean maximum and mean minimum temperature and seasonal rainfall data from November to February. The graph in figure 14, shows the relationship between the actual dry spell duration and dry spell duration.

Figure 14: Graph showing the Multiple Linear Regression Model

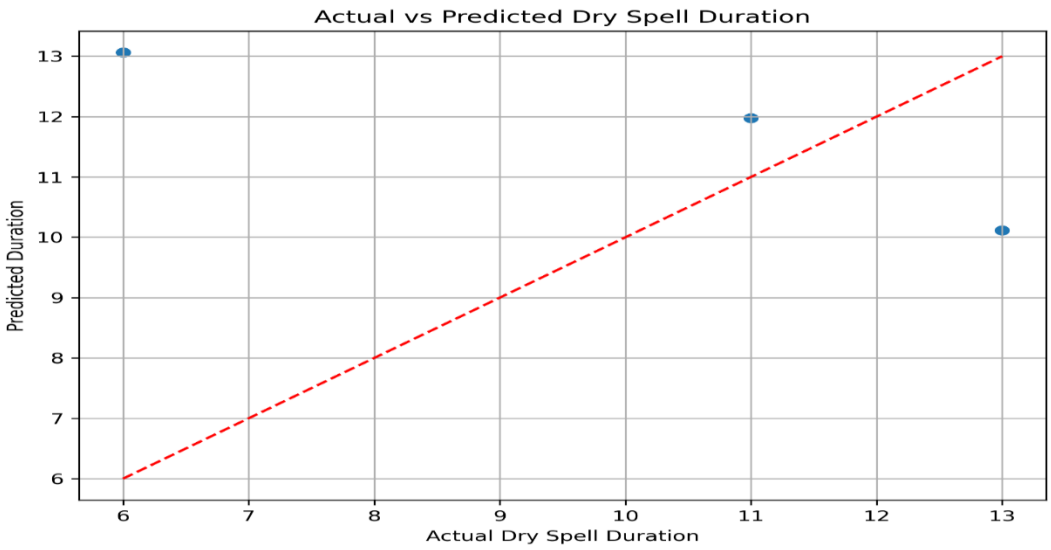


Table 8: Linear Regression Model Results.

R^2 Score	Mean Squared Error	Intercept (β_0)
1.2759	19.7	72.7

Regression Model as: **CDD (Jan_Feb) = 72.71 − 4.01·X_1 + 3.37·X_2 − 0.0091·X_3**

Where: X_1 = Mean.MaxTemp (°C)_Nov_Feb

X_2 = Mean_MinTemp (°C)_Nov_Feb

X_3 = Annual_Rainfall (mm)

72.71= Intercept

According to the Linear regression model above, the mean maximum Temperature (November to February) coefficient (4.01) showed that 1°C increase is associated with a decrease of approximately 4.01 CDD in January and February. While the mean Minimum Temperature (November–February) coefficient (3.37) showed that 1°C increase is associated with an increase of approximately 3.37 CDD. Finally, Annual Rainfall Coefficient indicated that every additional mm of annual rainfall reduces dry spell days by approximately 0.0091 days. Therefore, the multiple linear regression model indicated that

higher maximum temperatures and lower rainfall marginally contributed to longer dry spells. However, these findings contradict with what M. Mkandawire (2014) during his study of investigating dry spells occurrence during the rainfall season in Malawi, where he concluded that maximum length of the dry spell (MLDS) and annual maximum dry spell length (AMDSL) are the contributing factors and variables for dry spell duration. Consequently, the model had a relatively low R^2 score (1.28), indicating limited predictive power, likely due to variability in local microclimates and other factors which were not

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1. Conclusion

This study has investigated the occurrence, frequency, and characteristics of dry spells in Malawi, with a focus on their implications for maize production. Using historical rainfall, temperature and CDD data across different agro-ecological zones in Zomba District and statistical analysis, the research revealed that dry spells are a recurrent feature during the rainy season, particularly in January and February, which are critical periods for crop growth.

However, the results showed no significant trend Dry spells are a significant climatic risk factor for maize production in Zomba District, especially in January when maize is highly sensitive to water stress. No significant long-term trends were observed in rainfall, temperature, or CDD between 2009 and 2023, yet inter-annual variability remains high. January dry spells negatively and significantly affect maize yield, making this period critical for drought monitoring and mitigation. Predictive models showed moderate performance, indicating that while weather data can offer insights, additional variables are needed to improve forecasting accuracy.

The results show significant temporal variations in dry spell occurrences, with the Zomba being more vulnerable. The frequency of prolonged dry spells during critical crop development stages poses a substantial risk to rain-fed agriculture, which remains the mainstay of Malawi's food security and rural livelihoods. These findings underscore the importance of understanding the dynamics of dry spells in guiding agricultural planning and adaptation strategies. Integrating dry spell analysis into agricultural decision-making can enhance resilience and productivity in the face of climate change.

5.2. Limitations

Gaps in weather and yield records posed challenges, and interpolated data may not capture true local variability data availability and quality since the Maize yield data was measured in kilograms per hectare which might not reflect the actual products from the local community.

Spatial Resolution was limited since the analysis was done using the Makoka and Zomba agricultural weather stations data, which are few as compared to the spatial coverage of Zomba District. This may not reflect the entire district's microclimates variables thereby affecting the results of our data.

In addition, other influencing factors like soil fertility, pest pressure, farmer management practices, and fertilizer use were not considered but could have influenced maize yield for Zomba district.

Furthermore, simplicity of the logistic and linear regression models, though they are useful, they were limited in scope and predictive strength, however advanced machine learning techniques could improve its accuracy.

Finally, the temporal constraints of 15 years from 2009 to 2023 span, while reasonable because of the Maize yield data that was available, it may not fully capture long-term climatic trends or cycles such as ENSO influences.

5.3. Recommendations

The study was conducted using statistical climate data, it is recommended that other studies should be conducted using other different types of Global Climate Models as well Regional Models in order to have results that will give a more detailed picture about future occurrences of dry spells so as to find the right adaptation and mitigation measures on how to deal with these impacts of climate variability on maize production. To reduce the problems caused by dry spells and help farmers in Malawi, the following actions are recommended:

Early Warning Systems building, that are localized and simple to Zomba like radio or SMS alerts; to monitor and warn farmers about coming dry spells so they can prepare in advance especially during January and February. Also encouraging the planting of other crop that are drought-resistant thus those that can survive longer without rain, such as sorghum, millet, or drought-resistant maize varieties.

Advising and educate farmers on the timing, risks of dry spells and best time to plant crops, based on weather patterns, to avoid dry spells during critical growth stages. And also promoting affordable irrigation methods such as treadle pumps, water harvesting, or small dams to provide water during dry periods.

Policymakers like Ministry of Agriculture, Ministry of Climate Change etc., must prioritize funding for climate-resilient agriculture, including research on drought-tolerant maize varieties and investment in small-scale irrigation schemes. Consequently, they must integrate dry spell risk assessments into national food security and climate adaptation policies, aligning with SDG 2 (Zero Hunger) and SDG 13 (Climate Action). DCCMS must enhance meteorological infrastructure by expanding weather station coverage and upgrading data transmission systems in rural areas.

Agricultural extension officers must promote conservation agriculture techniques such as mulching, intercropping, and minimum tillage to retain soil moisture during dry spells They must also support community-level training on interpreting seasonal forecasts and using them for planting decisions. On the other hand, they should facilitate on-farm trials of supplemental irrigation and drought-resistant seed varieties to demonstrate resilience-building strategies. Also work with local farmer groups or cooperatives to invest in small-scale water harvesting or irrigation solutions where feasible.

Finally, farmers need to practice soil moisture conservation through the use of organic mulches and ridge farming to reduce water stress during critical growth stages.

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