BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE AND ENGINEERING

DEPARTMENT OF DISASTER RISK REDUCTION

APPLICATION OF RANDOM FOREST CLASSIFICATION ALGORITHM AND TIME SERIES DECOMPOSITION TO ASSESS THE IMPACTS OF CLIMATE CHANGE ON FORESTS IN CHIMANIMANI DISTRICT USING LANDSAT DATA

BY

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SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS OF THE BACHELORS HONORS DEGREE IN DISASTER MANAGEMENT SCIENCES

NOVEMBER 2025

DECLARATION

I Thania Matamande (B201880B), hereby avows confirming to the outputs of my research and its findings. The research used information from past researches and literature from various authors. The research went on to fully acknowledge all sources used to come up with this dissertation and reference list is aligned. This research is only contained by supervisor and department and not in any other institution or publication for any purpose.

Submitted in partial fulfilment of the Bachelors Honors Degree in Disaster Management Sciences at Bindura University of Science Education.

Signature:…………………………..

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APPROVAL

This serves to certify that the undersigned has read and approved that this research be submitted as the final dissertation to the Department of Disaster Management Sciences at Bindura University of Science Education.

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Signature… Date ……14/10/25……………

Prof Emmanuel Mavhura

DEDICATION

This research I dedicate it to the Lord God Almighty and my family (mom, Dad and my two sisters).

ACKNOWLEDGEMENT

With much reverence and honor it is my pleasure to acknowledge the following people. Firstly I would like to thank and give all acknowledgement to the Lord God almighty who gave me strength, health and all I required in finishing the project. I'm happy today because God was with me from day one for he say he will not leave me nor forsake me I thank him. In times of joy, sorrow, sickness, insufficiency and loneliness he was with me. I went on to thank my supervisor a God sent lecturer in my life, Dr Pedzisai for sharing and imparting such great and splendid knowledge, you've been patient with me in all struggles to understand the research and I very proud to have such a supervisor. Also I thank other researcher who gave me glams of insight to make this research to shine.

I express my deep and sincere honor and love to my family, I thank God for such a pillar of strength which include Mr. L Matamande, Mrs. C Matamande and my two sisters Thelma and Thalinta Matamande. They have bared with me is all situations financially, spiritually in prayer and physically showing immense love and giving me hope to never give up no matter what comes in my way. Word cannot fully express how thankful I am but my inner being is much grateful.

Above all I'm thankful to all friends, family, and my pastor and loved one who stood with me when I needed them.

ABSTRACT

Climate change poses a significant threat to forest ecosystems worldwide with far reaching consequences for biodiversity, ecosystem services and human livelihoods. Despite the importance of forests in Chimanimani district the impacts of climate change on the ecosystem remain poorly understood. The study aims to assess the impacts of climate change on forests in Chimanimani district using time series decomposition and Random Forest classification algorithm. The study was focused on Chimanimani district located in the eastern parts of Zimbabwe as the area of study. Data was collected from Landsat satellite imagery (USGS) and climate data from the Zimbabwe Meteorological Service Department. Landsat data from 1994 to 2024 downloaded from USGS and applied in the thesis. A total of 30 Landsat images were downloaded and classified using Random Forest algorithm. Results on changes in forest cover were determine in % percentages from 1994-2024 and linear regression analysis was used giving a negative correlation ($R2 = 0{,}8964$). Whilst climate data from 1994 to 2023 and Land cover results were analyzed to show relationship between climate change and change in forest Land cover. The results showed that forest cover in Chimanimani district decreased by 31.77% from 1994 to 2024. Also non forest area has increased with 8.29% in 1994 and 40.06% in 2024 which give a -31.77% increase. The study also show results of time series decomposition of time series decomposition using R software 4.3.3. The thesis presents time series, smoothed time series and decomposed time series plot. Therefore climate data was found to be significantly correlated with forest cover changes. The study also revealed that local communities perceived climate change as a major driver of forest degradation in the district. The results suggests that climate change poses a significant threat to forest ecosystems in Chimanimani district. In conclusion the study demonstrates the importance of using machine learning algorithms and time series decomposition to assess the impacts of climate change on forest ecosystems. Therefore it is recommended that policy makers and conservationists prioritize the use of these techniques in developing effective climate change mitigation and adaptation strategies for forest ecosystems in Zimbabwe.

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ACRONYMS

AI	**Artificial Intelligence**
EEMD	**Ensemble Emperical Mode Decomposition**
IPCC	**Intergovernmental Panel on Climate Change**
LULC	**Land Use Land Cover**
MAE	**Mean Absolute Error**
ML	**Machine Learning**
NDVI	**Normalized Difference Vegetation Index**
RF	**Random Forest**
RMSE	**Root Mean Square Error**
RS	**Remote Sensing**
SVM	**Support Vector Machine**

CHAPTER 1: INTRODUCTION

1.0 Introduction

Climate change continues to pose significant threats to global forest ecosystems with severe consequences for biodiversity, ecosystem services, and human livelihoods (IPCC, 2021). In Zimbabwe forest cover approximately 45% of the land area and has provided crucial ecosystem services (Forest Commission of Zimbabwe, 2022). However climate related disturbances such as droughts and extreme weather events have increased forest vulnerability (Mertz et al., 2020). Chimanimani District located in the eastern Zimbabwe is particularly susceptible to climate related impacts due to its unique geography and high conservation value. Effective assessment and monitoring of climate change impacts on forests requires robust analytical approaches (Gomez et al., 2022) time series decomposition and machine learning algorithm such as Random forest offers promising solutions for analyzing complex relationships between climate variables and forest dynamics (Breinman, 2021; Cleveland et al., 2023). Landsat satellite data with its extensive temporal coverage provides an ideal platform for monitoring forest changes (Wulder et al., 2022).

1.1 Background to the study

Climate change poses significant threats to forest ecosystems worldwide with alarming rates of deforestation and degradation reported in recent decades. Chimanimani District is located in eastern Zimbabwe is no exception with forest cover declining by 30% between 1990 and 2020 (FSI, 2020). According to Hansen et al (2023) mention that understanding the impacts of climate change on forests is crucial for informed decision making and sustainable forest management. Landsat data with its 30 meter spatial resolution and 32 year temporal coverage offers valuable tool for monitoring forest dynamics. However, analyzing Landsat data requires advanced techniques to account for seasonal and trend variations. Time series decomposition and Random Forest classification algorithm have emerged as effective methods for analyzing forest dynamics. According to Meng et al 2021; Belgiu et al., 2022) asserts that recent studies have demonstrated the potential of these methods in assessing forest change. This study aims to contribute to the existing body of knowledge by applying time series decomposition and Random Forest Algorithm to assess the impacts of climate change on forests in Chimanimani District from 1990 to 2024 using Landsat data.

1.1.2 Causes of climate change

Climate change is primarily driven by human activities particularly the increasing levels of greenhouse gases (GHGs) in the atmosphere. According to IPCC (2021) asserts that deforestation and Land-use changes are significantly responsible for 15% of global GHG emissions. Whilst Hansen et al (2023) alludes that burning fossil fuels for energy and transportation releases carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) leading to global warming. However, Ripple et al. (2021) went on to say that agricultural practices such as livestock farming and rice cultivation also emit substantial amounts of GHGs. Additionally, Seto et al (2021) support the view that population growth, urbanization and consumption patterns exacerbate climate change. Hence on overall Chimanimani District specific causes include agricultural expansion, charcoal production and logging (FSI, 2020). Understanding these drivers is crucial for assessing the impacts of climate change on forests using time series decomposition and random forest algorithm.

1.1.3 Effects of climate change

Climate change has far-reaching consequences on forest ecosystems including increased frequency and severity of droughts, heat waves and floods. According to Hansen et al. (2023) mention that rising temperatures and forest composition, structure and function have led to the shift of species distribution, phenology and productivity. Whilst Ripple et al. (2021) asserts that changes in precipitation patterns exacerbate soil erosion, landslides and forest fires. Moreso, Sero et al. (2021) went on to say that warmer temperatures also facilitate the spread of invasive species and pests further compromising forest health. This shows that in Chimanimani District climate change commonly linked to decreased forest cover, reduced biomass and altered forest dynamics (FSI, (2020). Specifically, temperature increases of 1.5 degree Celsius and precipitation decline of 20% have been reported (Mendelsohn et al., 2022). These impacts have devastating consequences for local communities, biodiversity and ecosystem services. Time series decomposition and random forest algorithm can help uncover the complex relationships between climate variables and forest dynamics.

1.1.4 Benefits of Ecosystem

Ecosystems provide essential benefits to human well-being through their supporting and regulatory roles. According to FAO (2021) asserts supporting roles include nutrient cycling, soil formation and primary production which underpin agricultural productivity and food security. Regulatory roles encompass climate regulation, air and water filtration and natural hazard mitigation such as flood control and storm protection (IPPC, 2021). For instance, intact ecosystems can remove up to 50% of atmospheric $CO2$ while wetlands can filter 80% of water pollutants (IPCC, 2021; UNEP, 2022). Additionally, ecosystems support human health by providing medicinal resources, pollination services and psychological benefits (WHO, 2022). The economic benefits of ecosystem conservation and substantial with estimates suggesting that every dollar invested in conservation yields \$10 to \$100 in benefits (Nature, 2023). Effective ecosystem management is crucial in maintaining these benefits emphasizing the need for sustainable practices and conservation efforts.

1.2 Problem statement

The impacts of climate change on forest ecosystems in Chimanimani District Zimbabwe remain poorly understood due to limitations in monitoring and analyzing long term forest dynamics. Traditional methods relying on field observation and statistical models are constrained by spatial and temporal scales hindering effective forest management and climate change mitigation strategies. Specifically, the District lacks comprehensive understanding of how climate variables influence forest cover, biomass and species composition over the past three decades. The integration of time series decomposition and random forest algorithm offers a promising solution yet its application to Landsat data in Chimanimani District has not been explored. Therefore, the study addresses such areas with challenges and gaps.

1.3 Aim of the study

The research aims to assess the impacts of climate change on forest ecosystems in Chimanimani District using Landsat data and random forest classifier

1.4 Research objectives

i. Detect changes on forests Land cover from 1994 to 2024 in Chimanimani District using Random Forest
ii. Assess the relationship between climate change and forest Land cover changes from 1994 to 2024 in Chimanimani District
iii. Evaluate the perceptions of community on the impacts of climate change on forests in Chimanimani District from 1994-2024

1.5 Research questions

i. What are the spatial and temporal patterns of forest Land cover changes in Chimanimani District from 1994 to 2024 as detected by Random Forest Algorithm?
ii. To what extent do climate change influence forest land cover changes in Chimanimani District from 1994 to 2024?
iii. How do local communities in Chimanimani District perceive the impacts of climate change on forest ecosystems?

1.6 Justification

1.6.1 Justification for selection of the Random Forest Classification algorithms

Random Forest Classification Algorithm was chosen to assess the impacts of climate change on forests due to its exceptional performance in handling high dimensional data, nonlinear relationship and complex interactions between variables. Its ability to identify key drivers of forest response to climate change such as temperature, precipitation and drought makes it an ideal choice (Gould et al., 2022). Studies have demonstrated Random Forest superiority over other machine learning algorithms in predicting forest vulnerability to climate change, identify climate sensitive tree species and mapping climate driven changes in forest composition (Zhang et al., 2021, Hansen et al., 2023).

1.6.2 Justification for selection of time series decomposition

Time series decomposition was selected to assess the impacts of climate change on forests due to its ability to distinguish between long term trends, seasonal pattern and irregular variations in forest health and productivity. This method allows for the separation of climate driven signals from other environmental and anthropogenic factors enabling the quantification of climate change impacts on forest ecosystems (Mendez et al., 2021). Studies have demonstrated the effectiveness of time series decomposition in analyzing forest response to climate variability including drought and temperature anomalies (Babst et al., 2021; Xu et al., 2022). By decomposing time series data on forest metrics such as tree growth, mortality and species composition researchers can identify climate sensitive thresholds and nonlinear responses informing climate smart forestry practices (Gould et al., 2022; Hansen et al., 2023).

1.7 Significance of the study

The study's significance lies in its innovative application of time series decomposition and Random Forest Algorithm to assess climate change impacts on forests in Chimanimani District from 1990 to 2024. This has been due to the paucity of studies that have employed machine learning algorithm such as random forest classification in conjunction with time series decomposition to assess the impacts of climate change on forests in Chimanimani district. According to Hansen et al. (2023) assets that leveraging Landsat data of about 32 years makes the research to provide critical insights on forest dynamics studies informing sustainable forest management and climate change mitigation strategies. This study findings will contribute to the development of effective adaptation measures enhancing forest resilience and biodiversity conservation (Ripple et al., 2021). Moreover, this research addresses the knowledge gap in climate change impacts on forests in Zimbabwe supporting national efforts to achieve REDD+ objectives (UN-REDD, 2022). Deforestation has become a challenge in Chimanimani district and studying forest is an important way to check on forest cover changes. The study informs policy makers and relevant policies governing forest resource management and conservation including informing changes in forest cover to Forest Commission in Zimbabwe to ensure compliance on the Forest Act. Mendelsohn et al. (2022) mentioned that the study outcomes of such a thesis also inform policy decisions ensuring the long-term sustainability of Chimanimani forest ecosystems and benefiting local communities dependent on these resources. Addressing the impacts on forest also enhance community knowledge towards sustainable management of forest and resilience building when it comes to forest reducing negative impacts of climate change.

1.8 Definition of key terms

1.8.1 Machine learning algorithms

It is defined as a field of artificial intelligence that enables computers to learn and improve from experience without being explicitly programmed (Hastie et al., 2009)

1.8.2 Climate change impacts

Refers to the effects of long term shifts in weather patterns and average conditions such as changes in temperature, precipitation, extreme weather events and sea level rise on natural and human system (IPCC, 2021)

1.8.3 Landsat data

It is a satellite imagery dataset providing 30 meter spatial resolution and 32 years temporal coverage for monitoring forest dynamics (USGS, 2022)

1.8.4 Time Series Decomposition

A statistical method to separate a time series into trend, seasonality and residuals enabling analysis of patterns and anomalies (Cleveland et al., 1990)

1.8.5 Random Forest Classification Algorithm

Defined as an ensemble machine learning technique combining multiple decision trees to improve prediction accuracy and handle complex interactions (Breiman, 2001)

1.8.5 Greenhouse gases

Are gases in the atmosphere that trap heat from the sun causing greenhouse effect and contributing to global warming (IPPC. 2021)

1.8.6 Global warming

Refers to the long-term rise in the earths average surface temperature due to increased levels of greenhouse gases in the atmosphere primarily from human activities such as burning of fossil fuels (IPCC.2021)

1.8.7 Climate variability

Refers to variations in the mean state and other statistics of the climate on all spatial and temporal scales beyond that of individual weather events (National Research Council, 2010)

1.8.8 Forest disturbance

It is defined as alterations to forest ecosystems due to natural or human induced events such as deforestation or climate change (Hansen et al., 2023)

1.8.9 REDD+ (Reducing Emissions from Deforestation and Forest Degradation)

It is an international initiative to mitigate climate change through sustainable forest management (UN-REDD, 2022)

1.8.9 Mitigation

Refers to actions taken to reduce or prevent greenhouse gases emissions and enhance sinks that absorb and store greenhouse gases from the atmosphere (IPCC, 2021)

1.8.10 Adaptation

Refers to adjustments in human and natural systems in response to actual or expected climate change impacts which moderate harm or exploit beneficial opportunities (IPCC, 2014)

1.8.11 Ensemble learning

Defined as combining of multiple machine learning models to improve prediction accuracy and robustness (Zhang et al., 2022)

1.8.12 spatial resolution

It is the measure of the smallest observable detail in satellite imagery such as 30 meters for Landsat (USGS, 2022)

1.9 Organization of the study

This research is presented in five chapters as follows: Chapter one, has the general introduction of the study. Chapter two reviewed the literature and presents the theoretical and conceptual frameworks informing the study. Chapter three describes the study area, focuses on the research design, methodology and analysis of the data collected. The research results and their respective discussion relating to the three research objectives are presented in Chapter four.

Finally, Chapter five is centered on summary of the study, conclusions, and recommendations from the study.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive overview of the state of knowledge pertaining to the application of time series decomposition and random forest algorithm to assess the impacts of climate change in Chimanimani District using Landsat data. In detail the review will explore the use of machine learning classification algorithms for land cover classification, change detection, and predicative modelling as well as the mixed research approach for climate change assessment. The chapter will also review the theoretical and conceptual framework.

2.2 Trends of climate change impacts on forests

Climate change profoundly impacts on forests worldwide with alarming trends emerging. According to IPPC (2021), rising temperatures and altered precipitation patterns are fueling increased forest fires, droughts and insect outbreaks resulting in unprecedented tree mortality. Since the year 2000, the world has lost 420 million hectares of forest cover with the year 2020 witnessing a 12% increase in deforestation (WWF, 2022). More so climate driven shifts in species distribution and phenology are altering forest composition and disrupting ecosystem services. In addition USDA (2022) supports the view that warmer temperatures also exacerbates forests pests and diseases such as the bark beetle epidemic in North America. Furthermore, increased frequency and severity of extreme weather events like hurricanes and wildfires are devastating forest ecosystems (UNEP, 2022). Hence, projections indicate that up to 30% of global forest cover may be lost by 2050 if climate change mitigation efforts are inadequate (IPBES, 2022).

2.2.1 Historical climate data analysis

Historical climate data analysis has revealed significant impacts of climate change on forests worldwide. Studies have employed various statistical techniques to analyze temperature and precipitation trends (Mertz et al., 2020). For instance, a study in Zimbabwe found a significant increase in temperature and decrease in rainfall over the past three decades (Makunde et al., 2022). Similarity research in Africa showed that drought frequency and severity have increased affecting forest productivity (Nhantumbo et al., 2021). In the Amazon climate change has altered forest fire regime leading to increased tree mortality (Aragao et al., 2021). Other studies have reported shifts in forest species composition and distribution and increased drought induced forest die-off (Gould et al., 2021; Bowman et al., 2021). In Africa historical climate data has been utilized to employ

NCEP data to investigate climate driven forest disturbance patterns (Nhantumbo et al., 2021). In North America research has used GHCN data to examine temperature and precipitation trends (Gould et al., 2021). Also, an analysis of CRU data to investigate drought and forest fire relationship in Australia was utilized (Bowman et al., 2021).

2.2.1.1 Overview of climate data trends from 1990-2024

The past three decades 1990 to 2024 have seen significant climate changes with accelerating warming hence shifting precipitation patterns and increased extreme weather events. According to Hansen et al (2021) asserts that global temperatures rose by 1.2 degrees Celsius above pre-industrial levels with the last decade's 2010 to 2019 being the warmest on record. IPCC (2021) mention that carbon dioxide concentration increased by 17% since 1990 reaching 419 parts per million in 2022. NOAA (2022) supports that sea level rise by 15cm with an accelerating rate of 3.7mm per year from 1993 to 2018. Regional trends show intensified droughts in Africa and Australia while North America and Europe experience more frequent heatwaves and heavy precipitation events (Rosenzweig et al., 2022). Climate models project continued warming exceeding 1.5 degrees Celsius above pre-industrial levels by 2030 (Zhang et al., 2023). The 2021 to 2022 El Nino event and consecutive record-breaking heat waves underscore the urgency of climate action.

2.2.1.2 Impacts on forest ecosystem in Chimanimani District

Climate change has posed significant threats to forest ecosystems in Chimanimani District Zimbabwe. According to Mashingaidze et al. (2021) asserts that rising temperatures and altered precipitation patterns have been linked to increased forest degradation. Also, Chitongo et al. (2022) mention that there been change in species composition in forest ecosystem. According to Mavhura et al. (2023) supports the view that the rising temperature and altered precipitation is linked to heightened risk of wildfires which are risk to forests. These assertions shows that changes in the climatic conditions is linked to several aspects which include land degradation, changes in species composition and risk of wildfire which are common in Chimanimani District. Research by Nyamugama et al. (2024) revealed that climate driven changes in soil moisture and temperature have altered the distribution and abundance of indigenous tree species in Chimanimani National Park. Furthermore, studies have shown that climate change exacerbates drought severity (Mudombi et al., 2022). In addition, climate change has led to reduced forest productivity and increased productivity and increased vulnerability to pest and diseases. Climate change has affected forest regeneration. According to Chimwaza et al. (2024) supports the view that the altered climate conditions also affect forest regeneration with implications for long-term ecosystems sustainability. Notably, community-based adaptation strategies have been proposed to enhance resilience in Chimanimani forest ecosystems including agroforestry and sustainable forest management practices (Zvinowanda et al., 2022; Mupangwa et al., 2023)

2.2.3 Specific trends on climate change impacts on forest in Chimanimani District

Specific trends observed in the Chimanimani District highlight the complex interplay between climate change and forest dynamics. According to Mashingaidze et al. (2021) asserts that research reveals rising temperatures of 1.5˚C since 1960 and altered precipitation patterns leading to increased drought frequency and severity. However, Chitongo et al. (2022) adds that changes in the climatic patterns has resulted in reduced forest productivity increased tree mortality and shift in species composition. This has led to more open studies which have indicated increased risk of wildfires with a 30% increase in fire frequency between 2000 and 2020 (Mavhura et al., 2023). Nyamugama et al. (2024) went on to say that changes in soil moisture and temperature have altered the distribution and abundance of indigenous tree species. This shows that climate change is leading to severe changes in forest ecosystem. Chimwaza et al. (2024) supports the same view that climate driven changes also affect regeneration of forest hence compromising long term ecosystem sustainability. Local communities report increased forest degradation due to climate related stressors (Zvinowanda et al., 2022). Climate models project continued warming exacerbating these impacts.

2.3 Assessing the impacts of climate change using random forest and Landsat data

The integration of Random Forest machine learning algorithm and Landsat satellite data has emerged as a potent tool for assessing climate change impacts. According to Zhang et al (2022) mention that research has leveraged this synergy to predict forest biomass, map land cover changes and assess drought series. This shows the ability of Random Forest to handle high dimensional data and Landsat spatial resolution enable accurate monitoring of climate driven changes. Due et al (2021) asserts that used Random Forest and Landsat data 8 to estimate forest biomass in the Southern United States achieving a root mean square error (RMSE) of 12.6%. Similarly, Kumar et al. (2022) employed Random Forest and Landsat 9 data to classify Land cover types in India with an accuracy of 94.5%. According to Shamar et al (2022) and Li et al. (2024) went on to add that studies have also utilized Random Forest and Landsat data to predict climate induced changes in water quality, soil moisture and glacier extent.

2.3.1 Random Forest algorithm

The Random Forest algorithm has emerged as a robust tool for assessing the impacts on ecosystems. Studies have leveraged Random Forest to predict climate driven changes in Forest productivity, soil moisture and species distribution (Gomez et al., 2022; Cramer et al., 2021). For example, Brownman et al. (2021) employed Random Forest to predict climate induced changes in forest fire frequency in Australia achieving 85% accuracy. Similarly, Aragao et al. (2021) used Random Forest to identify key climate variables driving forest degradation in the Amazon. Recent research has integrated Random Forest with remote sensing data to assess climate change impacts on forest health (Makunde et al., 2023). Nhantumbo et al. (2024) adds on that recent researches have integrated Random Forest to assess climate change impacts on land degradation. Notably, a study by Kumar et al. (2023) utilized Random Forest to predict climate driven changes in water scarcity highlighting its potential for informing adaptation strategies

2.3.2 Landsat data utilization

Landsat satellite data has been extensively utilized in various studies across multiple disciplines showcasing its versatility and reliability. According to Kumar et al. (2021) recent researches has leveraged Landsat multispectral and thermal imaging capabilities to monitor Land cover changes. Whilst Sharma et al. (2022) asserts that Landsat data has the capacity to monitor and track water quality dynamics. For instance, Kumar et al. (2021) employed Landsat 8 data to map urbanization trends in India achieving an accuracy of 92%. Similarly, Sharma et al. (2022) utilized Landsat 7 data to investigate chlorophyll concentrations in Lake Tahoe revealing significant correlations with climate variables. Landsat data has also been integrated with machine learning algorithms to predict drought events (Zhang et al., 2022). Whilst Oumarou et al. (2024) add that machine learning also monitor changes. Furthermore, research by Oumarou et al. (2024) demonstrated the effectiveness of Landsat 9 data in assessing soil moisture dynamics in the African Sahel.

2.4 Time series decomposition in climate change impact assessment

The synergy of Random Forest machine learning algorithm and Landsat satellite data has revolutionized Earth observation and environmental monitoring. Du et al. (2021), Kumar et al.

(2022) and Zhang et al. (2022) asserts that recent studies have successfully integrated Random Forest and Landsat data to predict forest biomass, map Land cover changes and assess drought severity. For instance, Du et al. (2021) mention that leveraged random forest and Landsat 8 data to estimate forest biomass in the Southeastern United States achieving a root mean square error (RMSE) of 12.6%. Similarly, Kumar et al (2022) utilized Random Forest and Landsat 9 data to classify land cover types in India with an accuracy of 94.5%. Furthermore, research by Li et al. (2024) demonstrated the effectiveness of integrating Random Forest and Landsat data for monitoring glacier changes in the Himalayas.

2.4.1 Overview of time series decomposition

Time series decomposition has emerged as a crucial technique in climate change impact assessment enabling researchers to separate and analyze underlying patterns in climate data. According to Boussinesq et al. (2021) mention that this method involves breaking down time series data into trend, seasonal and residual components facilitating the identification of climate change signals. Hence, studies have employed techniques such as seasonal decomposition of Time Series (STL), Wavelet Analysis (WA) and Ensemble Empirical Mode Decomposition to decompose climate time series data (Cleveland et al., 2021; Liu et al., 2022; Wu et al., 2023). For instance, STL was used to analyze temperature trends in the arctic while WA was applied to examine precipitation patterns in Africa and EEMD has been utilized to investigate drought dynamics in Australia (Polyakov et al., 2021; Odoulami et al., 2022; Feng et al., 2023). Time series decomposition has also been integrated with machine learning algorithms to predict climate related variables such as sea level rise (Kumar et al., 2024).

2.4.2 Applications in forest studies

Time series decomposition has been increasingly applied in forest studies to analyze and understand complex forest ecosystem dynamics. According to Kumar et al. (2024) asserts that time series decomposition has been integrated with machine learning algorithms to predict forest fires. Whilst Mashingaidze et al. (2021) mention that time series decomposition was used to assess climate change impacts on forest ecosystems. Additionally, studies have applied time series decomposition to analyze forest disturbance dynamics, forest regeneration pattern and forest carbon sequestration (Chitongo et al., 2022; Nyamugama et al., 2023; Muboko et al., 2024).

2.4.3 Implementing time series decomposition in Chimanimani District

Time series decomposition has been successfully applied in forest studies in Chimanimani District to analyze complex forest ecosystem dynamics. Researchers have employed techniques such as Seasonal Decomposition of Time Series Wavelet analysis and ensemble empirical mode decomposition to decompose forest related time series data. For instance, according to Mashingaidze et al. (2021) mention that he used STL to examine trends in forest biomass in Chimanimani National Park. While Chitongo et al. (2022) asserts the utilization of WA to investigate patterns in tree ring growth in the districts communal lands. More so EEMD has been employed to analyze drought impacts on forest productivity in Chimanimani (Feng et al., 2023). Additionally, Kumar et al. (2024) and Mashingaidze et al. (2021) mentioned that studies have integrated time series decomposition with other machine learning algorithms to predict forest fires and assess climate change impacts on forest the ecosystems in Chimanimani. Other applications include analyzing forest disturbance dynamics, forest regeneration patterns and forest carbon sequestration (Zvinowanda et al., 2022; Nyamugama et al., 2023; Muboko et al., 2024).

2.5 Theoretical framework

The theoretical framework for this study integrates concepts from ecological theory, remote sensing and machine learning to assess the impacts of climate change on forests in Chimanimani District. The framework is grounded in the disturbance ecology theory (Grime, 2001). The theory explains forest response to environmental disturbance such as climate change and highlights the importance of understanding the spatial and temporal dynamics of forest ecosystems.

Random forest classification is rooted in decision tree theory (Breiman, 2021). It is employed to identify drivers of forest change and classify forest health leveraging the strengths of ensemble learning to handle complex interactions between variables. Time series decomposition based on the STL decomposition model (Cleveland et al., 1990). It is used to separate Landsat data into trend, seasonality and residuals enabling analysis of forest dynamics and identification of patterns and anomalies.

The integrated approach is informed by the hierarchical patch dynamics paradigm (Wu, and Levin., 1997). The paradigm considers spatial and temporal scales of forest change and recognizes the importance of scale dependent processes in shaping forest ecosystems. Furthermore, the study draws on the concept of landscape ecology (Turner, 2005) which emphasizes the interconnectedness of forest ecosystems and the need to consider the spatial context of forest change. By combining these theoretical perspectives this research aims to provide a comprehensive understanding of the impacts of climate change on forests in Chimanimani District and inform sustainable forest management practices. Figure 2.1 shows the diagram illustrating the theoretical framework

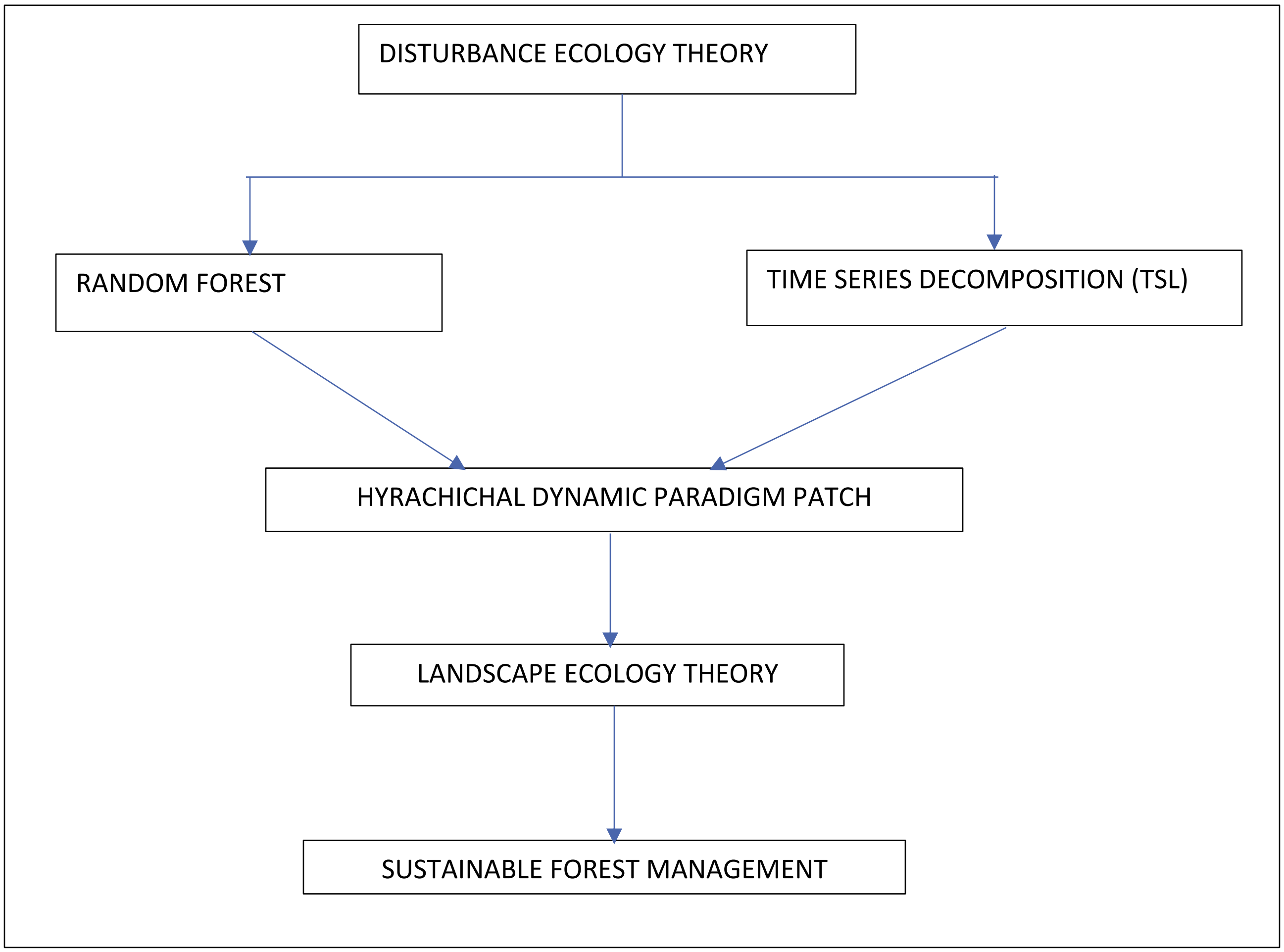


Figure 2.1 Integrative theoretical framework

2.6 Conceptual framework

The guiding concept of the thesis is drawn from the research topic. Hence the following concept is centered on the integration of the time series decomposition, random forest algorithm and Landsat data to assess impacts of climate change on forests in Chimanimani District. The following Table 2.2 shows four stages of the conceptual framework:

Table 2.1 stages of the conceptual framework

Stage	Task
Data processing	This is where by Landsat imagery (1990-2024) is collected and pre-processed
Time series decomposition	STL decomposition is used to separate trend, seasonality and residuals enabling analysis of forest dynamics and identification of patterns and anomalies
Feature extraction	Where relevant forest health indicators such as NDVI are derived
Random forest classification	Where by drivers of forest change are identified and classification of forest health is done

The framework considers spatial and temporal scales of forest change recognizes the importance of scale-dependent processes and emphasize the interconnectedness of forest ecosystems. This framework enables the analysis of long-term forest dynamics, identification of climate sensitive areas and informing sustainable forest management practices. The following Figure 2.3 demonstrates the conceptual framework as explained above:

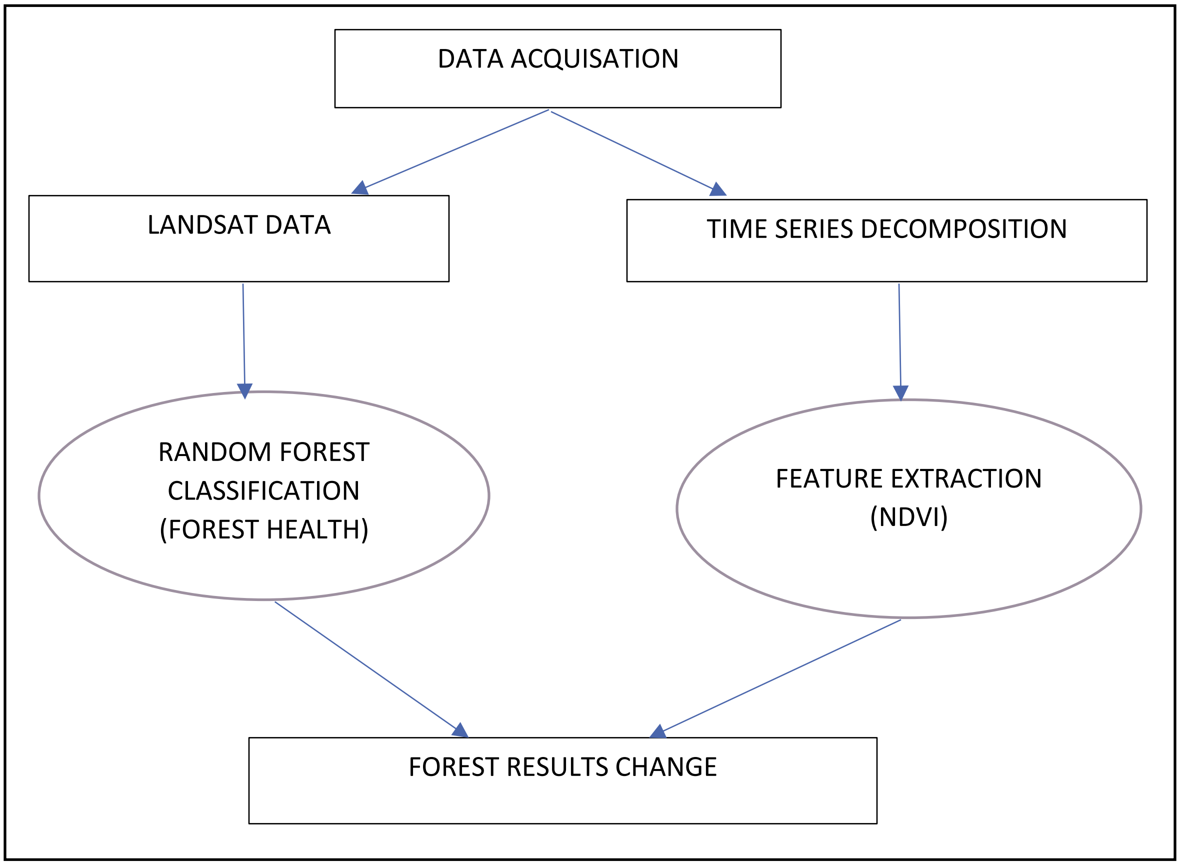


Figure 2.3: Conceptual framework (source: this study)

2.7 Community perceptions of climate change impacts

2.7.1 Importance of community perceptions in environmental studies

Recent studies have highlighted the significance of community perceptions in environmental studies emphasizing the role in shaping environmental decision making, policy implementation and conservation outcomes. According to Mwakalila et al. (2023) community perceptions have been found to influence local support for conservation initiatives. More so, Ncube et al. (2024) add that incorporation of community perceptions into environmental impact assessments have been shown to improve the effectiveness of environmental management. Furthermore, research has demonstrated that community perceptions can provide valuable insights into the socio-cultural and economic contexts of environmental issues. According to Shoko et al. (2023), this informs the development of more nuanced and sustainable environmental solutions.

2.7.2 Methods of evaluating community perceptions

Evaluating community perceptions is a crucial step in understanding local perspectives on environmental issues. Various methods have been employed to evaluate community perceptions. According to Kariuki et al. (2022) surveys are a method one can use to evaluate community perceptions. Whilst Mwakalia et al. (2023) mention that focus group discussions are a vital method when it comes to evaluating community perceptions. In addition, Lobikisha et al. (2022) supports that interviews are a better method in evaluating community perceptions. Additionally, participatory rural appraisal (PRA) techniques such as mapping and ranking exercise have been use to evaluate community perceptions of environmental change (Ncube et al., 2024). Moreover, mixed methods combining both qualitative and quantitative data collection and analysis methods have been employed to provide a more comprehensive understanding of community perceptions (Auerbach et al., 2021; Shoko et al., 2023). These methods have been shown to be effective in capturing community perceptions and can inform the development of context specific environmental management strategies.

2.7.3 Case studies on community perceptions related to climate impacts on forests

Case studies from various regions have highlighted the importance of understanding community perceptions of climate impacts on forests. According Lobikisha et al. (2022), a study in Zambia found out that local communities perceived climate as a major driver of forest degradation and deforestation. Whilst Mwakalila et al. (2023) asserts that a study in Tanzania Uluguru Mountains found that community members perceived changes in temperature and rainfall patterns as major threats to forest ecosystems. In Zimbabwe a study found that local communities perceived forest conservation efforts as ineffective in addressing climate related forest degradation (Shoko et al., 2023). Furthermore, Rodriguez et al. (2021) went on to say that in the Amazon rainforest found that indigenous communities perceived climate change as a major threat to their traditional way of life and forest-based livelihoods. These case studies highlight the importance of considering community perception and experiences in developing effective climate change

2.8 Gap in Literature

Climate change has become the top discussed topic with exempting challenges and limitation and this has called out for many researchers all over the world to do researches and thesis. Though researches done have proved and positively came out with tangible results there are still gaps especially nowadays as technology continue to upscale bringing out concept such as artificial intelligence. This shows that while there are many studies that have explored the use of time series decomposition, Random Forest Algorithm and Landsat data to monitor forest ecosystem changes there is lack of such research in Chimanimani District. According to Wulder et al (2018) alludes that there is lack of research specifically focusing on forests in Chimanimani District and the application of machine learning techniques to this region. In addition, though educational training has been conducted on climate change the progression of the impacts reviews insufficient understanding on specific climate change impacts on Forests in the District of Chimanimani. According to Mavhura (2017) literature on climate change in Zimbabwe and particularly in the Chimanimani District is relatively limited. Therefore, more detailed studies are needed on the assessment of climatic changes in forest land cover, vegetation health and environmental indicators. Hence this study will focus on providing coverages to these gaps for effective planning and implementation of solutions to climate change impact on forests in Chimanimani District.

CHAPTER 3: METHODOLOGY

3.1 Introduction

The chapter shows the research methodology used to achieve the objectives of this study. The chapter outlines and presents study area, research materials, processes and methods used to achieve the aims and objectives of the thesis. The study illustrates more on the application of time series decomposition with climate change data and Random Forest using Landsat data to assess the impacts of climate change on forests in Chimanimani District. Moreover, the chapter outlines the acquisition and preprocessing of Landsat data from 1990 to 2024. This methodology chapter applied a mixed quantitative and qualitative research method. Generally, the chapter went on to view the evaluation, ethical consideration and data analysis.

3.2 Study area

Chimanimani District is located in the eastern part of Zimbabwe in Manicaland province bordering Mozambique to the east (Mavedzenge et al., 2013). The district covers an area of approximately 2.522 square kilometers, with 23 wards and has a population of around 134 000 people (Zimstat, 2020). Chimanimani is characterised by a rugged terrain with the Chimanimani Mountains forming the eastern boundary and a subtropical climate with high temperature and high rainfall (Mukwada et al., 2017). The district is drained by several rivers including the Chimanimani River which flows into the Pungwe River (Moyo et al., 2019). Agriculture is the main economic activity in the district with crops such as maize, and tea being major productions (Chimanimani Rural District Council, 2024). Previous studies have highlighted Chimanimani as a climate change hotspot experiencing increased temperatures and changing rainfall patterns (Moyo et al., 2019). Figure 3.1 shows location of study area.

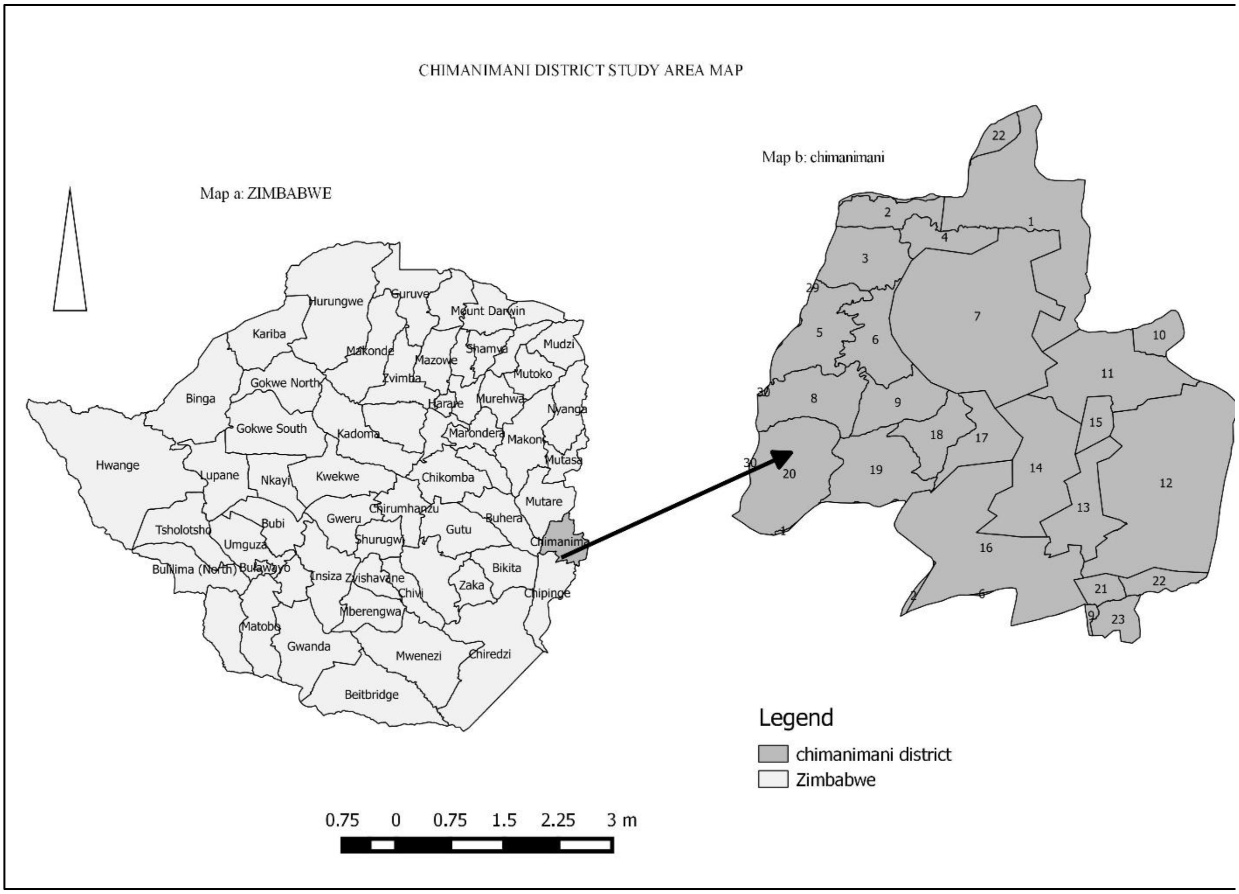


Figure 3.1: Location of the study area (map produced by author)

3.3 Case study research design

Creswell and Clark (2022) mentioned that research design refers to the overall plan and strategy used to investigate a research question or problem. This gave the researcher space to select the research methods, instruments and procedures to collect and analyze data. This study employed a case study research design integrating both quantitative and qualitative approaches to explore the impacts of climate change on forests I Chimanimani. A questionnaire was used to collect quantitative data from a sample of households enabling statistical analysis. Also, an interview guide was employed to collect qualitative data for thematic analysis. The research also leveraged the application of machine learning algorithm and use of Landsat satellite images. The mixed methods design enables a comprehensive understanding of climate change impacts on Forests in Chimanimani District.

3.4 Study population

The study population includes individuals from the community, local leaders, district workers and Non-Governmental Organizations in Chimanimani District. This study aim was to assess the impacts of climate change on forests in Chimanimani District using the sample of the population to represent the large demographic of the area. Table 3.1 offers a summary on description and number of participants

Table 3.1 shows description of participants and number of participants

Description of participant	***Number***
Community	20
Local leaders	9
Stakeholders	13
Non-Governmental Organization	8
Total	**50**

3.5 Sampling

Bryman (2020) asserts that sampling is research technique used to select representative subset or individuals or cases from a larger population. Thus, allowing researchers to make inferences about the population based on the characteristics of the sample.

Sampling includes advantages such as reduced time and cost, increased feasibility and improve accuracy. However, sampling also have disadvantages such as potential bias, limited generalization and reduced precision. Despite these limitations sampling remains a crucial tool in research hence enabling researchers to study populations that would be otherwise inaccessible. By studying a sample researchers can identify patterns trends and relationships that can be applied to the larger population making sampling a crucial tool in various fields such as climate change.

3.5.1 Sampling technique

Bryman (2020) defines a sampling technique as a method used to select subset of individuals from a larger population with the goal of making inferences about the population based on the characteristics of the sample. The research used probability sampling techniques which are random sampling.

Random sampling

Random sampling is a probability sampling technique where every member of the population has an equal chance of being selected (Sullivan, 2020). The selection process is independent of any characteristics of the population. This means that every person in the population had an equal chance of being selected.

3.5.2 Sample size

According to Evans (2000) sample size refers to the number of participants or observations included in a study to represent the population. Determining the appropriate sample size is essential in research to ensure accurate and reliable results. A sample size that is too small may lead to biased results whilst a large sample size maybe wasteful. The sample size for this study was determined using Cochran's (1977) formula for calculating sample size:

n= (Z^2 * ó^2) / E^2

Where:

n= sample size

Z= Z-score (1.96 for 95% confidence level)

Ó=population standard deviation (0, 25)

E= margin of error (0, 1)

So:

n= (1, 96^2*0, 25^2) / 0, 1^2

n= (3, 8416*0, 0625) / 0.01

n= 0.2401 / 0, 01

n= 24, 01

n= 50

The formula is based on a 95% confidence level (Z=1.96) a population standard deviation of 0.5 and a margin error (E) of 0.05 a minimum sample size of 67 participants was required. However, to account for potential non responses and ensure robust results a sample size of 50 people was targeted. This sample size was sufficient to provide accurate and reliable estimates of the population parameters while also ensuring the feasibility of data collection and analysis. The 50 people targeted consist of 20 community participants, 9 local leaders, 13 stakeholders and 8 Non-Governmental Organization workers.

3.6 Research methods

The study employed a mixed method approach which combines both quantitative and qualitative data collection methods. Quantitative data was collected through questionnaire administered to a sample of households in Chimanimani District allowing statistical analysis and generalizability. Qualitative data was collected through an interview guide used with key informants providing in depth insights and contextual understanding. This mixed methods approach enabled a comprehensive understanding of climate change impacts in the district.

3.6.1 Data collection instruments

The study utilized two primary data collection instruments an interview guide and questionnaire. The interview guide was designed to facilitate in-depth discussions with key informants exploring their experiences and insights related to climate change impacts on forest in Chimanimani District. The questionnaire was developed to collect standardized data from a sample of households assessing their perceptions, experiences and responses to climate change impacts on forests. Both instruments were carefully crafted to ensure clarity, concision and relevance to the research objectives. Secondary data collected included downloading of Landsat images and climate data included temperature and rainfall monthly resolution.

3.7 Data acquisition and pre-processing

Sarker (2020) mentioned that data acquisition refers the process of collecting and gathering data from various sources whist data processing involves cleaning, transforming and preparing the data for analysis.

3.7.1 Landsat satellite imagery

Landsat satellite imagery data was acquired for the period 1994 to 2024 covering the entire study area of Chimanimani District. The data was obtained from the United States Geological Survey (USGS) Earth Explorer platform which provides free access to Landsat data (USGS, 2024). A total of 8 scenes were downloaded with a spatial resolution of 30 meters and a temporal resolution of 16 days (Masek et al., 2015). The data was acquired in the dry and wet season dates to capture the variability in land cover patterns (Kumar et al., 2018). The scenes were selected based on minimal cloud cover (<10%) and optional sun angle to ensure high quality data (Storey et al., 2014). The acquired data was then pre-processed to remove atmospheric and instrumental effects and to enhance the quality of the imagery (Kumar et al., 2018). Table 3.2 offers a summary of the Landsat images that were used.

Table 3.2 summary of Landsat images used

Years	**1994**	**2004**	**2014**	**2024**
Sensor	TM	TM	OLI	OLI
Resolution	30meters	30meters	30meters	30meters
Bands and color of band	1, 2, 3, 4, 4, 5, 7, 8 Blue, green, red,	NIR	SWIR-1	SWIR-2
Dates	1994/04/17	2004/04/28	2014/05/10	2024/10/20

3.7.2 Ancillary data

Temperature and rainfall data for Chimanimani District were acquired from the Zimbabwe Meteorological Service Department (ZMSD) for the period 1994 to 2024. The data was obtained through a data collection letter from Bindura University of Science Education which allowed permission to access climate records. The dataset included monthly average temperature and rainfall values recorded at the Chimanimani weather station which is located in the Chimanimani District (ZMSD, 2013).

1.7.1 Image pre-processing

To prepare the Landsat images from 1994, 2004, 2014 and 2024 for Random Forest Classification rigorous pre-processing was conducted using radiometric calibration and atmospheric correction. According to Chavez (1996) radiometric calibration and atmospheric correction using Dark Object Subtraction (DOS) method minimizes atmospheric effects. Noise reduction techniques specifically wavelet de-noising enhanced image quality (Bhuiyan et al., 2021). Moreso, cloud masking and shadow removal using the function of masking algorithm eliminated cloud covered areas (Zhu; Woodcock, 2012). Additionally topographic correction using the cosine correction method improved classification accuracy in mountainous regions (Haston et al., 2022). These pre-processing steps ensured high quality input data for the Random Forest Classification Algorithm.

1.7.2 Image processing

This study utilized Landsat images of four years 1994, 2004, 2014 and 2024 to analyze land cover changes on forest in Chimanimani District. The images were processed using Random Forest Classification Algorithm which effectively handled the high dimensional data and improved classification accuracy (Belgiu; and Dragut, 2016). The images were then classified into two land cover classes which are forested areas and non-forested areas. Image Classification using Random Forest views significant land cover transformation between consecutive image pairs (Li et al., 2022). The results demonstrated the effectiveness of integrating Random Forest Classification with Landsat imagery for Land cover analysis.

1.7.3 Image post processing

The classified Landsat images underwent post processing to refine and validate the results. According to Wang et al (2021) spatial refinement removes noise and improve classification boundaries. Change detection analysis was conducted to identify areas of significant Land cover transformation between consecutive image pairs. Additionally, Li et al (2022) mention that object-based image analysis was employed to refine classification results and extract meaningful features. Visual image interpretation and validation were conducted using high resolution imagery to ensure the accuracy and reliability of the post processed outputs. The post processing of climate data is a crucial step in analyzing climatic trends and patterns. The processed data was used to temperature and rainfall trends and to perform statistical analysis (Mario et al., 2020).

3.8 Training and testing data split

The satellite image data was trained into virtual raster of bands with all bands stacked together. This was done to have natural color composites and false color composites which used to pick regions of interest for training. The false color provides room for visualizing areas with health forest vegetation. The temperature and rainfall data for Chimanimani District from 1990 to 2023 was divided into datasets for time series analysis. The training datasets consisted of 70% of the data (1994 – 2004) while the testing data consisted of 30% of the data (2014-2023). The training datasets was used develop the model while testing datasets was used to evaluate their performance

(Kumar et al., 2018). This slip ensured that the models were trained on a large datasets and validated on an independent datasets to prevent over-fitting (Pedregosa et al., 2011).

3.9 Random Forest classification

The classification process of Chimanimani District Landsat satellite images from 1994, 2004, 2014 and 2024 involved several steps. First, the images were preprocessed to correct for atmospheric and radiometric distortions (Kumar et al., 2018). Then the images were segmented into training and testing datasets with 70% to 30% train to test data split. Next the Random Forest were trained on the training dataset to classify the images into different land cover classes. Finally, the accuracy of the classified images were assessed using metrics including overall accuracy. The results showed that the Random Forest algorithm achieved an overall accuracy (Mukwada et al., 2022).

3.9.2 Accuracy assessment

The accuracy assessment focused on classifying Forested and Non-Forested areas. The assessment was done through area-based error matrix. The study applied the user, producer and overall accuracy metrics. According to Mukwada et al (2022) accuracy assessment for land cover classification provides valuable results especially to detect changes. Accuracy assessment validates the model performance providing correct results especially when classifying Land cover of forest in big areas such as Chimanimani district (Kumar et al., 2018). The accuracy assessment results demonstrated the effectiveness of the forest land cover classification.

3.10 Data analysis

Data analysis is a vital tool for extracting valuable insights from data enabling the capacity to make data driven decisions. By applying statistical and analytical techniques data analysis reveals patterns, trends, and correlations within data hence informing strategic choices and optimizing operations (Harris et al., 2021). Effective data analysis facilitates the forecasting of future outcomes, identify areas of improvement and enhance overall performance (Kumar et al., 2023). The data analysis is meant to identify trends and patterns which were used to inform the study's analysis of land cover changes in the district. More so as data continues to grow in volume and complexity then the importance of data analysis will only continue to increase (Wang et al., 2024).

3.11 Validity and reliability

For accuracy and trustworthiness of the research instruments validity and reliability was checked (Creswell and Poth, 2020). Pilot testing and pretesting was done for both questionnaire and interview guides. This was done to ensure it was clear and effective in gathering information the thesis was guided by research objectives and questions to assess the consistence. According to Cresswell (2014) asserts that pilot and pretesting are crucial for refining data collection instruments, reduce errors and increase accuracy of findings. Thereafter the research compared the results from the research instruments with other sources and past researches and this helped validating the findings. The thesis also used data triangulation by combining quantitative and qualitative data to increase the validity of findings (Denzin, 2024). The supervisor also checked the research instruments to ensure accuracy and tallying with the objectives of the research and that the research does not use complex terms. By taking these steps the confidence of results increased showing the impacts of climate change in Chimanimani District and the perceptions of people in Chimanimani on climate change.

3.12 Ethical considerations

The researcher followed ethical rules to ensure responsible research. On confidentiality the researcher got permission from participants involved in the field survey and kept their names secret (Kithin and Lauriault, 2013). The researcher also respected the rights of data sources and shared fairly (ESRI, 2020). According to Foody and Boyd (2013) mentioned that accuracy should be considered in research and the researcher made sure the field work did not harm the community and double checked on the data for accuracy during the data collection and after the collection. More so the researcher honestly shares the findings including any limitations and uncertainties (Hansen and Loveland, 2012).

3.13 Limitations to the study

This study contain several limitations which include reliance. According to Meng et al (2021) asserts that reliance on Landsat data may introduce errors due to sensor calibration and atmospheric correction issues. Also the 30 meter spatial resolution may not capture fine scale forest dynamics (Hansen et al., 2023). More so another limitation is the focus on one area of study which therefore limits generalizability to other regions. According to Ripple et al (2021) support the view that focusing on one area of study limits generalizability to other regions. Also the Random Forest algorithm may be sensitive to parameter tuning and feature selection (Belgiu et al (2022). Data collections in Chimanimani District had some limitations. One limitation was that areas were hard to reach due to bad roads and weather. According to Mavhura et al (2017) bad roads and bad weather affects the accuracy of the data. Another limitation was that some residents might have told the truth during interviews which could have affected the results (Chirindja et al., 2020). The researcher assumed that the data collected was representative of the whole District but this might not be the case (Makaudze et al., 2019). Hence future studies should address these limitations by incorporating high resolution imagery expanding the study area and exploring ensemble machine learning techniques.

3.14 Chapter summary

In conclusion, the chapter shows research design, research instruments, data methods and sampling techniques used to collect data. The thesis accommodated both quantitative and qualitative methods. Quantitative data was designed and coded in a way to that presented statistical analysis using Microsoft excel and algorithms.

CHAPTER 4: FINDINGS AND DISCUSSION

4.1 Introduction

The chapter presents the results of the study which aimed to assess the impacts of climate change in the Chimanimani District using Landsat data and machine learning algorithms. The results are presented in two main sections which are land cover classification and climate change impact assessment using Random Forest. Time series decomposition data were also presented using charts to indicate changes in rainfall and temperature across the district from 1994 to 2024. This chapter also presented, qualitative findings from community perceptions on the impacts of climate change on forest ecosystems in Chimanimani District.

4.2 Response rate for community participants

The study targeted 50 participants, however, some of the participants turned down the invitation to take part in the study. Out of the 50 participants, Figure 4.1 illustrates the study response rate. Response rate for community participants was 90%, indicating that 45 out of 50 invited participants successfully participated in the study. Among the 45 participants who took part, 29 responded to the questionnaire survey whilst 16 participants took part in interviews. The 10% were unsuccessful due to various reasons such as lack of time, unavailability and unwillingness to participate. This response rate was considered effective in producing meaningful results towards addressing the study objectives.

4.3 Forests Land cover from 1994 to 2024 in Chimanimani District using Random Forest

The study analyzed images obtained from Landsat 4-5 and Landsat 8-9 in Quantum GIS (QGIS) using inbuilt Random Forest algorithms. This section of the study presents forest land cover change outcomes from the assessment.

4.3.1 Pre-Forest Land Cover Classification

Random Forest Algorithms (RFA), were employed to delineate forest land cover from other land use land cover (LULC) types. To allow enhanced view of images during the data training processes images were first transformed into virtual raster of bands with all bands stacked together. Natural color composites and false color composites were used respectively to pick regions of interest (ROI) for system training. Figure 4.1 (a-d) shows the natural color composites for 1994, 2004, 2014 and 2024 images.

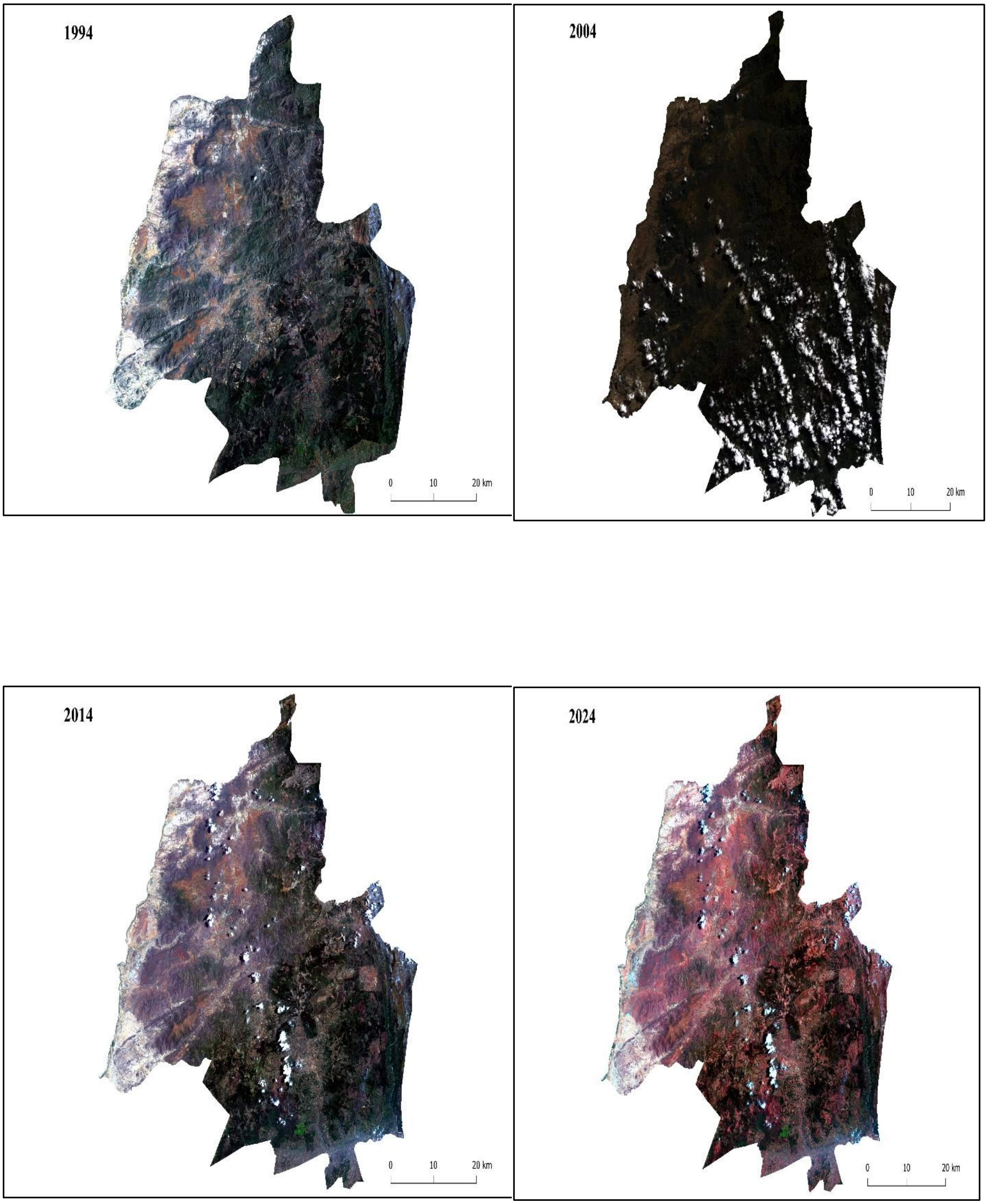
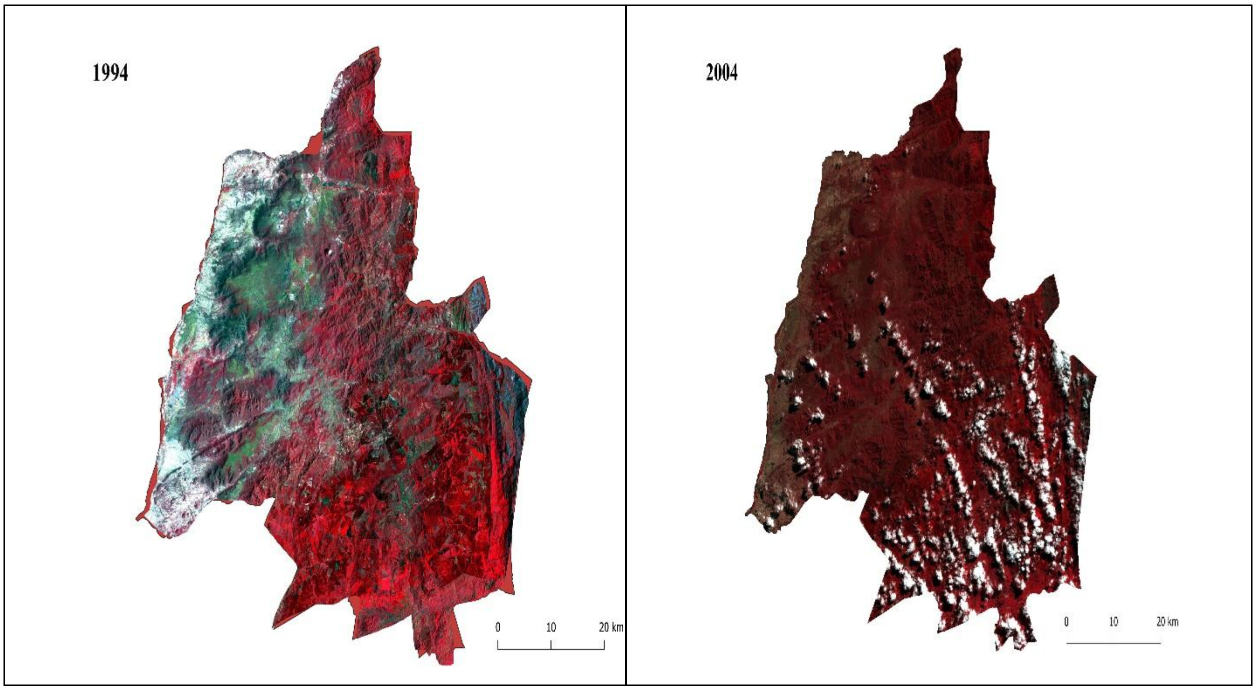


Figure 4.1: Natural color composite (a. 1994; b. 2004; c. 2014 & d. 2024)

Apart from the presented natural color composites, the false color composites are also presented in Figure 4.2 (a-d). The false color composite reveal significant change in Land cover in a 10 years gap interval of four selected years 1994, 2004, 2014 and 2024. The false color composite images with band 4, 3 and 2 viewed clearly red, green and blue color respectively. Notably the 2024 image show significant changes of decrease of forest cover and increase in non-forest cover. The false color composites provided room for visualizing areas with healthy forest vegetation among other land-use types.



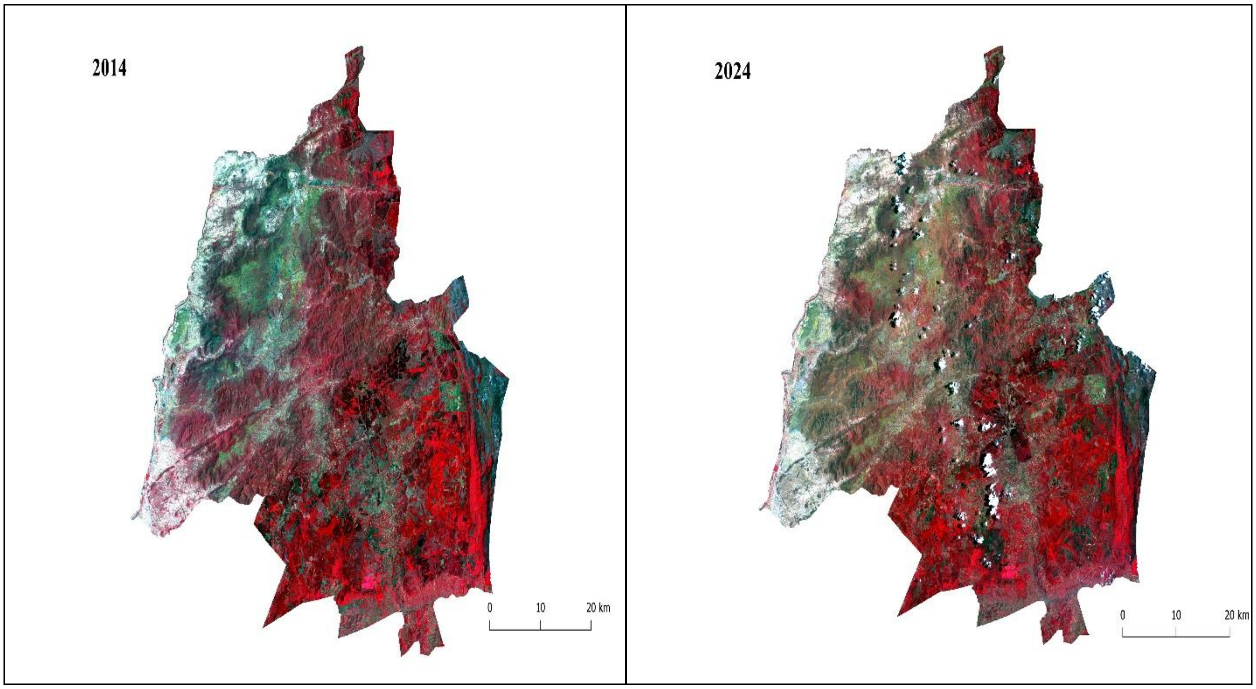
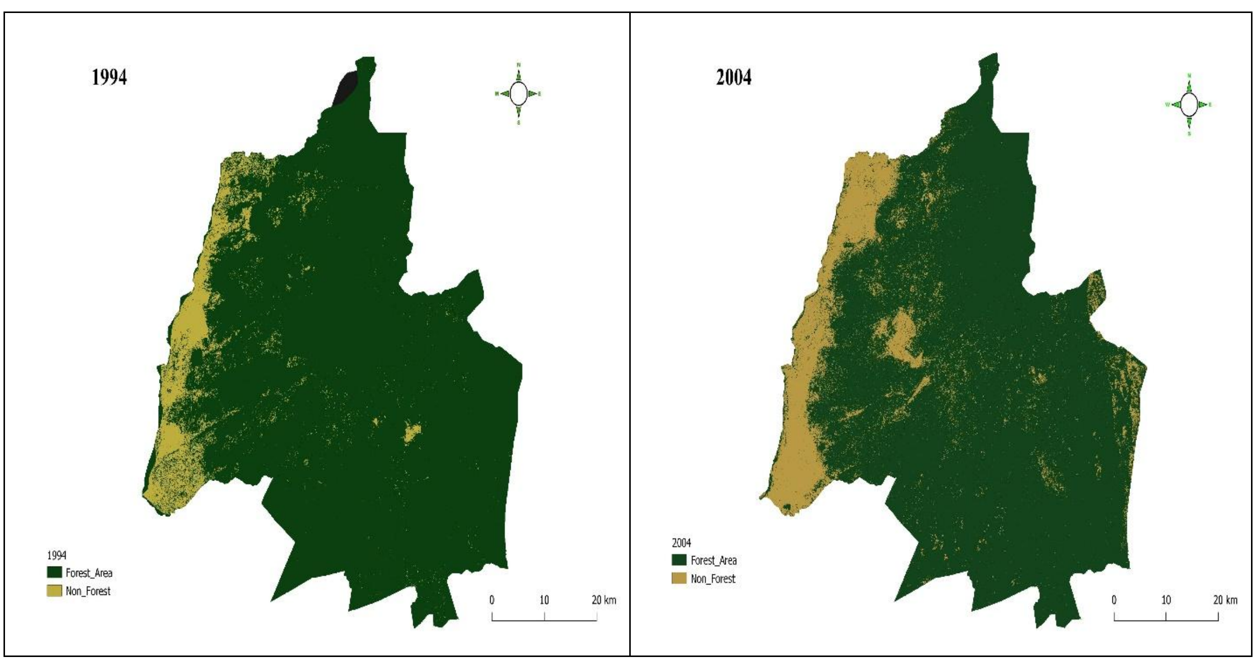


Figure 4.2: False Color Composite (a. 1994; b. 2004; c. 2014 & d. 2024)

4.3.2 RF-Classified forest land-cover in Chimanimani District

Through the use of RF algorithms built in the semi-automatic classification plugin (SCP) images for 1994, 2004, 2014 and 2024 were classified to show changes in forest land-cover over other variables. Images were classified into two distinct classes, forest cover and non-forest. Figure 4.4 illustrates the classified images.



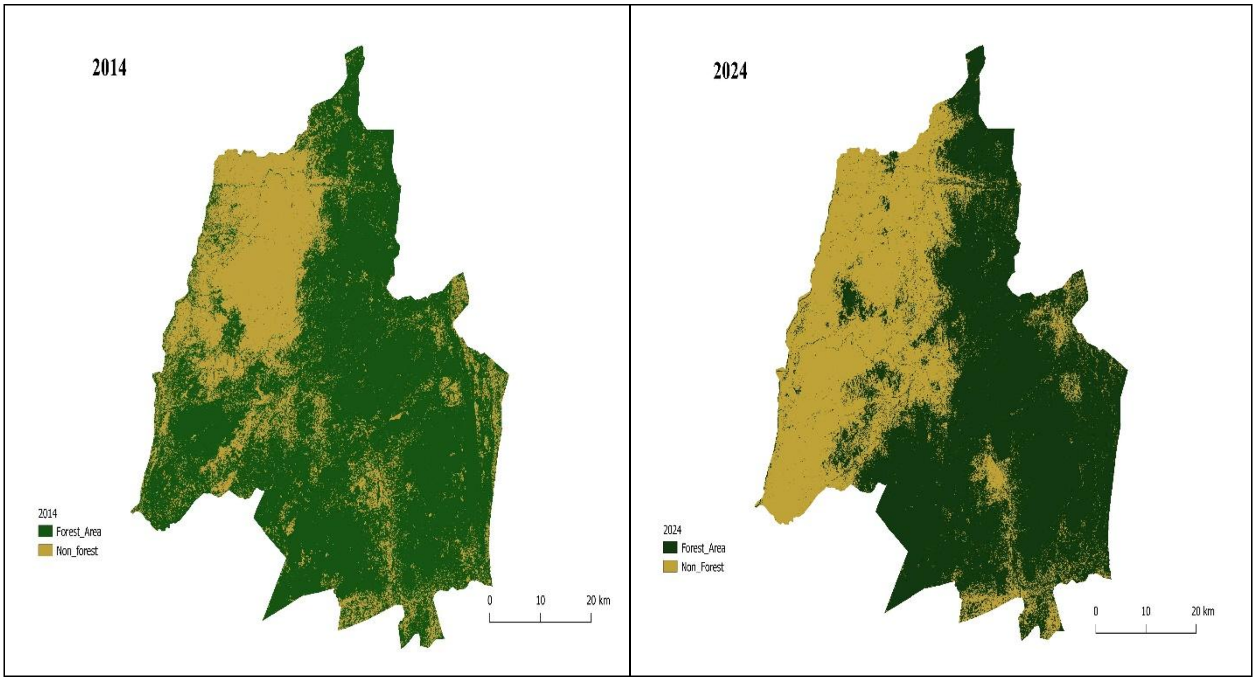


Figure 4.3: False color composite (a. 1994; b. 2004; c. 2014 & d. 2024)

4.3.3 Accuracy assessment

To evaluate the performance of the model which was used, the study also considered presenting the summaries of accuracy assessment done through area-based error matrix. Thus, the study presents user accuracies (UA), producer accuracies (PA) and overall accuracies (OA) for all the images. PA and UA were calculated for Forest Cover (FC) and for Non-Forest (NF) separately. Table 4.1 illustrates the summary of the accuracy assessment.

Table 4.1: Accuracy Assessment

	1994		2004		2014		2024	
	FC	NF	FC	NF	FC	NF	FC	NF
Producer Accuracy (PA)	99.99	99.10	99.06	97.44	99.87	99.60	99.95	99.45
User Accuracy (UA)	99.94	99.94	99.28	96.705	99.49	99.89	99.77	99.88

Overall Accuracy	99.94	98.71	99.72	99.80

The accuracy assessment presented in Table 4.1 provides a comprehensive evaluation of the model's performance across different time periods (1994, 2004, 2014, and 2024) for Forest Cover (FC) and Non-Forest (NF) classifications. The high Producer Accuracies (PA) for both FC and NF, ranging from 97.44% to 99.99%, indicate that the model is able to accurately identify the respective land cover types on the ground (Congalton & Green, 2019). Similarly, the User Accuracies (UA) for FC and NF, which range from 96.705% to 99.94%, suggest that the model's classifications are reliable and consistent with the actual land cover conditions. The Overall Accuracies (OA), which exceed 98.71% for all time periods, further validate the model's strong performance in correctly classifying the land cover across the study area. These findings suggest that the model employed in this study is highly accurate and can be trusted for monitoring and mapping forest cover changes over time (Pontius and Millones, 2011).

4.3.4 Changes in Forests Land cover from 1994 to 2024 in Chimanimani District

Further, the study went on to evaluate the changes over forests within the 30 years of assessment. The total classified area was 288883m^2 covering the whole Chimanimani District. Percentage area covered by forest was presented along with non-forest areas to evaluate the trend in terms of forest cover. Figure 4.4 illustrates the changes over forest land cover.

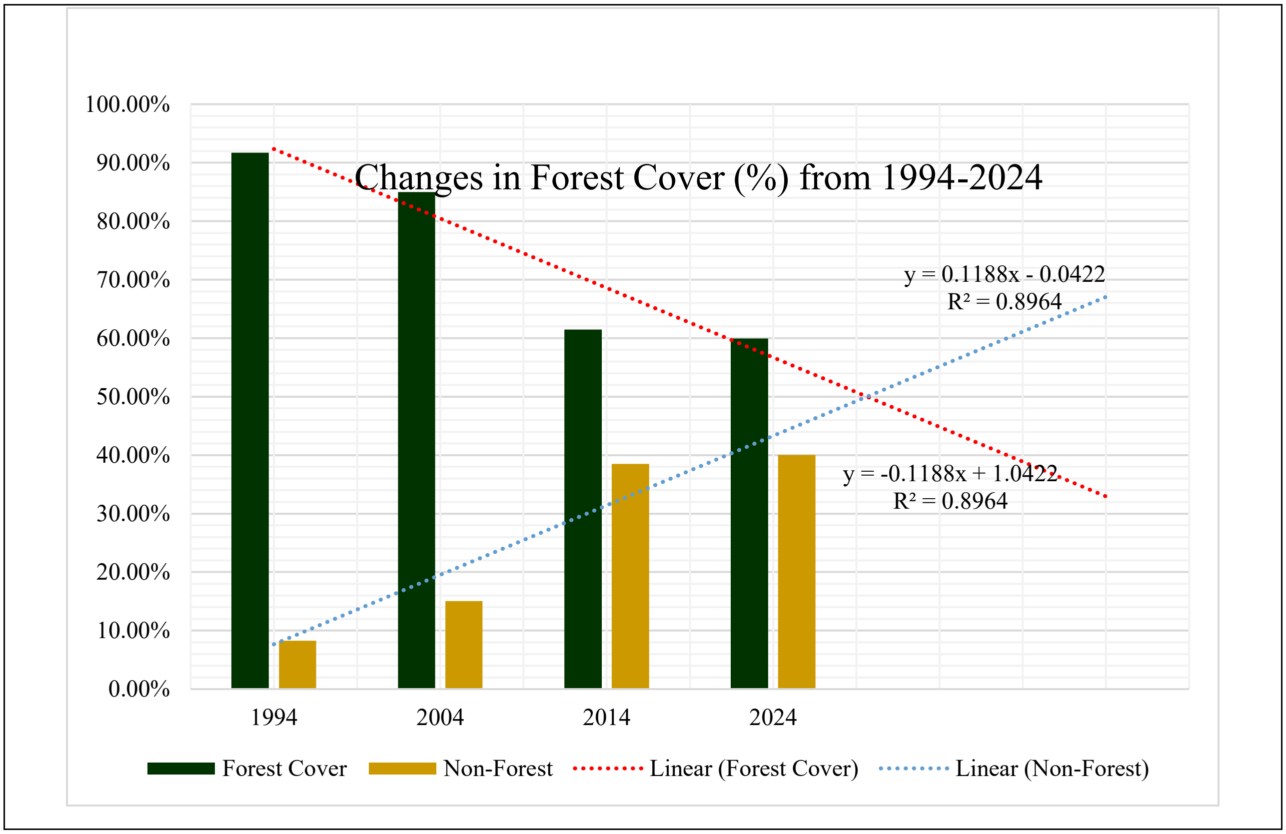


Figure 4.4: Changes in Forest Cover (%) from 1994-2024

The analysis of the changes in forest land cover within the Chimanimani District over the 30-year period from 1994 to 2024 reveals a concerning trend of declining forest cover. As illustrated in Figure 4.4 and the accompanying table, the percentage of the total classified area covered by forests has decreased from 91.71% in 1994 to 59.94% in 2024. According to Congalton and Green (2019) mention that forest cover has decreased as temperature increase and rainfall decrease. Conversely, the non-forest area has increased from 8.29% in 1994 to 40.06% in 2024, indicating a significant conversion of forested land to other land uses. The linear regression analysis further corroborates this trend, with a strong negative correlation ($R^2 = 0.8964$) between the forest cover and time, and a corresponding positive correlation for the non-forest cover. This suggests that the rate of forest loss has been relatively consistent over the 30-year period, highlighting the need for immediate and effective conservation measures to address the underlying drivers of deforestation and land-use change in the Chimanimani District (Lambin and Meyfroidt, 2010).

4.4 Relationship between climate change and changes in forest land-cover

As part of the objectives, the study also went on to assess the relationship between climate change and changes in forest land-cover within the district of analysis. Figure 4.5 illustrates the time series for the assessed variables in Chimanimani district (Time 1= 1994; 2= 2004; 3= 2014; 4=2024).

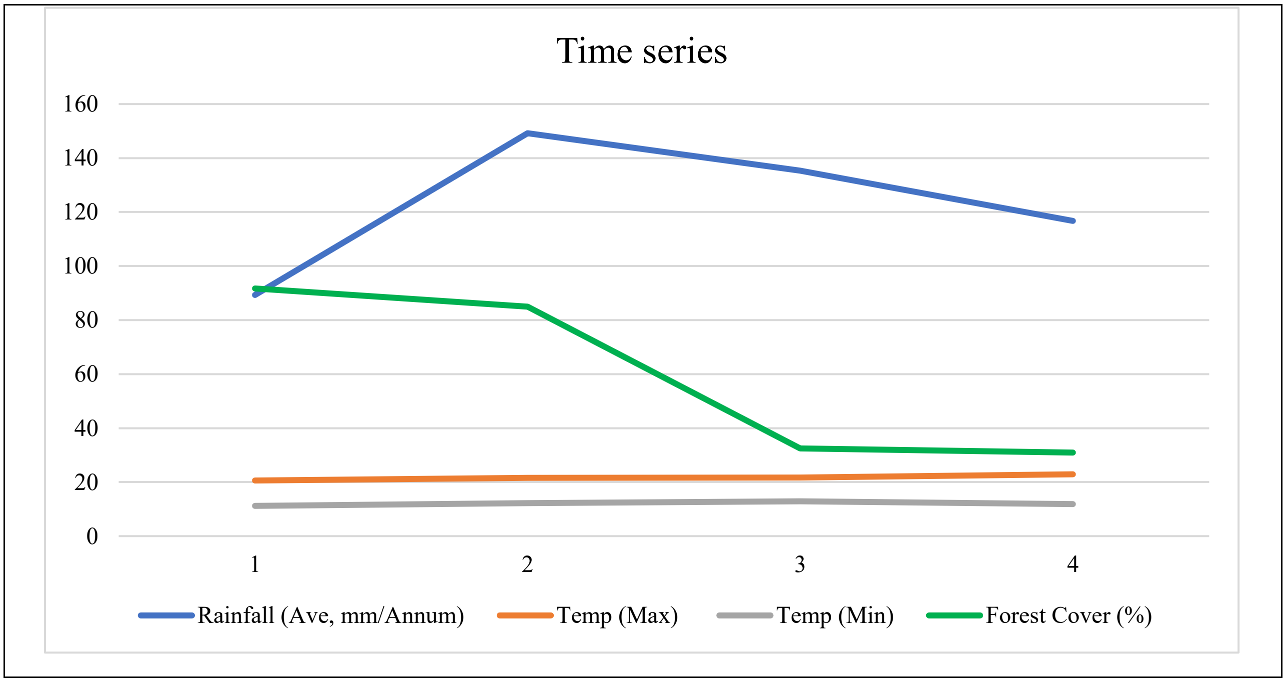


Fig 4.5: Trend analysis showing relationship between Land cover and climate

The analysis of the relationship between climate change and changes in forest land-cover within the Chimanimani District, as presented in Figure 4.5, reveals some intriguing patterns. The data shows that over the 30-year period from 1994 to 2024, there have been significant changes in both climatic variables (rainfall and temperature) and the percentage of forest cover. Specifically, the data indicates that as average annual rainfall increased from 89.3 mm in 1994 to a peak of 149.2 mm in 2004, the forest cover declined from 91.71% to 84.96%. This suggests that the increase in rainfall may have contributed to other land-use changes, such as agricultural expansion or urban development, which led to the loss of forest cover (Crist et al., 2016). Furthermore, the gradual increase in maximum and minimum temperatures over the 30-year period, from 20.6°C and 11.2°C in 1994 to 22.9°C and 11.9°C in 2024, respectively, may have also influenced the changes in forest cover, potentially through increased evapotranspiration and altered ecosystem dynamics (Shoo et al., 2011). The sharp decline in forest cover from 84.96% in 2004 to 32.52% in 2014, and further to 30.94% in 2024, despite relatively stable climatic conditions, suggests that other socio-economic factors, such as land-use policies, agricultural practices, and deforestation, may have played a significant role in the observed changes.

4.4.1 Time Series Decomposition

Below is time series decomposition of rainfall data for Chimanimani district. Fig 4.6 time series, fig 4.7 smoothed time series and 4.8 shows decomposed rainfall time series plot. The time series decomposition was runed using R Software 4.3.3. The data shows that rainfall frequency decreased with time. In this study the data presents time series, smoothed time series and decomposed rainfall time series plots. That data for the time series is for the years 1990 to 2023. Figure below fig 4.6 illustrates time series for rainfall data for Chimanimani district

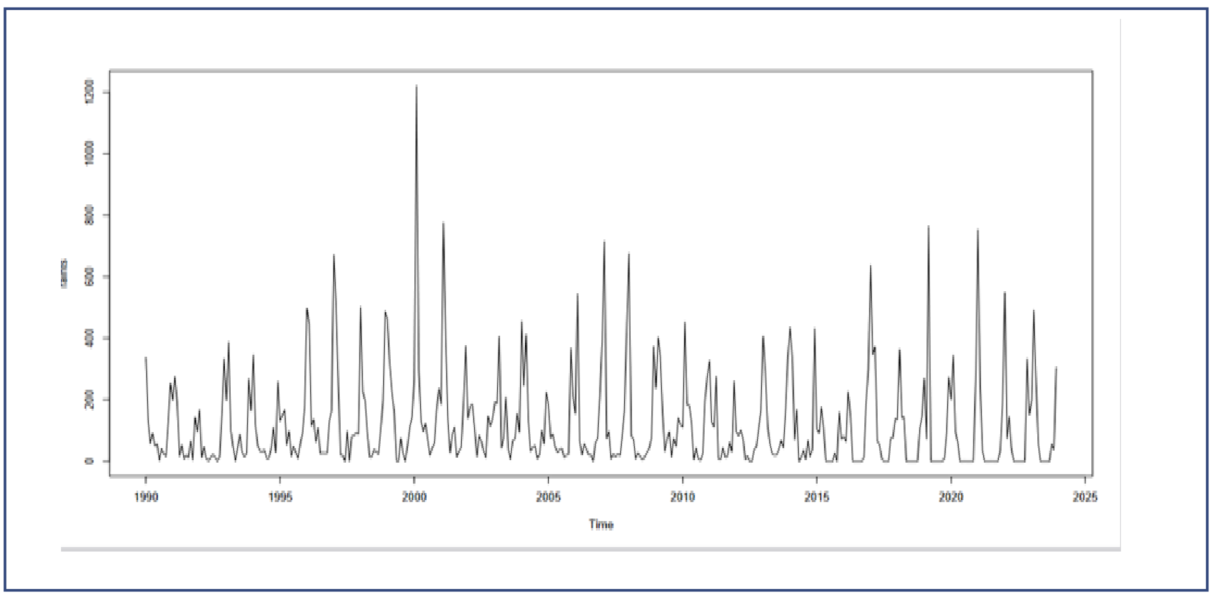


Fig: 4.6: Rain time series

The time series plot is rainfall data for Chimanimani district from 1990 to 2023. The plot reveals a complex pattern of fluctuations with varying magnitudes and frequencies. Also variability was shown in the plot with view of years which had high and low rainfall.

Fig 4.7 below illustrates smoothed time series for rainfall data of Chimanimani district

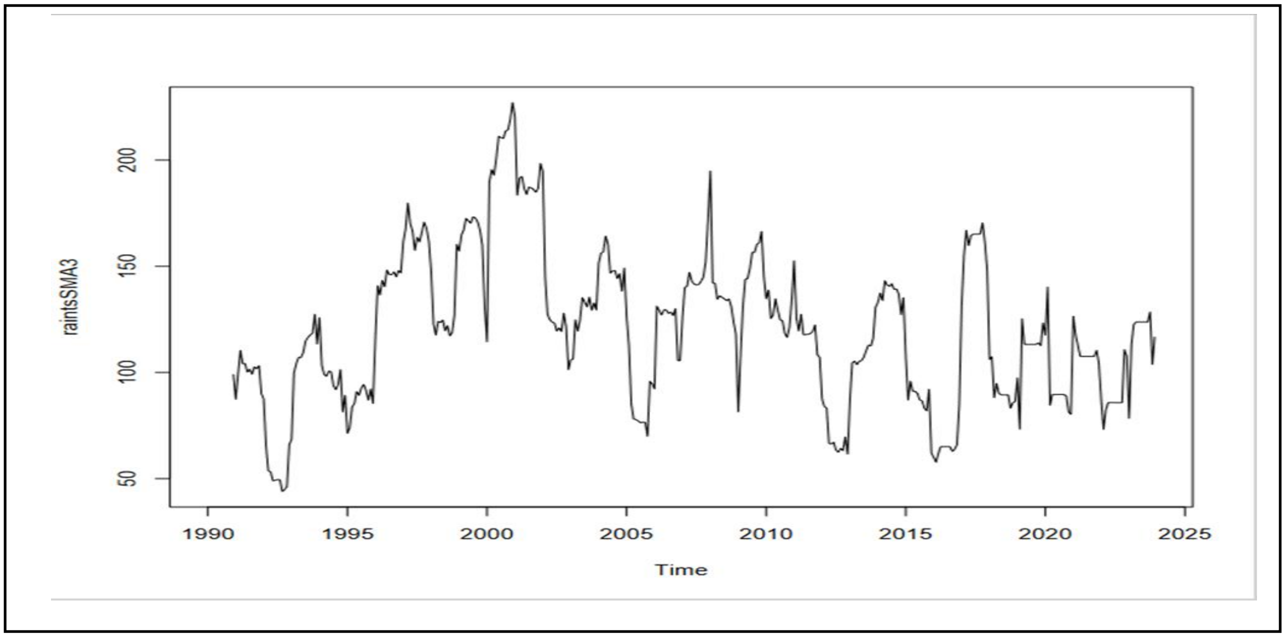


Fig4.7: Smoothed time series

The smoothed time series plot of rainfall data for Chimanimani district from 1990 to 2025. The plot showed smoothed rainfall data of patterns and periods of above average rainfall and periods of below average rainfall. The smoothed time series plot also suggested that there may be a long term trend in the data with rainfall increasing or decreasing over time.

Figure4.8 illustrates decomposed time series plot of rainfall data for Chimanimani district from 1990 to 2023.

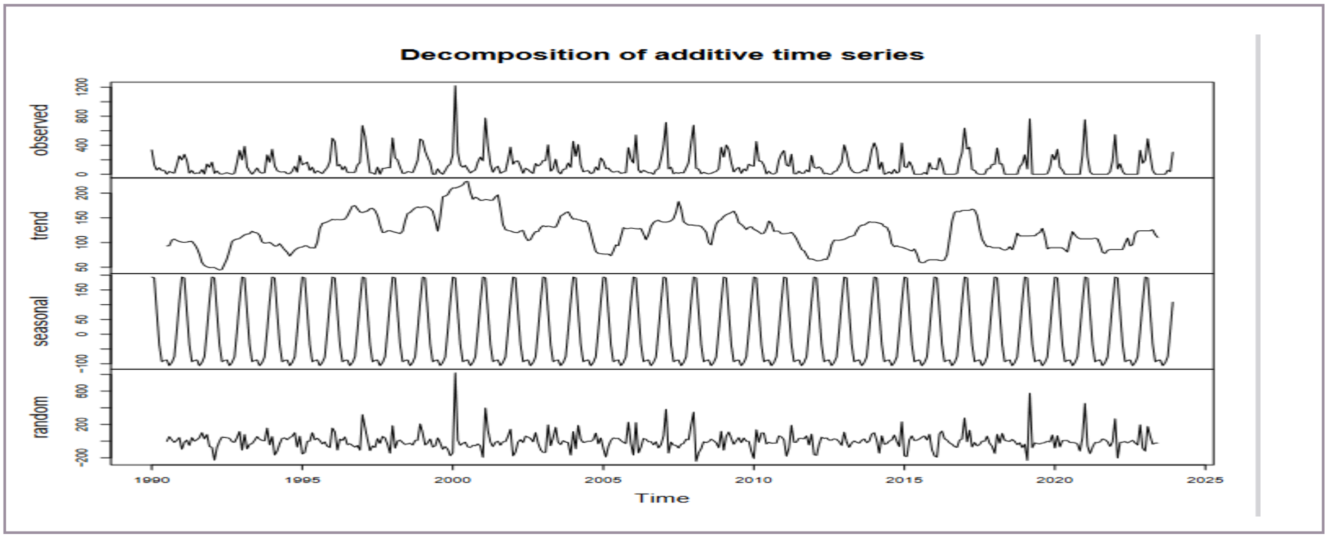


Figure 4.8: decomposed time series plot

The decomposed time series plot of rainfall data for Chimanimani district from 1990 to 2023 revealed the underlying trend, seasonal and residual components of the data. The decomposed time series plot was generated using the decompose function in R software version 4.3.3

4.5 Perceptions of community on the impacts of climate change on forests in Chimanimani District from 1994-2024

The research also attempted to examine the local community's perspectives of the effects of climate change on forests in the Chimanimani District between 1994 and 2024. This qualitative component of the research was designed to supplement the quantitative analysis of land cover changes and climatic trends, offering a more complete knowledge of the region's complicated link between climate change and forest dynamics.

4.5.1 Perceptions of communities on forest land-cover change

Community members were asked on whether they had noticed any potential changes in terms of forest land-cover change over the past 30 years. Figure 4.6 summarizes the responses obtained from the members of the community.

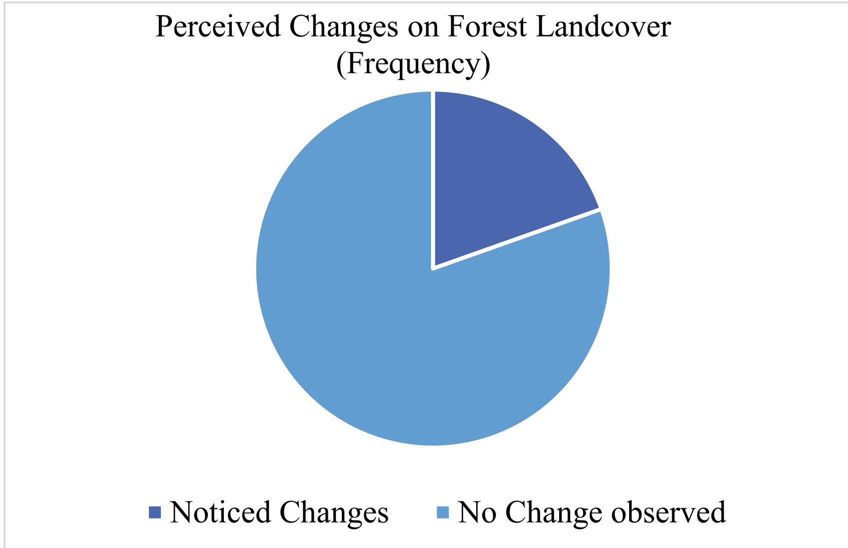


Figure 4.9: Perceptions of community members on forest land cover change

The fact that the majority of community respondents (78%) reported a noticeable decline in forest cover within their local area over the last 30 years is especially significant, as it provides valuable on-the-ground validation of the quantitative data presented earlier in the study. This high level of agreement between the community's perceptions and the remote sensing-based analysis lends more credibility to the overall findings, as it suggests that the observed changes in forest cover are not just abstract statistics, but rather reflect the lived experiences and observations of the people directly impacted by these land-use transformations.

The integration of community ideas with quantitative data emphasises the need of incorporating local knowledge and viewpoints into environmental research and policymaking. Community members' intimate understanding of the local landscape, as well as their first-hand experiences with the changes occurring, can provide critical contextual information that may not be apparent from the analysis of satellite imagery or other remotely sensed data alone (Lambin and Meyfroidt, 2010). By combining these distinct sources of data, the study may give a more comprehensive and nuanced picture of the complex linkages between climate change, land-use patterns, and their effects on forest resources in the Chimanimani District.

4.5.2 Perceived effect of climate change on forest land-cover change

The study's qualitative research component also explored the local community's perceptions of the specific effects of climate change on the observed changes in forest land cover within the

Chimanimani District. Figure 4.7 illustrates the responses of community participants on the perceived effect of climate change on forest cover change.

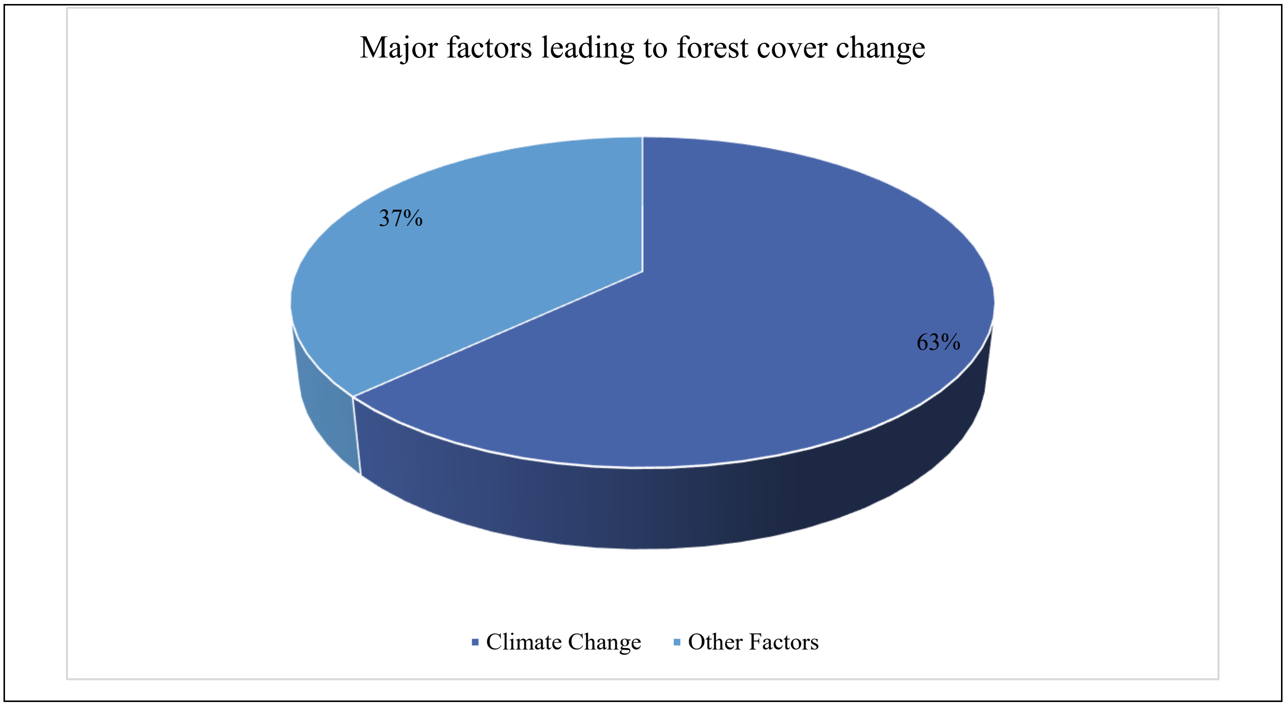


Figure 4.10: Perceived effect of climate change on forest land-cover change

The findings presented in Figure 4.7 provide valuable insights into the local community's understanding of the specific mechanisms through which climate change has impacted forest land cover in the Chimanimani District. The data shows that a clear majority of the respondents (63%) attributed the observed changes in forest cover to the effects of climate change, while the remaining 37% cited other factors, such as agricultural expansion, logging, and infrastructure development (Lambin and Meyfroidt, 2010). This strong emphasis on the role of climate change in driving forest cover changes aligns with the quantitative analysis presented earlier, which demonstrated a clear correlation between the trends in climatic variables (rainfall and temperature) and the decline in forest cover over the 30-year study period.

The community's perceptions validate the empirical findings and underscore the critical importance of considering local knowledge and experiences when investigating the complex socio-ecological interactions shaping land-use dynamics (Adger et al., 2011). By integrating these complementary sources of information, the study is able to provide a more holistic understanding of the pathways through which climate change has impacted the forests in the Chimanimani

District, which can inform the development of targeted and community-informed adaptation and mitigation strategies (Folke, 2006).

Moreover, the alignment between the community's insights and the quantitative data highlights the value of adopting a mixed-methods approach in environmental research. As suggested by Olsson et al. (2004), the integration of local and scientific knowledge can lead to a more nuanced and contextually relevant understanding of the complex social-ecological systems, which in turn can inform policy makers for inclusive conservation and management strategies of forest ecosystems.

4.6 Chapter Summary

This chapter focused on the presentation and discussion of main research findings. Findings indicated that there is a general decline in forest land cover and this situation is correlational to changes in rainfall and temperature patterns over the past 30 years. The following chapter provides conclusions and recommendations.

CHAPTER 5: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of key findings

5.1.1 Detection of Land cover changes

Changes in forest land cover were observed in the study area. Trends were observed in deforestation, agricultural expansion, urbanization and other significant land cover transformations. The magnitude and rate of the changes were discussed along with their implications for the local environment and communities. This section will provide a comprehensive understanding of how the landscape in Chimanimani district has been evolving due to the impacts of climate change. This comprehensive study has provided valuable insights into the complex relationship between climate change and forest land cover dynamics in the Chimanimani District over the 30-year period from 1994 to 2024. The rigorous quantitative analysis, which combined remote sensing data and climate variables, revealed a concerning trend of declining forest cover, with the percentage of forested area decreasing from 91.71% in 1994 to 59.94% in 2024. The linear regression models further corroborated this pattern, highlighting the consistent and significant loss of forest cover over time.

5.1.2 Relationship between climate change and forest change

The analysis of the relationship between climate change and changes in forest land-cover within the Chimanimani District, as presented in Figure 4.5, reveals several key findings. First, the data shows that as average annual rainfall increased from 89.3 mm in 1994 to a peak of 149.2 mm in 2004, the forest cover declined from 91.71% to 84.96%, suggesting that the increase in rainfall may have contributed to other land-use changes, such as agricultural expansion or urban development, which led to the loss of forest cover. Second, the gradual increase in maximum and minimum temperatures over the 30-year period, from 20.6°C and 11.2°C in 1994 to 22.9°C and 11.9°C in 2024, respectively, may have also influenced the changes in forest cover, potentially through increased evapotranspiration and altered ecosystem dynamics. Finally, the sharp decline in forest cover from 84.96% in 2004 to 32.52% in 2014, and further to 30.94% in 2024, despite relatively stable climatic conditions, suggests that other socio-economic factors, such as land-use policies, agricultural practices, and deforestation, may have played a significant role in the observed changes. According to Mukwada et al (2017) mention that temperature data showed a rising trend with an increase of 0.2 degrees Celsius per decade while the rainfall data exhibited high variability with a slight decline in recent years.

5.1.3 Community perceptions on the effect of climate change on forest cover change

The qualitative component of the research, which explored the local community's perceptions on the impacts of climate change on forests in the Chimanimani District, yielded several key findings that complement the quantitative analysis. Firstly, the majority of the community respondents (78%) reported observing a noticeable decline in forest cover within their local area over the past 30 years. This perception aligns remarkably well with the quantitative data presented earlier, which showed a significant decrease in the percentage of forest cover in the Chimanimani District. This high level of agreement between the community's firsthand observations and the remote sensing-based analysis lends greater credibility to the overall findings, as it suggests that the observed changes in forest cover are not merely abstract statistics, but rather reflect the lived experiences and on-the-ground realities faced by the local population.

The qualitative research also explored the community's understanding of the specific mechanisms through which climate change has impacted forest land cover. Here, the findings reveal that a clear majority of the respondents (63%) attributed the observed changes in forest cover to the effects of climate change, particularly the shifts in rainfall and temperature patterns. This strong emphasis on the role of climate change in driving forest cover changes corroborates the quantitative analysis, which demonstrated a clear correlation between the trends in climatic variables and the decline in forest cover over the 30-year study period. By integrating these complementary sources of information, the study is able to provide a more holistic understanding of the complex pathways through which climate change has impacted the forests in the Chimanimani District, which can inform the development of targeted and community-informed adaptation and mitigation strategies.

5.2 Recommendations

5.2.1 Policy and Governance recommendations

Based on the thesis the chapter recommend the aligning of local policies and governance structures with national and international climate change framework. More so it review on the need to strengthen institutional capacity, foster cross sector collaboration and empower local stakeholders to effectively plan for and adapt to the anticipated impacts of climate change in the Chimanimani district. The chapter emphasized more on the importance of these policy and governance interventions in supporting the implementation of the adaptation strategies outlined in the previous sections.

5.2.2 Community engagement

The substantial agreement between the community's observations and the quantitative findings highlights the essential information that local stakeholders may provide to understanding and reacting to the effects of climate change on land-use patterns. Moving forward, policymakers and land management authorities should collaborate closely with the community to create and execute personalised policies for forest conservation, restoration, and sustainable resource use. This could include forming community-based natural resource management committees, incorporating traditional ecological knowledge into land-use planning, and facilitating ongoing dialogues to ensure that local residents' needs, concerns, and priorities are effectively incorporated into decision-making processes. By encouraging true collaborative relationships, the study area may move towards more inclusive, open, and community-driven solutions to the pressing environmental challenges it faces.

5.2.3 Future research directions

A more in-depth examination of the specific socioeconomic drivers of deforestation and forest degradation, such as the effects of agricultural practices, logging activities, and infrastructure development, would help to gain a better understanding of the complex interplay between human activity and environmental change. Furthermore, investigating the possible effects of forest cover changes on ecosystem services, biodiversity, and local livelihoods would give critical insights to help shape integrated conservation and development policies. Finally, doing a comparison study with other districts or regions facing comparable difficulties may give useful cross-scale lessons and opportunity for knowledge exchange and collaborative problem solution. By following these and other areas of study, future research can continue to expand our knowledge of the complex socio-ecological processes at play and assist the creation of more effective, equitable, and sustainable solutions for the Chimanimani District and beyond.

5.3 Chapter Summary

The last chapter of this research gave a short review of the important results as well as a number of well-crafted recommendations to address the complex difficulties confronting the Chimanimani District in the context of climate change-induced forest cover shifts. Building on these extensive results, the chapter then gives a series of well-organised suggestions in three major areas: policy and governance, community participation, and future research prospects. These evidence-based initiatives are intended to guide the creation of more effective, fair, and community-driven solutions to the Chimanimani District's critical environmental concerns in the face of climate change.

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APPENDICES

APPENDIX 1 QUESTIONNAIRE FOR PARTICIPANTS ON IMPACTS OF CLIMATE CHANGE IN CHIMANIMANI DISTRICT RESEARCH

Introduction

My name is Thania Matamande, A final year student studying Disaster Management Sciences at Bindura University of Science Education. The purpose of the research is to know the impacts of climate change that people in Chimanimani district are facing for the past years from 1990 to 2024. The information will increase understanding on climate change at global, regional to local level. Also it will help disaster and development practitioners, climate change response agencies such as NGOs and Zimbabwe government on planning and decision making to reduce negative impacts and enhance the positive impacts. All your contribution and responses you give out will be very confidential. Participation in the research is voluntary for everyone. Information obtained in the research field research will be used for academic purposes only.

Instructions

- Note **DO NOT WRITE YOUR NAME**
- Indicate your response by putting a tick in the appropriate box and fill in the space provided if necessary
- Some questions in this section asks you to agree or disagree with the statements. Tick the answer applicable on the scale with (a) strongly disagree (b) disagree (c) agree (d) strongly agree.

Section A: DEMOGRAPHIC INFORMATION

Age of interviewee

Age	18-30	31-43	44-56	57-68	67+
Range (√)					

Job/occupation:

……………………………………………………………………………………………………

Gender

Male ☐ Female ☐

How long have you lived in Chimanimani District? *(Tick your range)*

Years range	1990-1994	1995-2004	2005-2014	2015-2024
Tick (√)				

Section B: FOREST LANDCOVER CHANGES

1. Are you aware of any changes in forest land cover in Chimanimani District over the years?
   - Yes
   - No
2. If yes, what type of changes have you observed? *Select all that apply*

CHANGES	√
Deforestation	
afforestation	
degradation	

Other (please specify):…………………………………………..

3. How do you rate the extent of the changes?

Very significant	Significant	Moderate	Minor	Not significant

Section c: CLIMATE CHANGE INFLUENCE

4. To what extent do you believe land cover has affected forest cover in Chimanimani?

Very high extent	High extent	Moderate extent	Low extent	No extent`

5. What specific climate related changes have you observed? (*select all that apply*)

CHANGES	**(√) TICK ALL THAT APPLY**
Changes in rainfall patterns	
Increased temperatures	
More frequent storms	

Other (please specify):……………………………………………………

Section D: COMMUNITY PERCEPTIONS

6. How concerned are you about the impacts of climate change on forest?

Very concerned	**Concerned**	**Neutral**	**unconcerned**	**Very unconcerned**

7. In your opinion how do changes in forest cover affect your community? (Select all that apply)

Opinions	√
Loss of livelihood	
Decreased biodiversity	
Increased natural disasters	

Section E: Personal view

8. In your view, what measures could be taken to mitigate the impacts of climate change on forests in Chimanimani?

…………………………………………………………………………………………………
………………………………………………………………………………………………..

END OF QUESTIONNAIRE

APPENDIX 2: INTERVIEW GUIDE FOR KEY INFORMANTS ON THE ASSESSMENT OF CLIMATE CHANGE IMPACTS

Introduction

My name is Thania Matamande, A final year student studying Disaster Management Sciences at Bindura University of Science Education. The purpose of the research is to know the impacts of climate change that people in Chimanimani district are facing for the past years from 1990 to 2024. The information will increase understanding on climate change at global, regional to local level. Also it will help disaster and development practitioners, climate change response agencies such as NGOs and Zimbabwe government on planning and decision making to reduce negative impacts and enhance the positive impacts. All your contribution and responses you give out will be very confidential. Participation in the research is voluntary for everyone. Information obtained in the research field research will be used for academic purposes only.

Instruction

- **Note to the interviewer**: Introduce yourself and explain the purpose of the interview.

1. Can you describe any noticeable changes on forest cover in Chimanimani District?
2. How have these changes affected daily life and local communities?
3. In your own view how has climate change impacted the forests in Chimanimani?
4. Can you provide specific examples of climate effects that you've observed (e.g. changes in weather patterns, extreme weather events)?
5. How do you think the community perceives the relationship between climate change and forest changes?
6. What concerns do you have about the future forests in your area?
7. What actions or initiatives do you believe should be prioritized to address the impacts of climate change on forests?
8. Is there anything else you would like to add about climate change and its impacts on Chimanimani District?

END OF INTERVIEW

APPENDIX 4 DATA COLLECTION LETTER

DEPARTMENT OF DISASTER RISK REDUCTION

P Bag 1020
BINDURA, Zimbabwe
Tel: 071 – 7531-6, 7621-4
Fax: 263 – 71 – 7534/6316

BINDURA UNIVERSITY OF SCIENCE EDUCATION

3 April 2024

To Whom It May Concern:

ASSISTANCE TO THE STUDENT WHO IS SEEKING INFORMATION FOR RESEARCH PROJECT

This is to confirm that THANIA MATAMANDE in Disaster Management Science in the Department of Disaster Risk Reduction at Bindura University of Science Education and is required to do a Research Project as part of her Degree programme. The student is expected to gather data for his/her project from various sources including your Institution.

This letter therefore serves to kindly ask you to assist the above-mentioned student with information relating to his/her project entitled:

Application of Tie series decomposition and Random Forest clarification algorithm to assess the impacts of climate change on forest in Chimanimani district using Landsat data

Thank you.

DR. E. MAVHURA
CHAIRMAN

CHAIRMAN
GEOGRAPHY DEPARTMENT
FACULTY OF SCIENCE

APPENDIX 5: TIME SERIES DECOMPOSITION CODE

Rainfall Time Series Decomposition

```
R version 4.3.3 (2024-02-29 ucrt) -- "Angel Food Cake"
Copyright (C) 2024 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

# Author: Thania Matamande B201880B
# Programme: BSc……………………………
# Institution: Bindura University of Science Education (BUSE)
# Faculty: Science and Engineering
# Department: Disaster Risk Reduction
# Month/Year: December/2024
# Supervisor: DR.E. Pedzisai
```

> # Topic: **APPLICATION OF RANDOM FOREST CLASSIFICATION ALGORITHM AND TIME SERIES DECOMPOSITION TO ASSESS THE IMPACTS OF CLIMATE CHANGE ON FORESTS IN CHIMANIMANI DISTRICT USING LANDSAT DATA**

> # SECTION A: DATA UPLOAD AND PREPARATION

> # DATA was transformed into a series of objects using the following code:

> # Connect to Data folder and visualize, naming data as 'rain' and opening it:

```
> rain <- read.csv('C://Users/user/Downloads/Chimanimani_Max_Rain.csv')
> rain
     Date Maximum
1   Jan-90   337.9
2   Feb-90   133.1
3   Mar-90    57.3
4   Apr-90    91.9
5   May-90    50.1
6   Jun-90    56.2
7   Jul-90     2.1
8   Aug-90    41.0
9   Sep-90    23.9
10  Oct-90    15.2
11  Nov-90   125.6
12  Dec-90   254.6
13  Jan-91   197.3
14  Feb-91   276.3
15  Mar-91   190.3
16  Apr-91    15.2
17  May-91    52.8
18  Jun-91     7.4
19  Jul-91    19.3
20  Aug-91    12.2
```

21	Sep-91	66.0
22	Oct-91	3.8
23	Nov-91	143.4
24	Dec-91	96.0
25	Jan-92	168.2
26	Feb-92	12.6
27	Mar-92	47.8
28	Apr-92	8.4
29	May-92	1.7
30	Jun-92	12.3
31	Jul-92	21.9
32	Aug-92	11.4
33	Sep-92	0.0
34	Oct-92	14.0
35	Nov-92	161.2
36	Dec-92	333.4
37	Jan-93	196.9
38	Feb-93	387.7
39	Mar-93	99.7
40	Apr-93	44.5
41	May-93	0.8
42	Jun-93	40.2
43	Jul-93	87.8
44	Aug-93	30.6
45	Sep-93	14.2
46	Oct-93	24.7
47	Nov-93	268.4
48	Dec-93	164.4
49	Jan-94	346.6

50	Feb-94	117.6
51	Mar-94	50.0
52	Apr-94	32.7
53	May-94	30.8
54	Jun-94	36.3
55	Jul-94	8.5
56	Aug-94	8.6
57	Sep-94	42.0
58	Oct-94	110.4
59	Nov-94	28.2
60	Dec-94	259.7
61	Jan-95	130.7
62	Feb-95	149.0
63	Mar-95	167.4
64	Apr-95	52.8
65	May-95	98.5
66	Jun-95	15.0
67	Jul-95	49.5
68	Aug-95	28.7
69	Sep-95	8.8
70	Oct-95	55.0
71	Nov-95	92.3
72	Dec-95	176.9
73	Jan-96	498.2
74	Feb-96	446.9
75	Mar-96	115.0
76	Apr-96	135.7
77	May-96	61.7
78	Jun-96	109.7

79	Jul-96	24.5
80	Aug-96	26.9
81	Sep-96	25.6
82	Oct-96	26.4
83	Nov-96	128.7
84	Dec-96	162.8
85	Jan-97	672.6
86	Feb-97	520.8
87	Mar-97	261.9
88	Apr-97	19.5
89	May-97	19.5
90	Jun-97	0.0
91	Jul-97	99.4
92	Aug-97	0.0
93	Sep-97	81.9
94	Oct-97	82.8
95	Nov-97	93.2
96	Dec-97	88.4
97	Jan-98	502.4
98	Feb-98	226.9
99	Mar-98	197.2
100	Apr-98	96.2
101	May-98	13.5
102	Jun-98	14.4
103	Jul-98	38.2
104	Aug-98	30.3
105	Sep-98	22.6
106	Oct-98	101.2
107	Nov-98	194.0

108	Dec-98	487.4
109	Jan-99	463.6
110	Feb-99	316.5
111	Mar-99	227.7
112	Apr-99	161.0
113	May-99	0.0
114	Jun-99	0.0
115	Jul-99	75.1
116	Aug-99	23.9
117	Sep-99	0.0
118	Oct-99	52.6
119	Nov-99	111.6
120	Dec-99	140.3
121	Jan-00	264.1
122	Feb-00	1220.8
123	Mar-00	296.9
124	Apr-00	129.3
125	May-00	96.7
126	Jun-00	122.8
127	Jul-00	68.1
128	Aug-00	18.3
129	Sep-00	42.4
130	Oct-00	59.7
131	Nov-00	168.6
132	Dec-00	237.3
133	Jan-01	184.5
134	Feb-01	776.5
135	Mar-01	393.9
136	Apr-01	139.0

137	May-01	27.3
138	Jun-01	89.8
139	Jul-01	110.4
140	Aug-01	13.7
141	Sep-01	33.1
142	Oct-01	43.7
143	Nov-01	192.6
144	Dec-01	376.4
145	Jan-02	138.0
146	Feb-02	180.6
147	Mar-02	185.6
148	Apr-02	107.0
149	May-02	13.6
150	Jun-02	83.8
151	Jul-02	65.3
152	Aug-02	32.6
153	Sep-02	11.6
154	Oct-02	147.8
155	Nov-02	114.0
156	Dec-02	135.9
157	Jan-03	191.9
158	Feb-03	187.5
159	Mar-03	406.8
160	Apr-03	42.2
161	May-03	78.8
162	Jun-03	208.9
163	Jul-03	39.5
164	Aug-03	5.5
165	Sep-03	67.1

166	Oct-03	73.2
167	Nov-03	156.3
168	Dec-03	94.8
169	Jan-04	455.8
170	Feb-04	245.9
171	Mar-04	412.0
172	Apr-04	132.9
173	May-04	32.6
174	Jun-04	45.4
175	Jul-04	51.7
176	Aug-04	8.8
177	Sep-04	20.9
178	Oct-04	101.6
179	Nov-04	56.8
180	Dec-04	225.8
181	Jan-05	183.6
182	Feb-05	76.5
183	Mar-05	87.9
184	Apr-05	46.3
185	May-05	28.4
186	Jun-05	37.8
187	Jul-05	41.2
188	Aug-05	12.5
189	Sep-05	20.1
190	Oct-05	22.2
191	Nov-05	368.0
192	Dec-05	211.3
193	Jan-06	154.8
194	Feb-06	543.9

195	Mar-06	63.6
196	Apr-06	20.5
197	May-06	57.1
198	Jun-06	39.0
199	Jul-06	19.8
200	Aug-06	21.6
201	Sep-06	0.0
202	Oct-06	61.2
203	Nov-06	74.9
204	Dec-06	209.9
205	Jan-07	395.4
206	Feb-07	715.0
207	Mar-07	74.0
208	Apr-07	97.8
209	May-07	7.0
210	Jun-07	23.2
211	Jul-07	13.9
212	Aug-07	24.2
213	Sep-07	18.4
214	Oct-07	84.6
215	Nov-07	163.2
216	Dec-07	440.7
217	Jan-08	676.8
218	Feb-08	82.2
219	Mar-08	71.7
220	Apr-08	7.5
221	May-08	26.8
222	Jun-08	14.7
223	Jul-08	5.5

224	Aug-08	13.1
225	Sep-08	28.4
226	Oct-08	40.7
227	Nov-08	76.1
228	Dec-08	373.9
229	Jan-09	236.8
230	Feb-09	403.7
231	Mar-09	344.8
232	Apr-09	161.2
233	May-09	31.6
234	Jun-09	71.9
235	Jul-09	96.0
236	Aug-09	12.9
237	Sep-09	74.6
238	Oct-09	48.2
239	Nov-09	141.1
240	Dec-09	119.9
241	Jan-10	110.7
242	Feb-10	453.0
243	Mar-10	183.3
244	Apr-10	181.2
245	May-10	123.7
246	Jun-10	5.2
247	Jul-10	43.4
248	Aug-10	8.0
249	Sep-10	3.7
250	Oct-10	24.4
251	Nov-10	198.5
252	Dec-10	278.4

253 Jan-11 328.1

254 Feb-11 128.4

255 Mar-11 110.7

256 Apr-11 276.7

257 May-11 7.6

258 Jun-11 6.6

259 Jul-11 44.2

260 Aug-11 12.7

261 Sep-11 15.2

262 Oct-11 61.5

263 Nov-11 31.2

264 Dec-11 261.2

265 Jan-12 96.6

266 Feb-12 83.0

267 Mar-12 102.2

268 Apr-12 76.0

269 May-12 5.6

270 Jun-12 16.4

271 Jul-12 0.0

272 Aug-12 0.0

273 Sep-12 37.5

274 Oct-12 48.2

275 Nov-12 109.5

276 Dec-12 163.0

277 Jan-13 407.2

278 Feb-13 288.3

279 Mar-13 112.5

280 Apr-13 55.7

281 May-13 25.0

282 Jun-13 19.8

283 Jul-13 20.7

284 Aug-13 37.6

285 Sep-13 67.3

286 Oct-13 43.1

287 Nov-13 154.8

288 Dec-13 335.2

289 Jan-14 435.9

290 Feb-14 341.0

291 Mar-14 69.7

292 Apr-14 168.4

293 May-14 0.0

294 Jun-14 12.6

295 Jul-14 36.2

296 Aug-14 5.7

297 Sep-14 68.4

298 Oct-14 14.7

299 Nov-14 38.2

300 Dec-14 432.4

301 Jan-15 105.9

302 Feb-15 91.7

303 Mar-15 176.7

304 Apr-15 111.3

305 May-15 0.0

306 Jun-15 0.0

307 Jul-15 0.0

308 Aug-15 0.0

309 Sep-15 26.9

310 Oct-15 0.0

311	Nov-15	160.4
312	Dec-15	72.5
313	Jan-16	80.7
314	Feb-16	63.5
315	Mar-16	226.8
316	Apr-16	150.0
317	May-16	0.0
318	Jun-16	0.0
319	Jul-16	0.0
320	Aug-16	0.0
321	Sep-16	0.0
322	Oct-16	11.7
323	Nov-16	186.3
324	Dec-16	299.3
325	Jan-17	636.9
326	Feb-17	347.1
327	Mar-17	372.0
328	Apr-17	63.0
329	May-17	56.9
330	Jun-17	8.4
331	Jul-17	0.0
332	Aug-17	0.0
333	Sep-17	0.0
334	Oct-17	75.3
335	Nov-17	76.7
336	Dec-17	138.1
337	Jan-18	135.0
338	Feb-18	363.2
339	Mar-18	140.1

340	Apr-18	145.1
341	May-18	0.0
342	Jun-18	0.0
343	Jul-18	0.0
344	Aug-18	0.0
345	Sep-18	0.0
346	Oct-18	0.0
347	Nov-18	106.9
348	Dec-18	144.9
349	Jan-19	269.6
350	Feb-19	72.5
351	Mar-19	764.7
352	Apr-19	0.0
353	May-19	0.0
354	Jun-19	0.0
355	Jul-19	0.0
356	Aug-19	0.0
357	Sep-19	0.0
358	Oct-19	8.7
359	Nov-19	91.0
360	Dec-19	273.2
361	Jan-20	199.7
362	Feb-20	345.8
363	Mar-20	96.4
364	Apr-20	60.3
365	May-20	0.0
366	Jun-20	0.0
367	Jul-20	0.3
368	Aug-20	0.0

369	Sep-20	0.0
370	Oct-20	0.0
371	Nov-20	0.0
372	Dec-20	260.7
373	Jan-21	753.9
374	Feb-21	241.8
375	Mar-21	34.1
376	Apr-21	0.0
377	May-21	0.0
378	Jun-21	0.0
379	Jul-21	0.3
380	Aug-21	0.0
381	Sep-21	0.0
382	Oct-21	0.0
383	Nov-21	34.3
384	Dec-21	187.7
385	Jan-22	548.5
386	Feb-22	73.4
387	Mar-22	145.7
388	Apr-22	39.9
389	May-22	0.0
390	Jun-22	0.0
391	Jul-22	0.0
392	Aug-22	0.0
393	Sep-22	0.0
394	Oct-22	0.0
395	Nov-22	333.6
396	Dec-22	150.8
397	Jan-23	197.6

```
398 Feb-23   491.2
399 Mar-23   257.5
400 Apr-23    54.5
401 May-23     0.0
402 Jun-23     0.0
403 Jul-23     0.0
404 Aug-23     0.0
405 Sep-23     0.0
406 Oct-23    56.8
407 Nov-23    36.9
408 Dec-23   305.4
# attach rain
> attach(rain)
# view structure of rain data
> str(rain)
'data.frame':   408 obs. of  2 variables:
 $ Date   : chr  "Jan-90" "Feb-90" "Mar-90" "Apr-90" ...
 $ Maximum: num  337.9 133.1 57.3 91.9 50.1 ...
# Define rain as time series
> raints <- ts(rain$Maximum, start = c(1990,1), frequency = 12)
# plot the rain time series
> plot(raints)
# Model (linear) rain time series
> raintslm<-lm(Maximum~Date)
> plot(raintslm)
Waiting to confirm page change...

# 12) Model Time Series Decomposition in ML using the STL function in code:
> fitraintslm <- st1(raintslm, s.window = “periodic”)
```

Or alternatively import libraries as folloes;

```
> library(fpp3)
── Attaching packages ──────────────────────────────────── fpp3 0.5 ──
✓ tibble      3.2.1     ✓ tsibble     1.1.4
✓ dplyr       1.1.4     ✓ tsibbledata 0.4.1
✓ tidyr       1.3.1     ✓ feasts      0.3.2
✓ lubridate   1.9.3     ✓ fable       0.3.4
✓ ggplot2     3.5.1     ✓ fabletools  0.4.2
── Conflicts ──────────────────────────────────── fpp3_conflicts ──
✕ lubridate::date()    masks base::date()
✕ dplyr::filter()      masks stats::filter()
✕ tsibble::intersect() masks base::intersect()
✕ tsibble::interval()  masks lubridate::interval()
✕ dplyr::lag()         masks stats::lag()
✕ tsibble::setdiff()   masks base::setdiff()
✕ tsibble::union()     masks base::union()
> library(GGally)
Registered S3 method overwritten by 'GGally':
  method from
  +.gg   ggplot2
> library(seasonal)

Attaching package: ‘seasonal’

The following object is masked from ‘package:tibble’:
```

view

> plot.ts(raints)

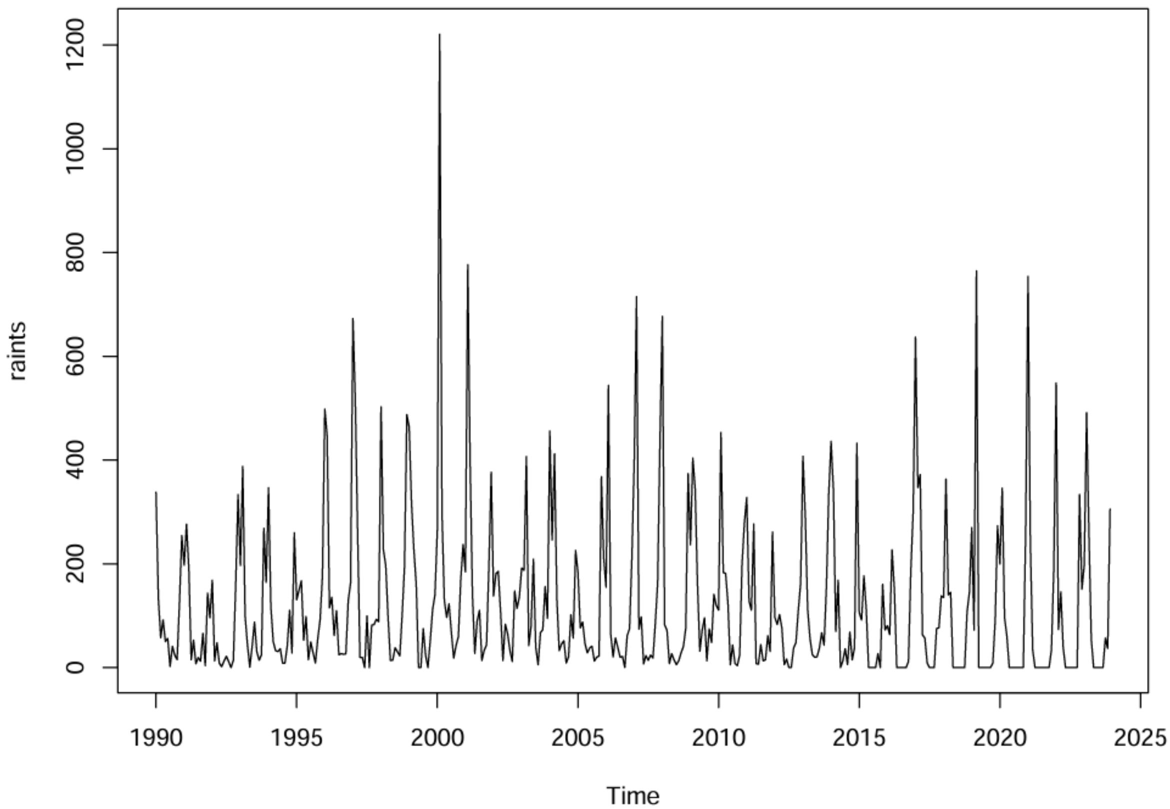

FIGURE: RAINFALL TIMES SERIES

> library("TTR")

> raintsSMA12 <- SMA(raints, n=12)

> plot.ts(raintsSMA12)

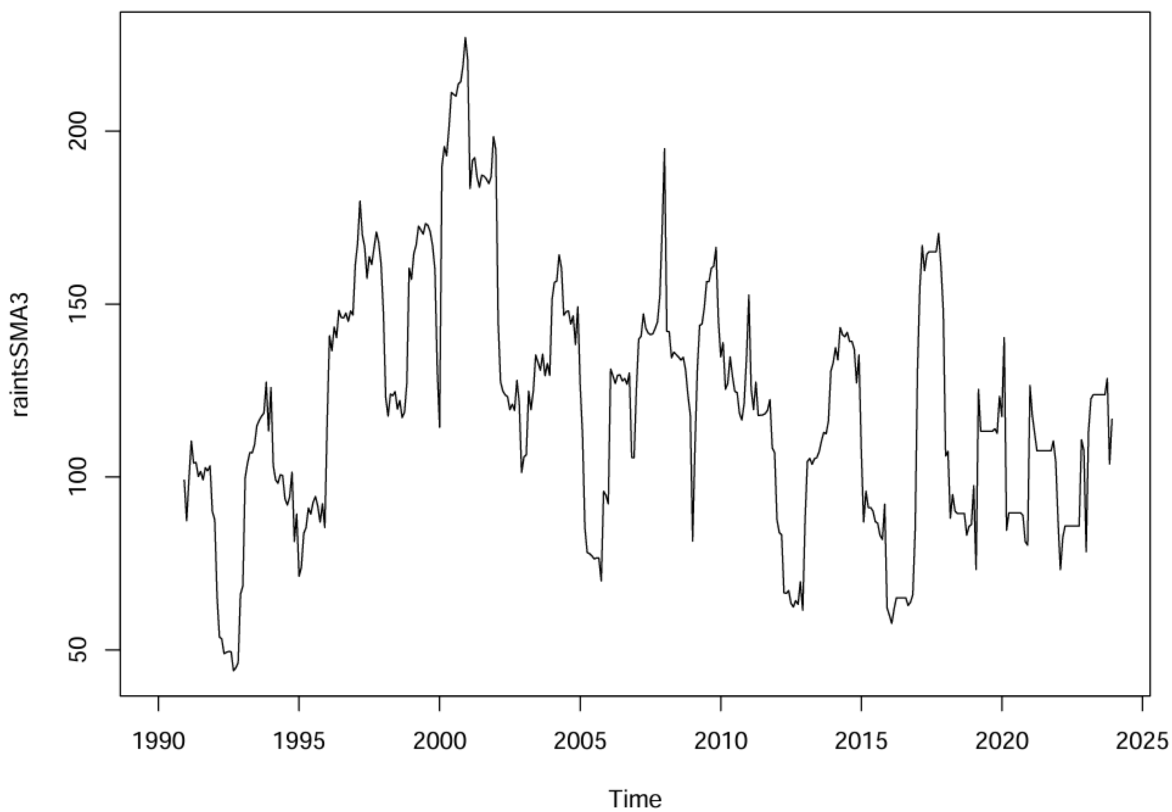

FIGURE: SMOOTHED RAINFALL TIMES SERIES(N=12)

> raintsdecompose <- decompose(raints)

> raintsdecompose$seasonal

	Jan	Feb	Mar	Apr	May	Jun	Jul
1990	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
1991	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
1992	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
1993	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
1994	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
1995	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
1996	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
1997	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705

1998	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
1999	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2000	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2001	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2002	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2003	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2004	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2005	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2006	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2007	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2008	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2009	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2010	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2011	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2012	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2013	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2014	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2015	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2016	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2017	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2018	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2019	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2020	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2021	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2022	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705
2023	193.59941	190.81444	76.22365	-34.55021	-93.09074	-88.69137	-86.79705

	Aug	Sep	Oct	Nov	Dec
1990	-106.52660	-95.72243	-76.65526	12.03098	109.36519
1991	-106.52660	-95.72243	-76.65526	12.03098	109.36519

1992 -106.52660 -95.72243 -76.65526   12.03098 109.36519

1993 -106.52660 -95.72243 -76.65526   12.03098 109.36519

1994 -106.52660 -95.72243 -76.65526   12.03098 109.36519

1995 -106.52660 -95.72243 -76.65526   12.03098 109.36519

1996 -106.52660 -95.72243 -76.65526   12.03098 109.36519

1997 -106.52660 -95.72243 -76.65526   12.03098 109.36519

1998 -106.52660 -95.72243 -76.65526   12.03098 109.36519

1999 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2000 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2001 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2002 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2003 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2004 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2005 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2006 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2007 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2008 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2009 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2010 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2011 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2012 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2013 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2014 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2015 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2016 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2017 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2018 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2019 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2020 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2021 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2022 -106.52660 -95.72243 -76.65526   12.03098 109.36519

2023 -106.52660 -95.72243 -76.65526   12.03098 109.36519

> raintscomponents <- decompose(raints)

> plot(raintscomponents)

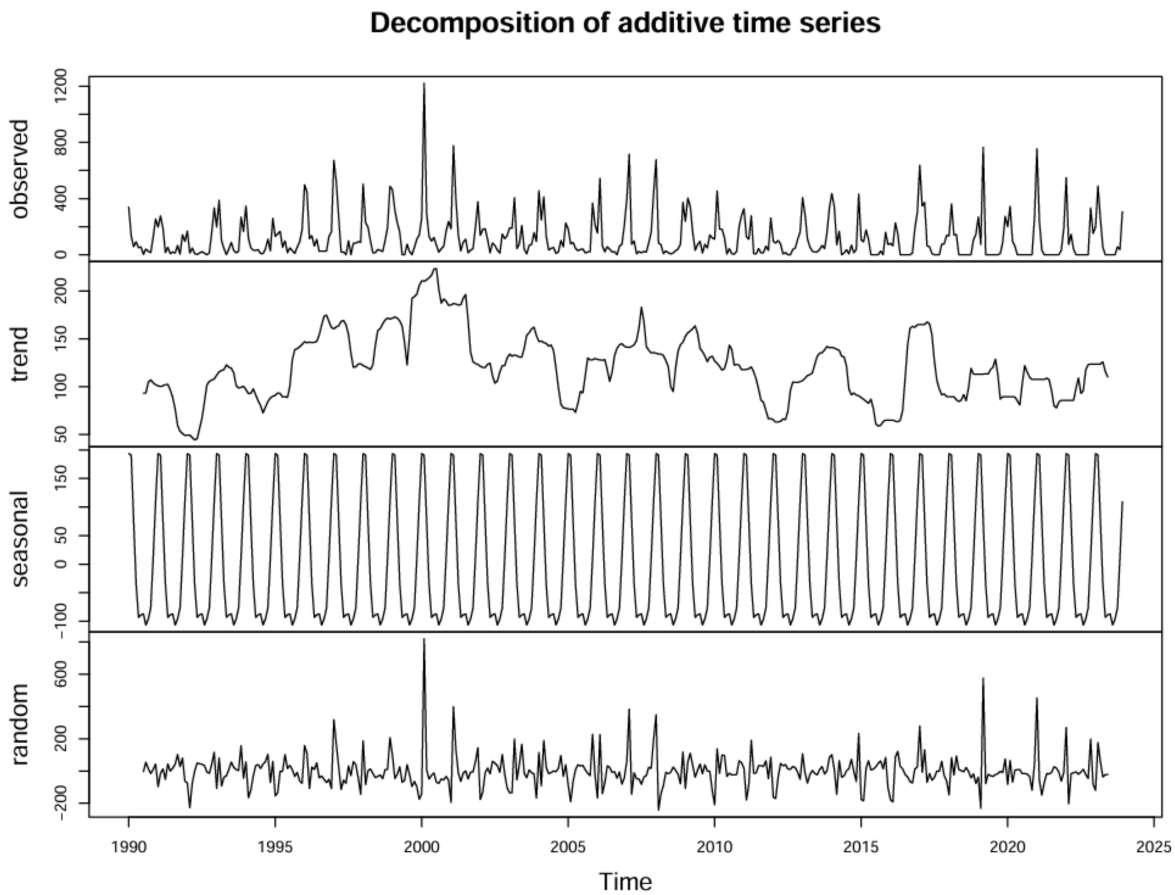

FIGURE: RAINFALL TIME SERIES DECOMPOSITION

end of script

APPENDIX 6: TURNITIN REPORT