Spatiotemporal analysis of vegetation fires using satellite data

UPENYU NAUME MUPFIGA
218086584

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School of Agricultural, Earth and Environmental Sciences

College of Agriculture, Engineering and Science

University of KwaZulu-Natal

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Supervisor: Professor Onisimo Mutanga

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ABSTRACT

Although vegetation fires are key in maintaining the savanna ecosystem, their uncontrolled occurrence profoundly threatens ecosystem stability, economies, and human safety. The increased risk of climate change requires robust spatiotemporal analysis methods to understand the impact of fire on ecosystems. Additionally, the accurate prediction of vegetation fire and the associated key drivers are critical in understanding fire regimes and the implementation of effective fire management strategies. This research utilised Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data to analyse the spatiotemporal dynamics of vegetation fires. The first objective focused on systematically reviewing literature on the effects of burning on various ecosystem services. The reviewed articles were extracted from Elsevier's Scopus, Web of Science and PubMed databases and analysed based on the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) method. The findings from the review highlighted that there has been an increase in publications since 2010 and most studies were carried out in Asia and the United States of America. The most common satellite data used for analysing the effects of burning on ecosystem services was Landsat, whilst information on fire occurrence was extracted from the MODIS satellite data. Very few studies utilised AVIRIS, PlanetScope, and ASTER satellite data. Moreso, findings from the review revealed fire as a threat to grassland, forest, soil and wetland ecosystems with the forest landscapes being widely studied. The atmosphere is also affected by vegetation fires through particulate matter and carbon emissions. The second objective focused on detecting fire intensity hotspots and cold spots in Zimbabwe by utilising spatial statistics and MODIS-derived fire radiative power (FRP), a proxy for fire intensity. The variability of fire intensity clusters within various topographic and vegetation conditions was also analysed. The results indicated that most (44%) of the vegetation fires remotely sensed in Zimbabwe by the MODIS satellite sensor were of low intensity, mostly occurring in the shrublands. On the other hand, high intensity fires (22%) were generally distributed within Zimbabwe's eastern and western regions. The third objective focused on detecting long-term spatiotemporal fire patterns in Zimbabwe using MODIS fire location data and a spatially explicit method (Emerging Hot Spot Analysis). The study also statistically analysed how the spatiotemporal distribution of vegetation fires is related to environmental factors. The research findings show that the occurrence of vegetation fire varies with seasons with the highest number of fires occurring in September. New information unveiled from the third objective indicated that fire activity tends to be high in June, July, and November despite these months being excluded from the official fire season in Zimbabwe, generally observed from August to October. Persistent, diminishing, oscillating, and historical spatiotemporal fire hotspots were observed in the northern regions of Zimbabwe. The final objective assessed the various topographic, bioclimatic, topographic, vegetation and anthropogenic factors that influence the occurrence of fires in Zimbabwe. The fire hazard levels were also predicted using the Maxent model based on the analysis of MODIS fire location data combined with topographic, bioclimatic, topographic, vegetation and anthropogenic factors. The jack-knife test evaluated the contribution of each variable towards the performance of the model, while the AUC (receiver operating characteristic curve) was used to estimate the model's accuracy. The research findings identified temperature annual range, precipitation seasonality, human influence and elevation as contributing highly to the occurrence of vegetation fires across Zimbabwe's landscapes. The average AUC of 0.77 demonstrated good model accuracy. Conclusively, results from this thesis reveal the utility of spatial statistics and machine learning methods based on satellite fire data to understand spatiotemporal patterns of fire in Zimbabwe. Specifically, the detection of spatiotemporal patterns of vegetation fires, fire intensity clusters and their predicted hazard levels were successfully mapped. The information derived from this study is valuable in improving fire management in Zimbabwe and other regions. The detection of spatiotemporal patterns of fire, fire intensity and fire hazard levels result in new valuable information important for the implementation of key fire management policies and strategies in Savanna ecosystems.

PREFACE

The research work contained in this thesis was completed by the candidate while based in the Discipline of Geography, School of Agricultural, Earth and Environmental Sciences of the College of Agriculture, Engineering and Science, University of KwaZulu-Natal, Pietermaritzburg Campus, South Africa under the supervision of Prof. Onisimo Mutanga.

The contents of this work have not been submitted in any form to another university. Except where the work of others is acknowledged in the text, the results reported are due to investigations done by the candidate.

____

Signed: **Upenyu Naume Mupfiga**

Student: [redacted] **Date**: 29 November 2024

Supervisor: [redacted] **Date**: 27/11/2024

DECLARATION 1: PLAGIARISM

I, **Upenyu Naume Mupfiga**, declare that:

(i) the research reported in this thesis, except where otherwise indicated or acknowledged, is my original work;

(ii) this thesis has not been submitted in full or in part for any degree or examination to any other university;

(iii) this thesis does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons;

(iv) this thesis does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

a) their words have been re-written but the general information attributed to them has been referenced;

b) where their exact words have been used, their writing has been placed inside quotation marks, and referenced;

(v) where I have used material for which publications followed, I have indicated in detail my role in the work;

(vi) this thesis is primarily a collection of material, prepared by myself, published as journal articles or presented as a poster and oral presentations at conferences. In some cases, additional material has been included;

(vii) this thesis does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the thesis and in the References sections.

< Upenyu Naume Mupfiga >

Signed: < [redacted]>

Date: < 29 November 2024

DECLARATION 2: PUBLICATIONS

The role of the candidate is shown in **bold:**

1. **Mupfiga, U.N** and Mutanga, O., 2024. A systematic review of the application of remote sensing in assessing the impact of fire on ecosystem services. (Manuscript submitted as a book chapter to: Revealing Ecosystem Services through Remote Sensing: Beyond the Surface. *Springer (Under Review)*

2. **Mupfiga, U.N.,** Mutanga, O., Dube, T., Kowe, P., 2022. Spatial Clustering of Vegetation Fire Intensity Using MODIS Satellite Data. Atmosphere 13. https://doi.org/10.3390/atmos13121972

3. **Mupfiga, U.N.,** Mutanga, O., Dube, T., 2024. National-scale spatiotemporal patterns of vegetation fire occurrences using MODIS satellite data. PLOS ONE 19, e0297309. https://doi.org/10.1371/journal.pone.0297309

4. **Mupfiga, U.,** Mutanga, O., Dube, T., 2025. Assessing drivers of vegetation fire occurrence in Zimbabwe - Insights from Maxent modelling and historical data analysis. Remote Sensing Applications: Society and Environment 37, 101404. https://doi.org/10.1016/j.rsase.2024.101404

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Signed: <Upenyu Naume Mupfiga>

Date: < 29 November 2024>

DEDICATION

I dedicate my PhD work:

1. To my late dear parents, Baba Beaven Stanley and Mhayi Gladys Nyatondo. Losing both of you during the PhD journey was the most painful time of my life. You are dearly missed and loved. Thank you for making me who I am. To my father, my cheerleader, *"Baba, kasikana kenyu kapedza Doctorate".* I know I have made you proud! I wish both of you were here to celebrate with me.
2. To my husband, Elvis and our 3 boys, my support system.
3. To my whole family: Here is our first PhD!

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ACRONYMS

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AUC	Operating Characteristic Curve
AVIRIS	Airborne Visible InfraRed Imaging Spectrometer
FRP	Fire Radiative Power
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-analysis

CHAPTER 1: GENERAL INTRODUCTION

1.1 Introduction

The African savanna ecosystems have been greatly shaped by the occurrence of vegetation fires. While fires are key in the maintenance of such terrestrial ecosystems, they also pose a significant natural hazard (Matz *et al.*, 2020). Although fires are beneficial to some ecosystems, for example, by controlling pests and diseases (Pereira *et al.*, 2021), they can alter landscapes, increase erosion risk and negatively affect hydrological processes (Wooster *et al.*, 2021; Stefanos Stefanidis, Alexandridis and Mallinis, 2022; Stefanidis *et al.*, 2022). Changes in the fire regimes significantly affect the landscape structure, species composition and various ecological processes (Herawati *et al.*, 2015; Semeraro *et al.*, 2019). Despite the mitigation and prevention measures, vegetation fires are still a major concern globally, threatening ecosystems and contributing to land degradation (Armenteras *et al.*, 2017a; Global Forest Watch, 2023; Mishra *et al.*, 2023). Most parts of sub-Saharan Africa, for example, is characterised by long, hot and dry seasons making them highly prone to fire occurrence (Wei *et al.*, 2021).

Vegetation burning transfers terrestrial carbon pools into the atmosphere hence contributing to climate change (Eskandari, Miesel and Pourghasemi, 2020). Several atmospheric pollutants including particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_x) and methane (CH4) are contained in the smoke emitted from fires degrade atmospheric air quality hence affecting public health (Matz *et al.*, 2020; Roberts and Wooster, 2021; Cobelo *et al.*, 2023).

Fires are largely influenced by climatic, vegetation, topographic and anthropogenic factors (Agata and Konrad, 2014). For example, the vegetation type and fuel load greatly determine the occurrence of vegetation fires (Strydom and Savage, 2016). Vegetation flammability is greatly determined by the characteristics of the vegetation. For instance, succulent vegetation generally resists burning due to higher fuel moisture content and reduced leaf litter (Graham, Dube and Mpakairi, 2023). Global climatic variability strongly alters the flammability and availability of vegetation fire fuel (Herawati *et al.*, 2015). The projected increase in climate change risk poses an anticipation for increased frequency of burning and fire season duration. The increased temperatures and reduced rainfall in Zimbabwe greatly manifest climate change and promote the occurrence of vegetation fires. The topographic characteristics of a landscape greatly determine the local temperature, and precipitation which controls the fuel flammability and availability (Zhang, Lim and Sharples, 2017). Higher temperatures and precipitation levels increase the likelihood of vegetation burning. Anthropogenic factors are also key in altering the natural fire regimes and threatening biodiversity (Reddy et al., 2019). Effective fire management hence requires a detailed understanding of the major factors driving fire regimes in a landscape.

The detection of vegetation fires using satellite sensors mostly utilizes the thermal and mid-infrared bands of the electromagnetic spectrum (Bin Hao *et al.*, 2022). Earth observation methods allow a repetitive and synoptic view of the spatial distribution of vegetation fire occurrence and their impacts on various ecosystems (Semeraro *et al.*, 2019; He, Shirowzhan and Pettit, 2022). Remote sensing satellites provide cost-effective and timely data for local and global spatiotemporal analysis of fire occurrence (Adab *et al.*, 2018). While large satellite datasets may be difficult to interpret, spatial statistics methods are critical in unveiling the spatiotemporal fire patterns vital for fire management. For instance, maps showing the spatiotemporal fire patterns can be used to decide on the implementation of fire management strategies.

Remotely sensed vegetation indices (VIs) are widely utilised in studies focusing on monitoring the effect of fires on vegetation characteristics. For instance, the Normalized Difference Vegetation Index (NDVI) and Normalised Burn Ratio (NBR) derived from satellite data are widely applied to assess pre-fire and post-fire vegetation conditions. Due to the algebraic combination of satellite spectral bands in the formulation of vegetation indices, they greatly detect changes in vegetation associated with fires. The NBR specifically measures the impact of burning on vegetation due to its utilization of the near-infrared and short-wave infrared spectral bands which are highly sensitive to fire damage (Hartung *et al.*, 2021a).

Limited studies have focused on assessing fire as a threat to ecosystem services utilizing remote sensing methods. The published reviews have mainly focused on methods in fire risk analysis (Molaudzi and Adelabu, 2019; Szpakowski and Jensen, 2019; Vigna *et al.*, 2021) and detection and monitoring of fires (Kurbanov *et al.*, 2022; Graham, Dube and Mpakairi, 2023). Although previous studies have focused on analysing literature on post-fire impacts and regeneration

(Chuvieco, 2019; Stavi, 2019; Montorio *et al.*, 2020), to the best of our knowledge, no review study has assessed the utilization of earth observation in evaluating the effect of vegetation fires on ecosystem services. The first objective of this thesis focused on a systematic review of published research articles dealing with the assessment of how vegetation fires threaten ecosystems using remote sensing methods.

One of the key fire regime descriptors is the level of energy produced during burning, the fire intensity (Keeley, 2009). The amount of vegetation biomass consumed during burning greatly determines the level of fire intensity. Previous studies analysed the fire intensity clusters and how they vary based on administrative boundaries. The few studies done in Zimbabwe have not analysed the fire intensity hotspots and national-scale fire studies have been limited. The second objective of this thesis focused on analysing the spatial variation in fire intensity across Zimbabwe's agroecological zones through incorporating topographic and climatic effects which was lacking in previous studies. Analysing fire intensity across landscapes is critical for developing effective management strategies as fire intensity is an important proxy for estimating extend of damage in affected areas (Said, Zahran and Shams, 2017). The fire intensity hot spot maps can be utilised for optimal allocation of resources towards fire management (Cizungu *et al.*, 2021). The findings for the second objective contributed to new information regarding the identification of the spatial distribution of fire intensity clusters in Zimbabwe.

The spatiotemporal analysis of vegetation fires utilises various hotspot analysis methods. Specifically, the Kernel Density and Moran's I have been widely used in various fire studies (Getis and Ord, 1992; Anselin, 1995; Vadrevu *et al.*, 2012; Said, Zahran and Shams, 2017). Applying local indicators of spatial autocorrelation (LISA) method in fire studies assesses where the fires are randomly spread or clustered within the landscape. For instance, the Getis-Ord (G_i*) statistic detects spatially dependent local pockets which are usually difficult to identify using global spatial autocorrelation methods (Getis and Ord, 1992). While hotspot analysis has been applied to study the occurrence of epidemics (Wubuli *et al.*, 2015), crime occurrence (Chainey, Tompson and Uhlig, 2008), and vegetation fragmentation (Kowe *et al.*, 2019, 2020), a few studies (Mpakairi *et al.*, 2018; Cizungu *et al.*, 2021; Shekede, Gwitira and Mamvura, 2021) have utilized spatial autocorrelation methods in fire studies. Outside Zimbabwe, studies that have utilised satellite-derived fire data and hotspot analysis methods to assess the spatial autocorrelation of fire intensity are scanty (Keeley, 2009; Vadrevu *et al.*, 2012). In India, fire intensity was analysed using the k-means spatial clustering method (Vadrevu *et al.*, 2012) while in northern Australia, Keeley (2009) assessed the fire intensity hotspots in a savanna landscape using MODIS fire data.

Effective fire management requires accurate and current information for the monitoring of spatiotemporal fire patterns especially in fire-prone regions such as the savanna ecosystems (Argibay, Sparacino and Espindola, 2020). The strength of this study also lies in the utilisation of spatial statistics and machine learning methods in analysing spatiotemporal variability of vegetation fires based on remotely sensed data. The study also assessed the drivers of vegetation fire occurrence and predicted the spatial variability of fire risk levels in Zimbabwe. This research used a nationwide approach to analysing spatiotemporal fire dynamics and identifying factors driving the fire occurrence. The research findings offer a wall-to-wall understanding of spatiotemporal fire dynamics in the various landscapes in Zimbabwe.

Although not explicitly mentioned, sustainable fire management is critical for the attainment of some of the United Nations Sustainable Development Goals (SDGs). The achievement of environmental protection, for example, requires planning for the effects of fire on various ecosystem services (Martin, 2018). Moreso, due to their contribution towards GHG emissions affecting global air quality, fires contribute towards climate change. The emission reduction strategies, for example, contribute to the achievement of the climate action group (Goal 13) (Haines *et al.*, 2017). The inclusion of a fire perspective in the SDG activities will greatly contribute to the goals' achievement (Martin, 2018).

1.3 Study Aims

The research aimed to analyse the spatial and temporal distribution of vegetation fires using satellite data.

1.4 Study Objectives

The specific objectives of the study were to:

- Review the utility of remote sensing methods in assessing the impacts of vegetation fires on ecosystem services;
- Explore the spatiotemporal patterns of vegetation fire occurrence in Zimbabwe;
- Determine the spatial distribution of vegetation fire intensity clusters in Zimbabwe;
- Develop a fire risk model for Zimbabwe using drivers of vegetation fire occurrence based on multisource spatial data and MaxEnt modelling.

1.5 Study area description

The thesis was based on a study done in Zimbabwe, a Southern African country which lies between 25°00″ - 33°10″ E and 15°30″ - 22°30″ S (Figure 1.1). Zimbabwe's elevation ranges from below 300 m to above 2500m above sea level, with lower areas distributed in the Southern regions and higher levels in the Eastern regions (Moyo et al., 2019). Three distinct seasons characterise Zimbabwe's climatic conditions, the dry and cool (May-August), the hot and wet (November-April) and the hot and dry (August-November) seasons. The fire season in Zimbabwe generally coincides with the dry season (Moyo *et al.*, 2019). Minimum temperatures in Zimbabwe are usually observed in winter (June to July), while the highest annual temperatures are usually recorded in October. The mean annual rainfall varies from lower than 400 mm in the southern and western districts to over 1500 mm in the Zimbabwean eastern regions (Manatsa *et al.*, 2020; Shekede, Gwitira and Mamvura, 2021). Zimbabwe covers seven agroecological zones, with decreasing mean annual rainfall from zone 1 (above 1250 mm) to Vb (below 400 mm). Additionally, elevation decreases from Zimbabwe's agroecological zones I to Vb (Manatsa *et al.*, 2020). The savannah woodlands cover almost 95% of the forest cover in Zimbabwe, characterised by grasses and trees co-existing and avail fuel for forest fire occurrence (Nyamadzawo *et al.*, 2013).

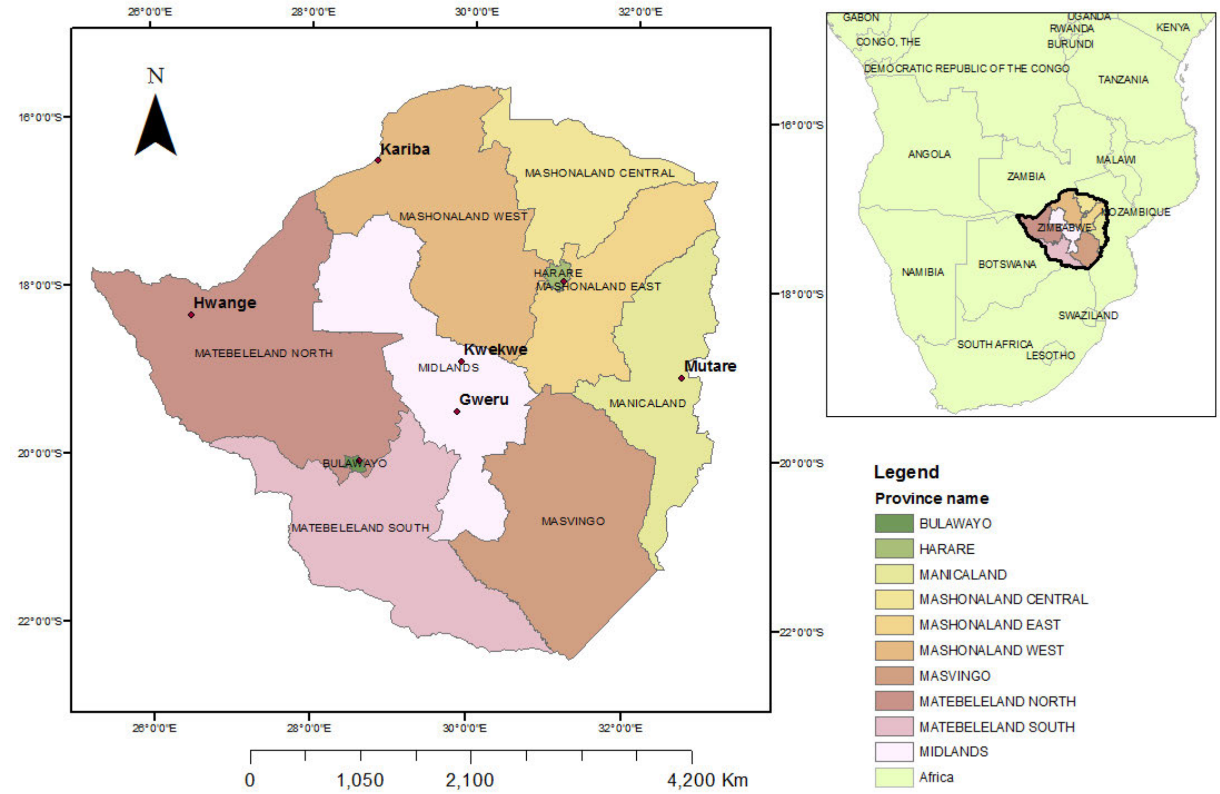

Fig 1.1. Location of the study area showing the provincial boundaries

1.6 Outline of thesis structure

This thesis covers six chapters, from the Introduction to the Synthesis. Chapter 1 gives a general introduction to the thesis and highlights the research objectives. Chapters 2 to 5 are characterised by research papers that address the study objectives outlined in section 1.4. Each paper includes the literature review, methodology, and results.

Chapter 2 focuses on a review of literature on the effects of vegetation fires on various ecosystem services. The effects of burning on various ecosystem services were identified using the PRISMA method for a systematic literature review. The literature review chapter provides evidence that fires significantly impact various ecosystem services. It hence justifies the importance of spatiotemporal analysis of vegetation fires which assist fire managers in fire management decision making.

Chapter 3 focuses on the spatial distribution of fire intensity in Zimbabwe. The analysis was based on MODIS satellite-derived fire occurrence data. The spatial autocorrelation approach was utilized to detect the spatial variability in fire intensity clusters. The spatial distribution of vegetation fire intensity cold and hotspots in Zimbabwe was therefore mapped.

Chapter 4 assessed the spatiotemporal patterns of fire occurrence over 21 years based on spatial pattern analysis. The historical MODIS satellite-derived fire data was utilised in the analysis which incorporated both the spatial and temporal dimensions of the long-term distribution of vegetation fires in Zimbabwe.

Chapter 5 explores the drivers of vegetation fire occurrence in Zimbabwe and predicts the level of fire risk across the landscape. The historical MODIS fire data was utilised to model the fire risk levels in Zimbabwe as determined by the topographical, climatic, vegetation and anthropogenic factors. The Maxent model, a machine learning approach, was utilised in the analysis to map the fire hazard zones and the main drivers governing the spatial occurrence of vegetation fires in Zimbabwe.

Chapter 6 synthesises all the research findings from the four research objectives. The chapter also provides conclusions and recommendations for future studies based on the study findings. The limitations of the study are also highlighted.

CHAPTER 2: LITERATURE REVIEW: A SYSTEMATIC REVIEW OF THE APPLICATION OF REMOTE SENSING IN ASSESSING THE IMPACT OF VEGETATION FIRES ON ECOSYSTEM SERVICES

This chapter is based on:

Mupfiga, U.N and Mutanga, O., 2024. *(Under Review)* A systematic review of the application of remote sensing in assessing the impact of fire on ecosystem services. (Manuscript submitted as a book chapter to*: Revealing Ecosystem Services through Remote Sensing: Beyond the Surface)*

Abstract

This paper focused on a systematic literature review of the current state of the utilization of remote sensing methods in assessing fire's impact on ecosystem services. Specific search strategies were used to search for the literature in Web of Science, Elsevier's Scopus and PubMed databases. The inclusion and exclusion of studies were done based on the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) protocol resulting in 25 papers being analyzed. The analysis of the retrieved research papers revealed a gradual increase in the publication of papers on the utilization of remote sensing in assessing the impact of fire on ecosystem services with most studies occurring in the United States of America. Landsat satellite data was mostly used to analyze the effects of vegetation fires on ecosystem services while MODIS was mostly used to detect fire occurrence in the landscape. The least utilized satellite data included PlanetScope, AVIRIS, and ASTER. The review revealed that vegetation fires affect forest, grassland, wetland, and soil ecosystems. Additionally, fires disturb the atmosphere through carbon and particulate matter emissions. The forest ecosystems were the most widely studied ecosystem. The study underscores the significance of remote sensing methods in assessing the effects of fires on ecosystem services. The limitations and research gaps within the field were also identified.

Keywords: fire; vegetation; ecosystem services; ecosystems; remote sensing

2.1 Introduction

Vegetation fires are intrinsic to the Mediterranean and Savanna ecosystems, contributing to the shaping of various ecological processes, determining species composition and ultimately influencing the landscape structure (Kugbe *et al.*, 2012; Herawati *et al.*, 2015; Semeraro *et al.*, 2019). Uncontrolled fires can, however, disturb ecosystems leading to biodiversity loss, vegetation cover loss, encouraging bush encroachment, and alien species invasion (Molaudzi and Adelabu, 2019; Semeraro *et al.*, 2019; Mupfiga, Mutanga and Dube, 2024). Additionally, vegetation fires are a significant natural disturbance threatening human life, economics, and public health (Chen et al., 2023; Bin Hao et al., 2022).

Climate variability has been increasingly contributing to the occurrence of fires by altering the vegetation flammability and fuel availability (Wasserman and Mueller, 2023). Recently, various ecosystems have been affected by the increased frequency and intensity of vegetation fires with likely environmental, economic, and health negative impacts (Souto-Oliveira et al., 2023). Ecosystem services refer to ecosystem-derived social and economic benefits enabled by productive and healthy ecosystems (Marambanyika *et al.*, 2021). They can be classified as provisioning, regulating, cultural supporting and ecosystem services (Millennium Ecosystem Assessment, 2005; Paula *et al.*, 2023). Global climate change projections predict an increase in fire events by up to 50% in fire-prone regions (Bowman et al., 2017). The increased risk of climate change across biomes has greatly exacerbated the frequency of wildfires, extent, and severity, threatening various ecosystem services (Qiu et al., 2023). Although wildfires can be beneficial, for example in pest and disease control, they generally have detrimental effects on ecosystem services (Pereira *et al.*, 2021).

Remote sensing methods allow large-scale observation of forest fires at low cost (Graham, Dube and Mpakairi, 2023). Specifically, the brightness temperature of thermal infrared and mid-infrared radiation bands are useful in detecting vegetation fires (Bin Hao *et al.*, 2022). Futhermore, earth observation methods provide a way of repetitively measuring the effects of fires on ecosystems at global, regional, and local scales in a synoptic view (He et al., 2021; Semeraro et al., 2019). Satellite-derived vegetation indices have been widely used to monitor vegetation status before and after fire occurrence. They are generally derived from the algebraic combination of different spectral band values. Although the use of individual spectral bands gives a simple method to analyze vegetation status, it is difficult to detect the heterogeneous nature of vegetation. The vegetation indices utilize the vegetation spectral properties such as the chlorophyll's strong red-light absorption capability and the ability to highly reflect the near-infrared spectra by the mesophyll layer of the leaf. The Normalized Difference Vegetation Index (NDVI), for example, is widely utilized in the assessment of vegetation conditions before, during, and after the fire. On the other hand, the Normalized Burn Ratio (NBR), which utilizes the near-infrared (NIR) and the short-wave infrared (SWIR) bands, strongly responds to fire but in the opposite direction of the NDVI. The NIR and SW spectral bands have a strong response to vegetation burning hence the NBR index is more useful for assessing the effect of fire on vegetation because it is highly sensitive to fire damage and vegetation regeneration and hence greatly used for assessing the severity of burning (Hartung *et al.*, 2021a).

Several studies have reviewed the utilization of remote sensing methods in mapping wildfire risk in various landscapes (Molaudzi and Adelabu, 2019; Szpakowski and Jensen, 2019; Vigna *et al.*, 2021). Also, some reviews focused on utilizing remote sensing methods in detecting and monitoring vegetation fires (Kurbanov *et al.*, 2022; Graham, Dube and Mpakairi, 2023). Although a few reviews have focused on the utilization of remote sensing in assessing post-fire effects and forest recovery patterns in forest and grassland landscapes (Chu and Guo, 2014; Chuvieco, 2019; Stavi, 2019; Pérez-Cabello, Montorio and Alves, 2021), limited studies have explored the use of earth observation in assessing the effect of fire on ecosystem services. This study specifically focuses on a comprehensive evaluation of published literature on the use of remote sensing in assessing the effect of vegetation fires on ecosystem services. The current review is based on a broad approach where all ecosystems that are possibly affected by burning were considered.

2.2 Methods

2.2.1 Literature search, inclusion, and exclusion strategy

The systematic review study was based on a thorough examination of research publications. An extensive search for peer-reviewed journal articles was done using the Web of Science, Scopus and PubMed databases. The search terms which were used included: "fire" AND "remote sensing" AND "ecosystem services", “fire” AND "remote sensing" AND "ecosystems" AND " threat”. To capture all the relevant studies, the time when the research was done was not restricted. The retrieved research articles were aggregated into a final count of research articles for each database. A total of 232, 19 and 100 references were collected from the Scopus, PubMed and Web of Science databases respectively.

The inclusion and exclusion analysis of the research studies was guided by the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) statement (Page *et al.*, 2021) due to its comprehensiveness and its ability to follow the scientific method. Figure 2.1 shows the process of the research article selection based on the PRISMA approach. The articles used in this systematic literature review included all types of peer-reviewed published research papers, including research articles, conference papers, book chapters, and review papers. The subject areas covered by the search criteria included agriculture and biological science, environmental science, computer science, earth and planetary science, and multidisciplinary. The review excluded papers that were duplicated, unavailable as full texts, not written in English, not GIS or remote sensing-based, and focusing on non-vegetation fires. Firstly, all 107 duplicated research papers were removed. The screening of titles and abstracts of the remaining papers was done to exclude 133 irrelevant research articles. From the remaining research articles, 47 articles could not be retrieved as full portable document files (pdf). A total of 25 research articles were finally considered for data extraction.

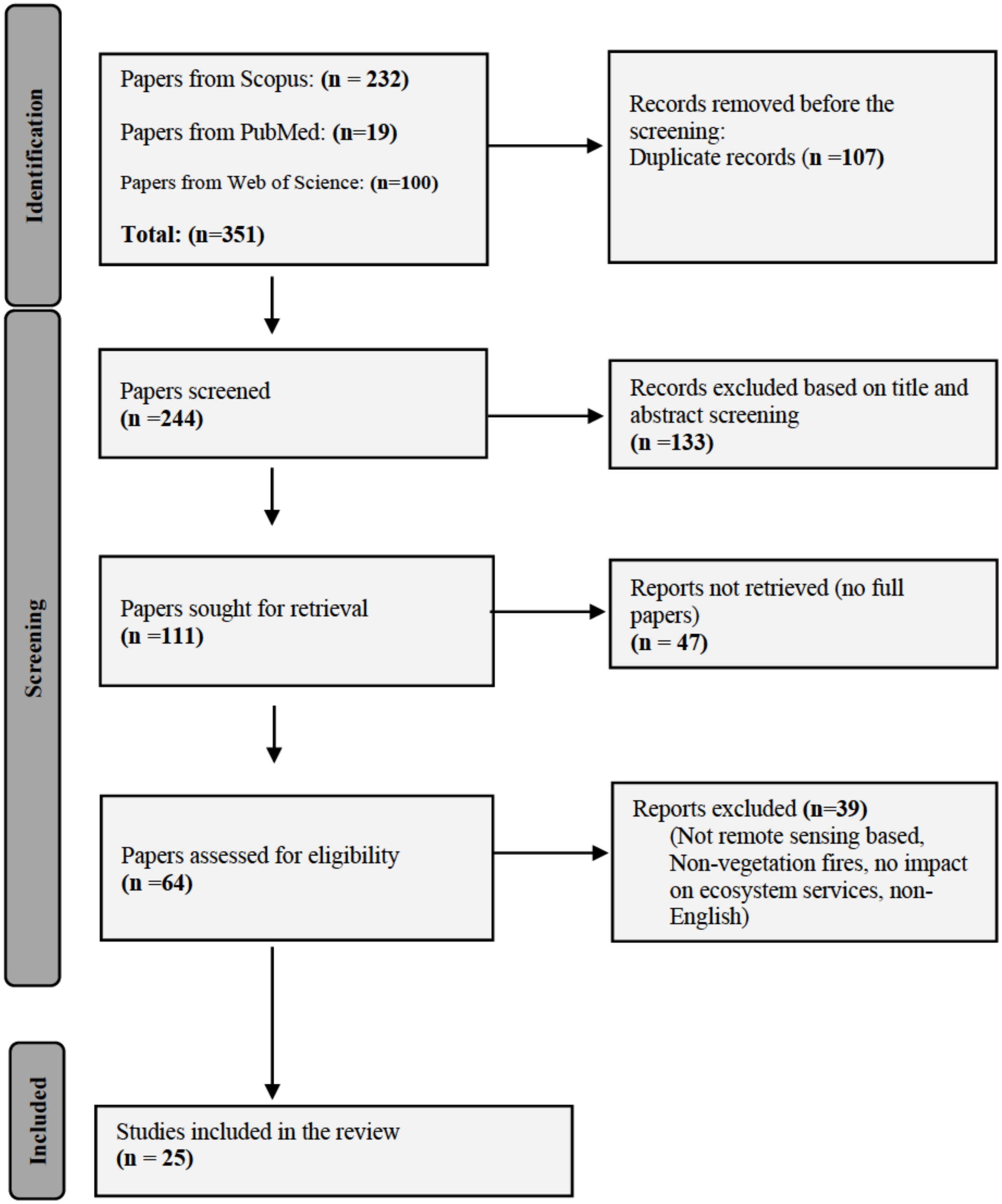

Figure 2.1: Schematic diagram of the papers selected based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) framework. (*Adapted from Page et., al 2021*)

2.2.2 Data extraction and analysis

The papers identified using the search criteria in the databases were exported as Microsoft Excel CSV files for quantitative and qualitative analysis. The references were exported to Zotero (version 6.0.36) reference management system. The VOSviewer software was utilized in the bibliometric analysis of the research articles to visualize the networks of occurrences and co-occurrences of the keywords identified in the research articles (Waltman, van Eck and Noyons, 2010; Perianes-Rodriguez, Waltman and van Eck, 2016). This allowed for the identification of interconnections of the keywords within a topic from the published research articles (Han *et al.*, 2020). The VOSviewer platform was used to create a map through a process of choosing the counting method, calculating the similarity index, calculating and displaying the most relevant items, and displaying a map created based on the extracted research articles. The input data for the bibliometric analysis in VOSviewer included keywords, abstracts, and titles of the extracted research articles. The output visualization was based on the co-occurrence of the key terms from the retrieved research articles.

The Microsoft Excel CSV file exported from the databases contained bibliographic data including the name of the author/s, year of publication, the title of the research paper, the name of the journal, the digital object identifier (DOI), the keywords, and the uniform resource locator (URL). Additionally, information on the location of the research, in terms of the country and continent was also collected. The quantitative analysis involved the determination of the frequency of research articles published over the study period and the continent where the study was done. The analysis also involved the classification of the studies extracted. The earth observation sensors and remote sensing methods utilized in the assessment of the impacts of vegetation fires on ecosystem services were also documented.

The structure of the review included two sections. The first one explores progress in the use of remotely sensed data in assessing the effects of vegetation fires on ecosystem services. The characteristics of the literature search, the temporal trend of the research studies, the satellite data, and the methods applied in the field were detailed in the first section of the review. The second section of the review utilized the findings from the first section to identify research gaps in the application of remote sensing in assessing the impact of vegetation fires on ecosystem services.

2.3. Results

2.3.1 Literature search characteristics

The analysis of literature in the VOSviewer software resulted in a network map shown in Figure 2.2 which grouped the retrieved literature into three clusters of key terms. The keywords within the red cluster included ‘forest fires, ‘burn severity’, ‘remote sensing’, ‘vegetation recovery’ and ‘ecosystem services’. This cluster shows the link between remote sensing data and forest fires and the utilization of remote sensing methods in assessing burn severity and vegetation recovery as post-fire impacts on ecosystem services. The repetition of the term ‘forest fire’ in the red cluster is evidence that the impact of fires on forest ecosystem services was highly studied in the reviewed studies. The green cluster is characterized by key terms such as ‘wildfire’, ‘biomass burning’, ‘air quality’, ‘particulate matter’, ‘air pollution’, ‘atmospheric pollution’, ‘ecosystem services’, and ‘forestry’. The interconnections between these keywords show that biomass burning is greatly associated with particulate matter emission resulting in air pollution which eventually affects ecosystem services such as air quality and biodiversity. The inclusion of the term ‘forestry’ in the green cluster clearly shows that most studies under review focused on the forest ecosystems. The blue cluster generally includes key terms such as ‘forest’, ‘fire’, ‘ecosystem’, ‘biodiversity’, ‘satellite imagery’, and ‘conservation’. The occurrence of these terms in the blue cluster implies that, from the retrieved studies, the effect of fires on ecosystem biodiversity can be analyzed using satellite imagery and has conservation implications.

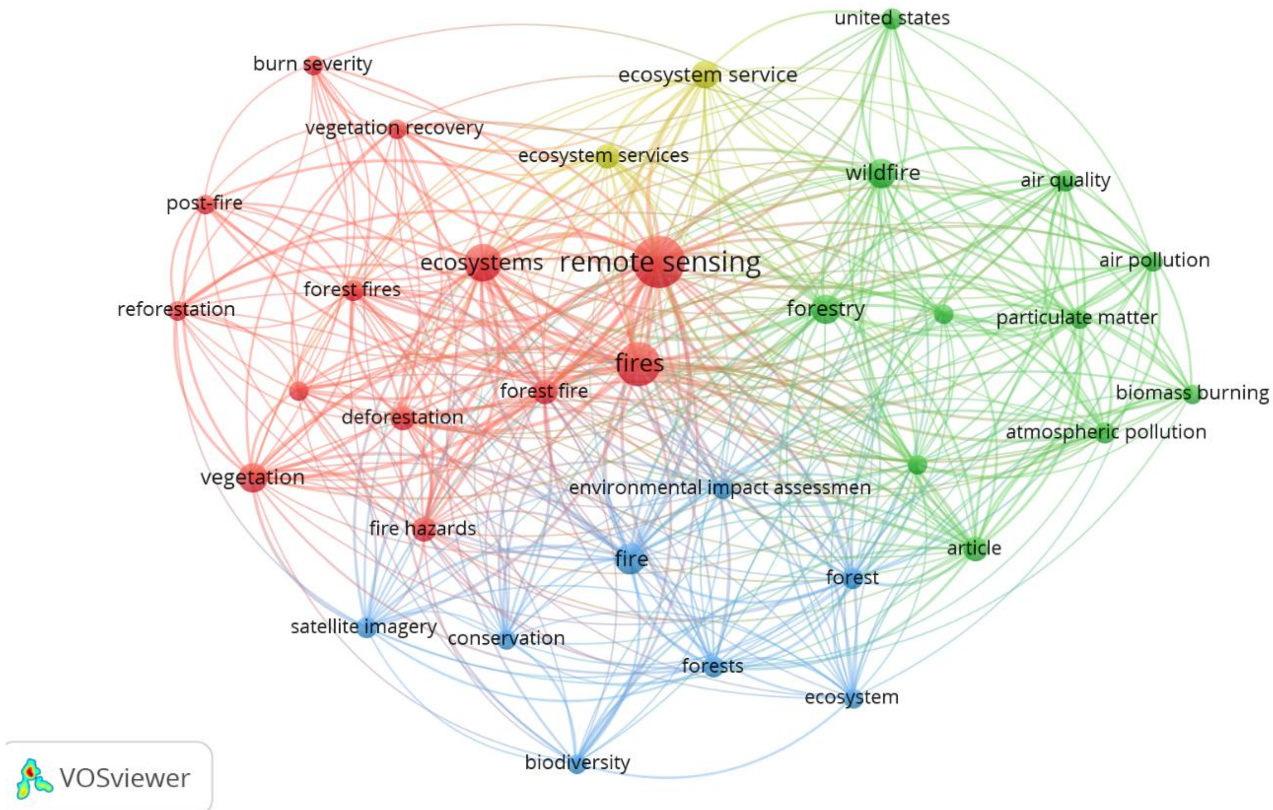

Figure 2.2. Major concepts extracted from article titles, abstracts, and keywords

2.3.2 Spatial and temporal distribution of publications

There has been a gradual increase in the number of publications focusing on assessing the impact of vegetation fires on ecosystem services (Figure 2.3) with recent years such as 2023 recording the highest number (12) of publications in the field. Notably, the first research study was published in 2010 and there was no noticeable increase in studies before 2015. Between 2015 and 2020 there was no consistent pattern in the trend of publications focusing on the impacts of fires on ecosystem services.

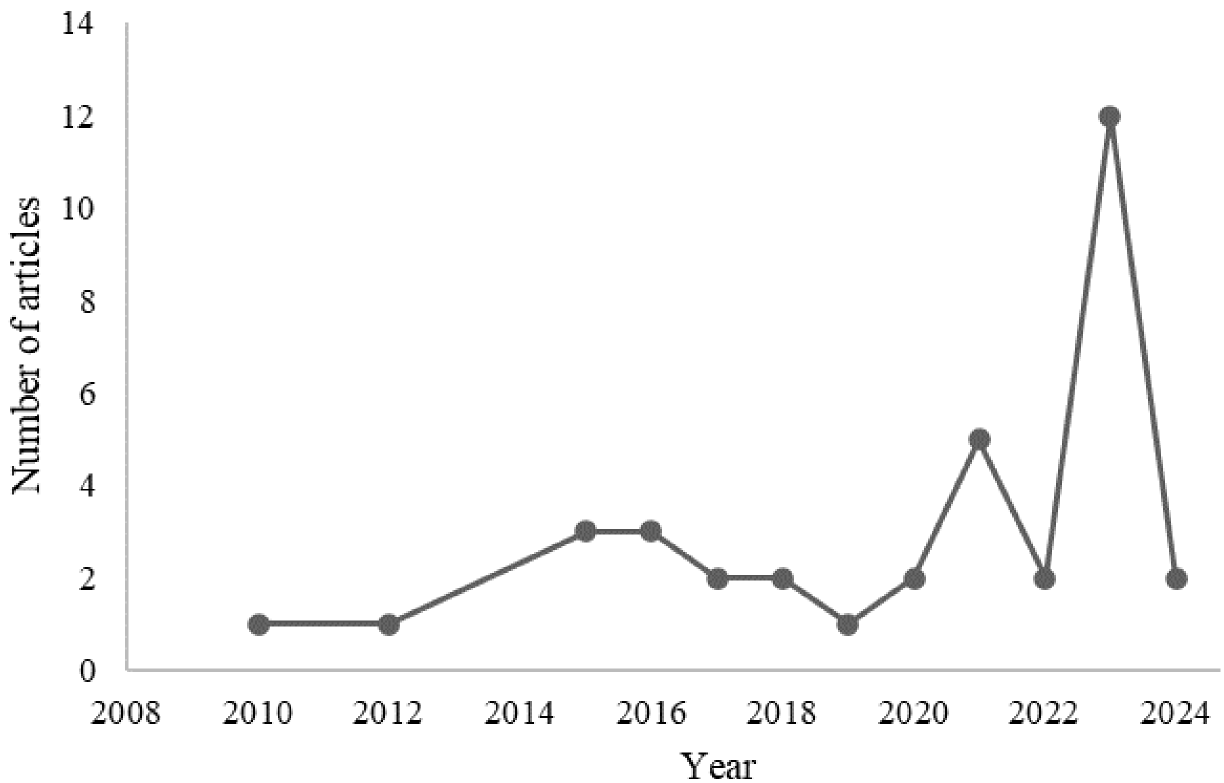

Figure 2.3. Temporal distribution of publications using remote sensing technologies to assess the impact of vegetation fires

Results from the review show that studies were done across the world with most of the studies generally coming from the United States of America (Figures 2.4a and 2.4b). It was observed that one study was recorded in Africa (Ghana) and only three studies were done in South America (Chile, Brazil and Bolivia), while the review recorded no study from Australia. In Asia, the studies included in the analysis were done in China, India, Israel and Indonesia. In Europe, case studies focusing on the impacts of fire on ecosystem services were done in Italy and Greece. Generally, the included case studies came from 12 countries. The nature of ecosystem services affected by fires in the case studies is highlighted in Figure 2.4c and Table 2.1.

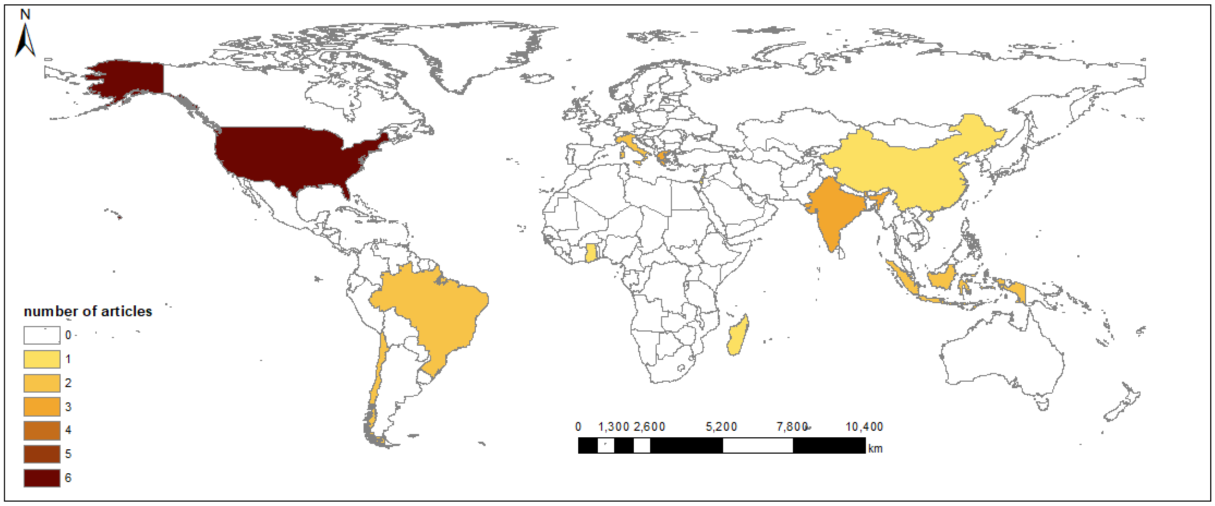

Figure 2.4a. Spatial distribution of studies on the application of remote sensing in the assessment of the impact of vegetation fires on ecosystem services.

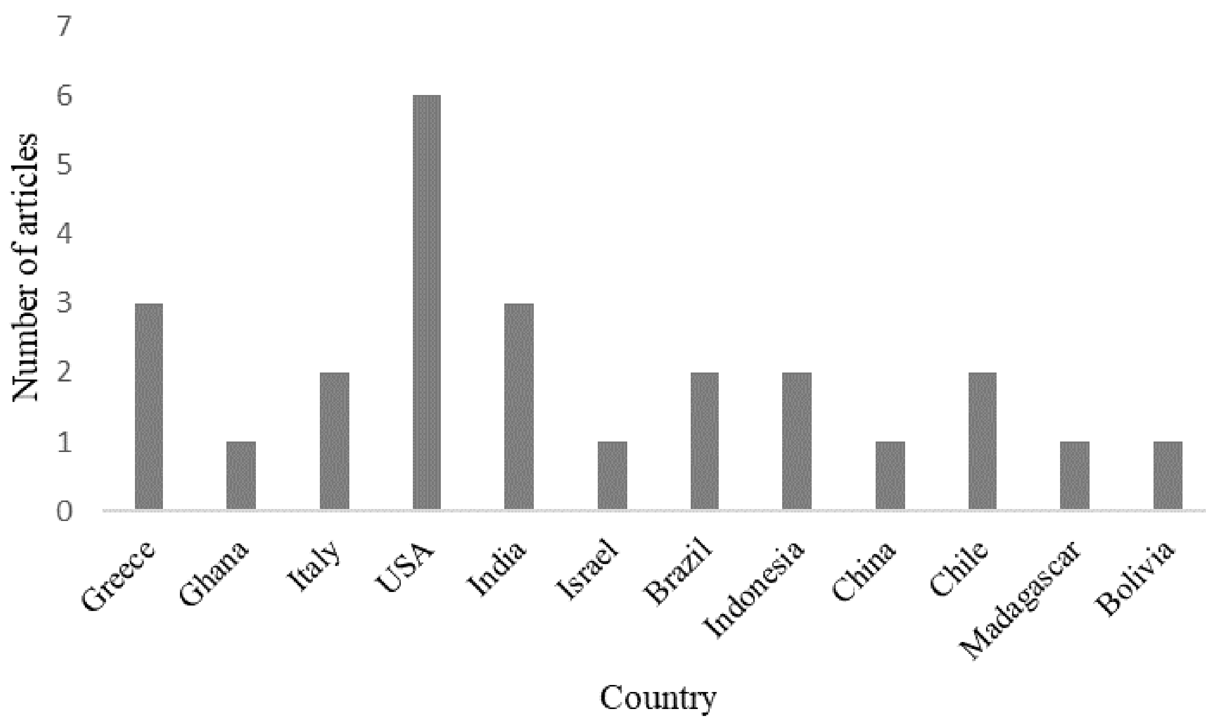

Figure 2.4b. Spatial distribution of studies on the application of remote sensing in the assessment of the impact of vegetation fires on ecosystem service

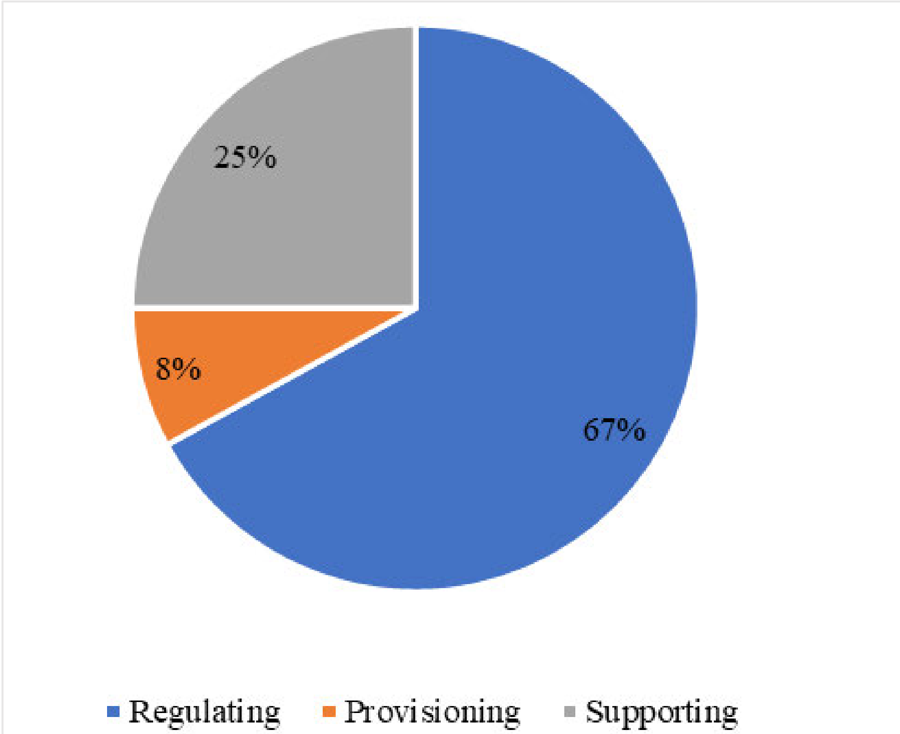

Figure 2.4c. Nature of the ecosystem services affected by vegetation fires as highlighted in the case studies

2.3.3 Satellite sensors utilized to assess the impact of vegetation fires on ecosystem services

Some (38%) of the studies utilized Landsat satellite data to analyze vegetation fires' impact on ecosystem services as shown in Figure 2.5. The Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) were used in the case studies, mainly as sources of data on the spatiotemporal occurrence of vegetation fires. In some studies, Landsat was used in combination with other datasets such as Sentinel (Tselka *et al.*, 2021; He, Shirowzhan and Pettit, 2022; Srivastava *et al.*, 2023) and MODIS (Barrera *et al.*, 2018; Hartung *et al.*, 2021a). PlanetScope, AVIRIS (Airborne Visible InfraRed Imaging Spectrometer), and ASTER satellite data were the least utilized by the published studies. Interestingly, only two studies utilized LIDAR data in their analysis (Souto-Oliveira *et al.*, 2023).

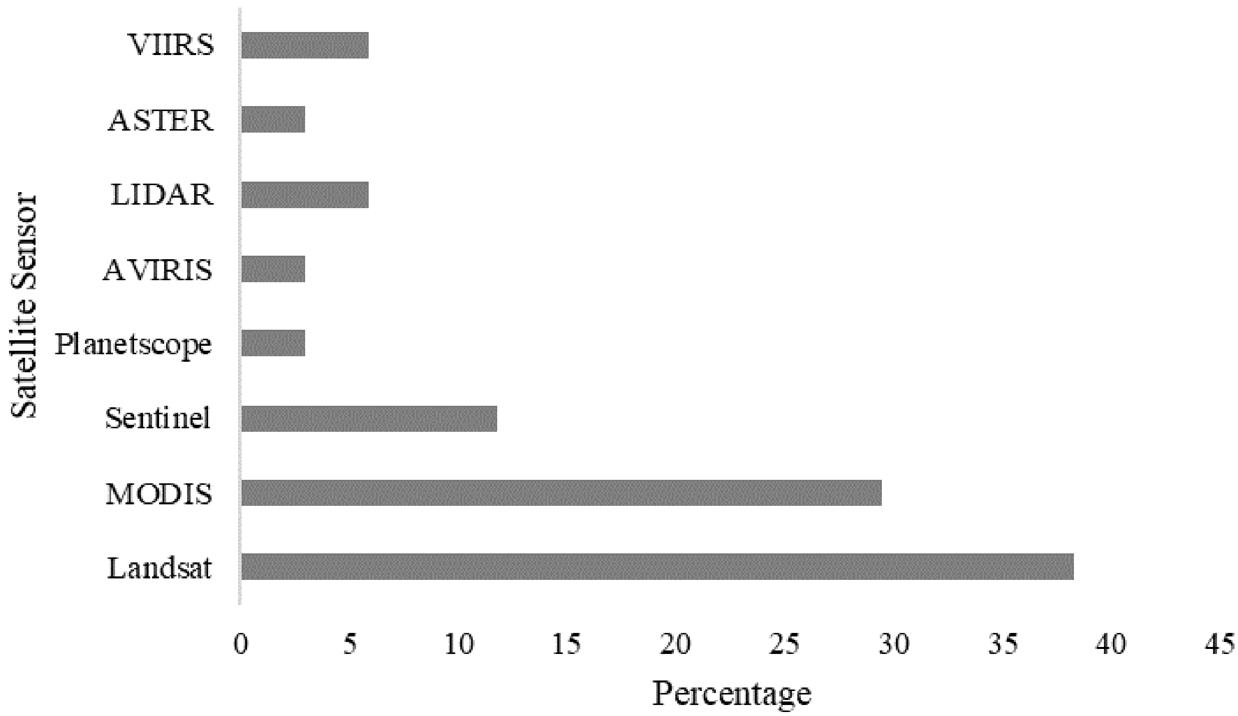

Figure 2.5: Earth observation sensors utilized in the studies on the assessment of the impact of vegetation fires on ecosystem services

2.3.4 Impacts of fire occurrence on ecosystem services

The review of the literature revealed that vegetation fires affect various ecosystem services from forests, grasslands, soil, and atmosphere. The analysis of the reviewed studies illustrated that vegetation fires greatly affect various ecosystem services as shown in Table 2.1. Most of the studies assessed the impacts of burning on forest ecosystem services. Vegetation indices such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Water Index (NDWI) and Normalized Burn Ratio (NBR) were widely utilized in the case studies. The Landsat data was mostly utilized to analyze vegetation status.

Table 2.1. Summary of studies assessing the impact of vegetation fires on ecosystem services

Ecosystem services	Impact of fire	References
Soil erosion regulation	Increase in soil loss after a fire event	(S. Stefanidis, Alexandridis and Mallinis, 2022) (Sankey *et al.*, 2017; Tselka *et al.*, 2021)
Sediment retention	Increased water body sedimentation due to post-fire soil erosion	Sankey et al., 2017
Air quality regulation	Fire contributed about 1-2.7% of global C emission. Contribution of fires to GHG emission. Fire identified as the major contributor to $PM_{2.5}$ Increased PM10 and PM2.5 associated with burning.	(Kugbe *et al.*, 2012) (Souto-Oliveira *et al.*, 2023) (Barrera *et al.*, 2018; Chen *et al.*, 2023)
Primary productivity	Burning induced the regeneration of plants producing better ones Reduced biomass and gross primary productivity	(Semeraro *et al.*, 2019) (Pandit, Dashti, A.T. Hudak, *et al.*, 2021)
Biodiversity	Burning transformed tall grassland ecosystems into shrubs Assessment of the impact of fires on seasonally dry tropical forests. Woody plants respond to fire by resprouting more than by seedling regeneration Transformation of forests to shrublands and grasslands	(Ratajczak *et al.*, 2016)

Ecosystem services	Impact of fire	References
Forest disturbance	Identification of forest degradation hotspots due to fires	(Reddy *et al.*, 2016)
	Strong correlation between forest loss and burned area	(Srivastava *et al.*, 2023)
	Creation of conservation priority zones based on forest loss characteristics	(Sutomo and van Etten, 2023)
	Reduction in plant cover and low post-fire recovery	
	Burning has an impact on carbon sequestration	
	Assessment of forest susceptibility and rate of recovery to fires.	
	Transformation of forests to shrublands and grasslands	
	Fire resilience increases with an increase in fire frequency	(He *et al.*, 2021)
	Relationship between burn severity with carbon emission and vegetation loss, postfire vegetation and carbon recovery. Higher severity is linked to higher emissions and higher vegetation loss	(Reddy *et al.*, 2016; Percival *et al.*, 2024) (Mancilla-Ruiz *et al.*, 2021)
	Effect of fire on decreasing forest surface biomass and surface-to-atmosphere water transfer and increased surface warming	(Hartung *et al.*, 2021b)
	Effect of fire on reduction of water use efficiency and growth of pine trees	(Michael *et al.*, 2018; Ivo *et al.*, 2020; Niccoli *et al.*, 2023; Qiu *et al.*, 2023)
	Assessment of vegetation regeneration after a major fire	
	Impact of fire severity and climatic factors on post-fire vegetation regeneration. Areas which were most severely burnt had the fastest recovery within 7-10 years	(Stephens, Collins and Rogan, 2020; Bin Hao *et al.*, 2022)

Ecosystem services	Impact of fire	References
Pest and Disease control	Fires increase pests and disease control Burning reduced tree disease spread and mortality.	(Pereira *et al.*, 2021) (Semeraro et al., 2019)
Natural hazards regulation	Detected increased post-fire flooding	(Alamanos *et al.*, 2024)

The analysis of selected research papers revealed that the effects of vegetation fires greatly vary among ecosystems. MODIS satellite-derived burned area data, for example, was utilized to assess the impact of fire frequency on forest resilience over a 20-year period (Hartung et al., 2021). Landsat-derived pre-fire and post-fire Normalized Burn Ratio (NBR) were used as a proxy for vegetation conditions within the burned area. Research findings show that resilience to burning increases with increasing frequency of burning. Burning was also associated with the transformation of forests into shrublands and grasslands thereby affecting the provisioning ecosystem services offered by forests.

Research also revealed that higher burn severity is greatly associated with higher carbon emission and vegetation loss as observed in a study done in California (Qiu *et al.*, 2023). In the study, MODIS-derived pre-fire and post-fire Enhanced Vegetation Index (EVI) was used to assess the vegetation conditions. Similarly, findings from the review highlight that vegetation burning increases the atmospheric concentration of particulate matter especially PM_{10} and $PM_{2.5,}$ and can have far-reaching air pollution effects on areas as far as more than 100km away from the burned location (Barrera *et al.*, 2018). Based on the utilization of Landsat-derived NBR, shrubs and forest ecosystems were mostly affected by the fires. Moreso, studies done in Alaska and Brazilian forests indicated the association between fires and increased $PM_{2.5}$ concentration in the atmosphere (Chen *et al.*, 2023; Souto-Oliveira *et al.*, 2023) and also contribute to GHG emissions. MODIS satellite fire data has been widely used in these studies. Therefore, clean air as a provisioning ecosystem service is negatively affected by vegetation fires.

According to the reviewed literature, fire occurrence reduces the primary productivity of vegetation across the fire-affected landscape. A 15-year time series analysis of MODIS-derived Enhanced Vegetation Index (EVI) and Normalized Difference Water Index (NDWI) revealed fire as a significant threat to a Mediterranean wetland primary productivity in southern Italy (Semeraro *et al.*, 2019). The utilized vegetation indices were applied as proxy measurements of the wetland photosynthetic activity and primary productivity. The resulting trend analysis revealed a drop in both the vegetation indices during the fire event while an increasing trend after the fire signified vegetation regeneration. This study also concluded that the fire-induced the regeneration of Phragmites and replaced the old individuals with new structurally and functionally better ones. Additionally, a study on the effect of fire on black pine using an integration of Landsat-derived NBR and NDVI and forest surveys in Italy revealed a decline in post-fire pine growth and alteration in the water use efficiency of the burned trees (Niccoli *et al.*, 2023).

Burning has been greatly associated with decreasing forest surface biomass (Ivo *et al.*, 2020). The utilization of Landsat-derived NDVI in the mentioned study has shown that the burning of forests decreases the surface-to-atmosphere water transfer and also tends to increase surface warming. Some of the effects of burning also include increased risk of landslides and flooding in areas outside the burned area as observed in the study by Barrera et al., 2018 in Chile.

Literature has revealed that the severity of burning greatly determines the rate at which post-fire vegetation recovery occurs. Findings from a research study show that areas that were most severely burnt had the fastest recovery (Hao et al., 2022). Vegetation spectral indices have been utilized to measure the severity of burning in various ecosystems. Research done by Hao et al., 2022, for example, utilized MODIS-derived Normalized Difference Vegetation Index (NDVI), Normalized Burn Ratio (NBR), Enhanced Vegetation Index (EVI), and Normalized Difference Moisture Index (NDMI) to detect the severe, moderate, and low severity of burning. High spatial resolution satellite data such as PlanetScope and Sentinel have been utilized in the assessment of urban forest burn severity (using NDVI, gNDVI, GCC) and the spatial distribution of economic loss associated with the burn severity (Michael *et al.*, 2018). Elsewhere, a study done in Greece utilized the Normalized Burn Ratio (NBR) index derived from Sentinel 2 satellite data to detect the vegetation conditions before and after the fire. Based on the study results, burning has been associated with an increased likelihood of post-fire flooding, affecting the regulating ecosystem services (Alamanos et al., 2024).

The assessment of vegetation regeneration after a major fire under different land management systems was also done (Stephens, Collins and Rogan, 2020). The Landsat 5 TM and Landsat 7 ETM+ satellite data were utilized to assess forest regeneration, a regulating ecosystem service.

The results from the study revealed a higher transformation of forest to shrublands within publicly owned land than in privately owned land. In contrast, greater regeneration of the forest ecosystem was higher in the privately owned forests than in publicly owned ones. The review has also shown that burning has the potential to transform grassland ecosystems (Ratajczak et al., 2016) into shrubs. Utilizing the MODIS burned area maps research findings have shown the impact of burning on grassland ecosystem services.

The review has revealed remotely sensed vegetation indices as key in monitoring changes in wetland primary productivity pre- and post-fire. A study by Semeraro et al., 2019 showed that fire can improve the primary productivity of a wetland ecosystem and regeneration produces better plant individuals. The findings from this study have also shown the association between fire occurrence and vegetation disease control.

While vegetation fires affect the available vegetation, soil-regulating ecosystem services are also greatly affected, where burning can be associated with soil loss. For example, a study that coupled Landsat satellite data analysis in a Google Earth Engine platform with the RUSLE model to monitor soil erosion revealed an increase in soil loss after a major fire event in Greece (Stefanidis *et al.*, 2022). Similarly, the RUSLE model was also utilized in the assessment of soil loss post-fire in a study by Tselka et al., 2021. Soil loss increased by 30% during the first year after a major fire and doubled in 5years (Tselka *et al.*, 2021). Landsat satellite data was utilized for deriving NBR and dNBR to assess the impact of the fire. Sentinel and Landsat satellite data were used to measure the vegetation cover management Factor (C) in the RUSLE model.

2.4 Discussion, limitations and research gaps

The gradual increase in publications is associated with the availability of open-source satellite data such as MODIS and Landsat. Moreso, the increase in expert knowledge enhances the utilization of earth observation data in assessing the impact of vegetation fires on ecosystem services. The common utilization of Landsat data may be attributed to its free availability and high applicability in vegetation assessment in ecosystems generally affected by fires (Graham, Dube and Mpakairi, 2023).

Most of the reviewed studies focused on the impacts of fire on forest ecosystems which highlights their key importance (Sudhakar Reddy *et al.*, 2015; Michael *et al.*, 2018; He *et al.*, 2021; Niccoli *et al.*, 2023; Srivastava *et al.*, 2023; Sutomo and van Etten, 2023; Percival *et al.*, 2024). Forests offer important ecosystem services to many livelihoods including indirect and direct ecosystem contributions to human and animal well-being including regulating, supporting, provisioning, supporting, and cultural services (Buthelezi et al., 202 4). They are key carbon sinks, mitigating negative impacts of climate change. Forests influence temperature and precipitation hence act as global and local climate regulators. The uncontrolled occurrence of fires therefore negatively affects these regulating, supporting, provisioning, supporting, and cultural services.

The review has shown that the ecosystem's primary productivity can be affected by the occurrence of fires. The primary productivity of wetland, forest and grassland ecosystems, for example, tends to drive the regulation and provisioning of ecosystem services. While several studies have shown fire occurrence as a threat to forest and grassland ecosystems, a study by Semeraro et al., 2019 revealed that fire induces the regeneration of the wetland ecosystem and replaces old plants with better ones. Contrary to other studies, the wetland primary productivity was higher after the fire than before the disturbance by fire occurrence. The occurrence of fire has a major effect on the primary productivity of such ecosystems and therefore disturbs the flow of the ecosystem services (Semeraro *et al.*, 2019). A study by Semeraro et al., 2019 revealed the utilization of remote sensing methods in monitoring the pre- and post-fire primary productivity of a wetland ecosystem.

The literature review has also shown that vegetation indices are widely used in the assessment of the impacts of fires on ecosystem services. Vegetation indices have been widely utilized as indicators of pre- and post-fire vegetation conditions (Graham, Dube and Mpakairi, 2023). While NDVI is widely utilized in fire monitoring, its value increases when regeneration occurs soon after the fire but quickly saturates due to its high sensitivity to leaf-related changes. The Normalized Burn Ratio (NBR), on the other hand, gradually increases with post-fire vegetation regeneration and thus becomes more suitable for this application (Hartung et al., 2021a).

Information about the resilience forests to burning is critical for proper management. For some forest types, resilience increases with a higher frequency of fire occurrence. For example, a study carried out in the Chiquitanía dry forest showed a decreasing resilience initially then increased after the third fire (Hartung *et al.*, 2021a). This is associated with the ecological transition from the usual vegetation type to increased abundance in fire-resilient species with the recurrence of burning. Recurrence of fires in such ecosystems tends to increase fire-tolerant plant species (Hartung et al., 2021a). Such information on the impacts of fire on specific ecosystems is essential for conservation managers.

Research findings also show that the occurrence of fires induces increased soil loss. This agrees with observations by Pereira et al., 2021 who highlighted that when the available vegetation is burned, soil protection is reduced. This may lead to the transportation of the produced ash, sediments and soil nutrients into nearby water bodies. Furthermore, reduced soil protection after burning increases the risk of flash floods and landslides (Brogan, Nelson and MacDonald, 2017; Wall, Roering and Rengers, 2020). The combination of soil organic carbon consumption and vegetation removal during burning greatly reduces the soil and water regulatory services by the ecosystem.

The review has also shown that vegetation fires greatly impact the ecosystem regulatory services. The occurrence of vegetation fires globally greatly affects the carbon cycle through carbon and particulate matter emissions (Qiu et al., 2023). Specifically, burning emits carbon in the form of carbon dioxide and greatly influences atmospheric greenhouse gas concentration. The removal of vegetation during burning decreases the vegetation's carbon sequestration capacity. On the other hand, the occurrence of fires negatively affects local and global climate regulation as the soil becomes a source of greenhouse gases (Ribeiro-Kumara *et al.*, 2020). The occurrence of fires has been associated with increased atmospheric pollutant emissions as emphasized by Pereira et al., 2021. Furthermore, the contribution of fires to atmospheric pollution and its damaging impacts on ecosystems, highlighted by the research findings is in line with the literature (Nowell *et al.*, 2018; Matz *et al.*, 2020). The atmospheric pollutants associated with fire extinguishing during fire suppression may contain hazardous pollutants which can be persistent in the environment. The post-fire transportation of such materials into water bodies may decrease water quality (Emmerton *et al.*, 2020; Pereira *et al.*, 2021).

The findings from this review have also shown the association between fire occurrence and vegetation disease control (Semeraro *et al.*, 2019). This is not surprising because several studies have also observed that the occurrence and transmission of diseases are greatly reduced after a fire event (Gleim *et al.*, 2019; Simler-Williamson *et al.*, 2021). Fires are widely known to control the occurrence of pests and reduce forest diseases.

The findings from this review are key to understanding how vegetation fires threaten various ecosystem services. This information is important for ecosystem and fire managers to make decisions regarding the protection of ecosystems. The research findings also highlight the importance of remote sensing methods in the long-term monitoring of the effects of burning on ecosystem services. The utilization of remote sensing methods to assess the impacts of fire on ecosystem services is greatly determined by the availability of satellite data. For example, Chu and Guo (2014) assessed the application of remote sensing techniques in modelling post-fire effects and forest recovery patterns in forest regions. The study findings revealed that remote sensing post-fire effects and forest recovery are mainly affected by gaps in data and the complications of fire regimes, and climatic conditions.

While this review study generally focused on all ecosystems, future review studies should focus on specific ecosystems to deepen the understanding of how fire affects the particular ecosystem. On the other hand, although ecosystem transitions have been associated with fire occurrence, the influence of changing climatic conditions has not been analyzed. Further studies should therefore look at the impact of a combination of fire occurrence and varying climatic conditions on ecosystem characteristics.

The research findings pointed to gaps in knowledge including the spatial coverage of research done and the satellite data utilized. Specifically, Africa was understudied while the Sentinel satellite data was underutilized in the studies reviewed with most studies covering Asian and American states. There is a need therefore for larger geographic coverage and utilization of a variety of satellite data by future studies. Even in geographical locations that were well studied, most studies concentrated on the forest ecosystem. The study findings are key in allowing ecosystem managers to make informed decisions in ecosystem management. The observations enabled by the utilization of remote sensing methods are important for guiding ecosystem conservation initiatives and the adequate allocation of resources. Finally, the findings from this literature review are critical to ecosystem managers in understanding the resilience and vulnerability of ecosystems.

The review clearly shows the controversy regarding the impact of fires on ecosystem services. For example, some terrestrial ecosystems are greatly shaped by fire and sustainable fire management ensures the support of ecosystem services. Although the occurrence of fire is intrinsic to ecosystems such as the Mediterranean and Savanna biomes, the high frequency and severity of human-caused fires can greatly harm ecosystems and disturb the proper functioning of ecosystem services.

2.5 Conclusions

In conclusion, the current study aimed to review literature focusing on the utilization of remote sensing in assessing the effects of vegetation fires on various ecosystems and the flow of ecosystem services. The findings from the review underscore the utility of remote sensing methods in assessing the impacts of fire on ecosystem services. There has been a gradual increase in research papers on the topic and the most utilized satellite data included Landsat and MODIS. The vegetation indices, such as the NDVI and NBR have been widely used to assess the vegetation conditions before and after fire occurrence. The study has shown that the African continent is understudied hence researchers should focus on Africa. Notably, the spatial distribution of the studies was biased towards the Asian and American continents. Furthermore, the review has shown that fire affects ecosystems including forests, wetlands, grasslands, soil, and the atmosphere and most studies focused on forests.

2.6 Summary and link to the next chapter

The chapter focused on systematically reviewing published research articles to analyse the effects of vegetation fires on various ecosystem services. The research findings indicate that while the occurrence of vegetation fires may benefit some ecosystems, it generally threatens several ecosystem services. The evidence from the reviewed literature is therefore a backbone for justifying the need for the objectives covered in this thesis. The analysis of the spatiotemporal distribution of vegetation fires is therefore critical to understanding how they affect various ecosystem services. For example, the intensity of burning determines the extent to which fire damages any ecosystem. The next chapter therefore focuses on detecting fire intensity clusters, one of the descriptors of fire regime, using satellite data and spatial autocorrelation methods. The association between the fire intensity clusters and the various ecosystems is also covered in the next chapter which is critical for the development and implementation of fire management strategies.

CHAPTER 3: SPATIAL CLUSTERING OF VEGETATION FIRE INTENSITY USING MODIS SATELLITE DATA

This chapter is based on;

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Spatial Clustering of Vegetation Fire Intensity Using MODIS Satellite Data

Upenyu Naume Mupfiga [1,*], Onisimo Mutanga [1], Timothy Dube [2] and Pedzisai Kowe [3]

[1] Discipline of Geography and Environmental Science, School of Agricultural Earth and Environmental Sciences, University of KwaZulu-Natal, Private Bag X01, Scottsville, Pietermaritzburg 3209, South Africa
[2] Institute of Water Studies, Department of Earth Sciences, The University of the Western Cape, Private Bag X17, Bellville 7535, South Africa
[3] Department of Geography, Environmental Sustainability and Resilience Building, Midlands State University, Gweru 9055, Zimbabwe
* Correspondence: nyatondou@gmail.com

Abstract

This work analyses the spatial clustering of fire intensity in Zimbabwe, using remotely sensed Moderate Resolution Imaging Spectroradiometer (MODIS) active fire occurrence data. To investigate the spatial pattern of fire intensity, MODIS-derived fire radiative power (FRP) was utilized. A local indicator of spatial autocorrelation, the Getis-Ord (G_i*) spatial statistic, was applied to show the spatial distribution of high and low fire intensity clusters. Analysis of the relationship between topographic variables, vegetation type, agroecological zones and fire intensity was done. According to the study's findings, the majority (44%) of active fires detected in the study area in 2019 were of low-intensity (cold spots), and the majority (49.3%) of them occurred in shrubland. High-intensity fires (22%) primarily occurred in the study area's eastern and western regions. The study findings demonstrate the utility of spatial statistics methods in conjunction with satellite fire data in detecting clusters of high and low-intensity fires (hot spots and cold spots).

Keywords: *active fire occurrence; fire intensity; fire radiative power; spatial clustering; hot spots; cold spots; spatial data; climate change*

3.1 Introduction

Fire has always been utilized as a useful management tool in maintaining ecosystem diversity mainly in semi-arid environments (Mupangwa, Walker and Twomlow, 2011; Andela and Van Der Werf, 2014; Rouget *et al.*, 2016; Benali *et al.*, 2017; Li *et al.*, 2018; Filipponi, 2019; Kganyago and Shikwambana, 2020). The occurrence of uncontrolled vegetation fires can, however, threaten the environment, economy and human safety (Gambiza *et al.*, 2005; Said, Zahran and Shams, 2017). Landscape fires produce significant amounts of particulate matter globally (Dwyer *et al.*, 2000), affecting air quality and hence leading to negative human health impacts (Roberts and Wooster, 2021). The loss of vegetation due to wildfires tends to alter landscape structure, with devastating effects on erosion dynamics (S. Stefanidis, Alexandridis and Mallinis, 2022; Stefanidis *et al.*, 2022) and ecosystem services footprint thereby affecting essential ecological and hydrological processes (Vadrevu *et al.*, 2012; Wooster *et al.*, 2021). Fires also contribute to climate change by transferring terrestrial to atmospheric carbon pools (Eskandari, Miesel and Pourghasemi, 2020). Although fires are largely due to anthropogenic factors, climatic conditions tend to greatly influence increased extreme fire events globally (Agata and Konrad, 2014). On the other hand, forest fires influence global climate change by emitting greenhouse gases such as CO_2 and CO.

Fire intensity is the energy which is released by a fire during combustion (Keeley, 2009) and is influenced by the fuel content (Drewa, 2003). The biomass which is consumed during burning influences fire intensity which is one key fire regime descriptor used by fire scientists (Lentile *et al.*, 2006). Fire intensity is usually confused with fire severity which focuses on the impacts of fire on the ecosystem.

The widely used hot spot analysis methods include Kernel Density (Getis and Ord, 1992; Getis, 2007; Vadrevu *et al.*, 2012; Said, Zahran and Shams, 2017) and Moran's I (Getis and Ord, 1992; Anselin, 1995). The Kernel density analysis usually generalizes point-based spatial data into continuous spatial data and considers search radius and cell size. On the other hand, the Getis-Ord (Gi*) statistic utilizes the magnitude of each spatial feature in relation to its neighbour's values to form clusters of the features in form of cold spots and hot spots (Getis and Ord, 1992). Local indicators of spatial autocorrelation (LISA) methods such as the Getis-Ord (Gi*) statistic, therefore, help in the determination of whether fires are clustered or randomly spread within a landscape. The Getis-Ord (Gi*) statistic allows for the detection of local pockets of spatial dependence which may be difficult to detect using global spatial autocorrelation methods (Getis and Ord, 1992). In other fields, hot spot analysis methods have been used to analyse the clustering of crimes (Chainey, Tompson and Uhlig, 2008), pulmonary tuberculosis incidences (Wubuli *et al.*, 2015), and vegetation fragmentation (Kowe *et al.*, 2019, 2020).

Currently, fire monitoring in Zimbabwe is done using both ground-based and satellite data, where the detected active fires and burned area are generally documented. Fire intensity is not measured and, therefore, not incorporated into the fire management system in Zimbabwe. Currently, no study has assessed the fire intensity in Zimbabwe. Previous studies such as (Mpakairi *et al.*, 2018; Kowe *et al.*, 2019, 2020; Shekede, Gwitira and Mamvura, 2021) focused on identifying hotspots and cold spots, which denoted areas with high and low fire occurrence. A study by Shekede et al., 2019, for example, assessed the spatial distribution of fire hot spots within districts in Zimbabwe using the location (coordinates) of MODIS active fire data. In Zimbabwe again, Mpakairi et al., 2018 analyzed the spatial clustering of active fires in a protected area using satellite data. These previous studies (Cizungu *et al.*, 2021; Shekede, Gwitira and Mamvura, 2021) generally utilized the geographic location of MODIS active fires to determine the spatial clustering of fires based on administrative boundaries. Administration boundaries generally do not follow any environmental gradient. Such studies lacked the analysis of critical fire variables such as fire intensity.

Across the globe, very few studies have been done on the spatial clustering of fire intensity based on satellite data and spatial autocorrelation methods. For instance, (Vadrevu *et al.*, 2012) utilized the k-means clustering method to detect fire intensity clusters based on MODIS fire radiative power (FRP) data in India, Asia. A study by Keeley (2009) utilized MODIS FRP to study forest fire activity and intensity in the tropical savanna of northern Australia. A study by Mohd Said et al., 2017 used ground-based fire data in a study where the spatial distribution of high and low-intensity fires in Brunei-Muara District Brunei Darussalam, Southeast Asia was examined. This is time-consuming, expensive, and does not cover large areas. On the other hand, satellite remote sensing allows for synoptic coverage, the ability to take repetitive measurements, and the ability to cover large areas.

Zimbabwe, for example, supports seven agroecological regions which are characterized by different climatic and topographic conditions. By analysing the variability of fire intensity clusters in the different agroecological zones, this study incorporates the effect of varying climatic, vegetation, and topographic conditions on fire intensity in the study area. Further, the study also analysed the contribution of topography, land cover, and agroecological zones to fire intensity which was not incorporated in previous studies (Wubuli *et al.*, 2015; Kganyago and Shikwambana, 2020; Shekede, Gwitira and Mamvura, 2021).

In Zimbabwe, climate change has manifested itself with an increase in temperatures and a decrease in rainfall (Mushore *et al.*, 2021) which is associated with a high recurrence of fires. With the risks of climate change becoming more real in Zimbabwe (Shoko, Masocha and Dube, 2015), information on fire intensity clusters becomes very critical for fire management strategies. This is because it gives fire managers an indication of the propagation of fire and how difficult or easy it will be to stop the fire. Information on fire intensity clusters also helps in identifying areas prone to fires of high-intensity, posing high risks to vegetation, infrastructure, and people (Said, Zahran and Shams, 2017). Fire managers can utilize fire hot spot maps to assist in decision-making for the appropriate allocation of fire management resources to priority areas (Zhang, He and Yang, 2008; Cizungu *et al.*, 2021). Findings from this study contribute novel knowledge in terms of utilizing spatial autocorrelation methods and earth observation data to identify fire intensity clusters in Zimbabwe, Southern Africa.

3.2 Materials and methods

3.2.1 Study Area

This study was carried out in Zimbabwe, Southern Africa and located between the coordinates 15°30″ - 22°30″ S and 25°00″ - 33°10″ E as shown in Figure 3.1. The elevation varies from below 300 m for the Southern districts to more than 2500 m above mean sea level for the Eastern regions of the study area. The climate is divided into three distinct seasons where the hot and wet season occurs from November to April while the cool and dry season occurs from May to around August. The hot and dry season which coincides with the fire season generally occurs from August to November (Shoko, Masocha and Dube, 2015). In Zimbabwe, minimum temperatures usually occur around June to July, while maximum temperatures are usually experienced in October. Annual rainfall in the study area varies from below 400 mm in the western and southern regions to above 1500 mm in the eastern regions of the study area [Shekede, Gwitira and Mamvura, 202], and this has been categorized into seven agroecological zones, as shown in Figure 1. Mean annual rainfall decreases with the transition from agroecological zones 1 (about 1250 mm) to Vb (below 400 mm). The study area is defined by decreasing elevation and increasing temperature from agroecological zones I to Vb (Manatsa *et al.*, 2020). Savannah woodlands characterize approximately 95% of Zimbabwe's forest cover, where trees and grasses co-exist and provide fuel load for forest fires (Archibald *et al.*, 2010; Nyamadzawo *et al.*, 2013). The peak fire season in the study area span from August to October, which is a period characterized by hot and dry conditions (Mpakairi et al., 2018).

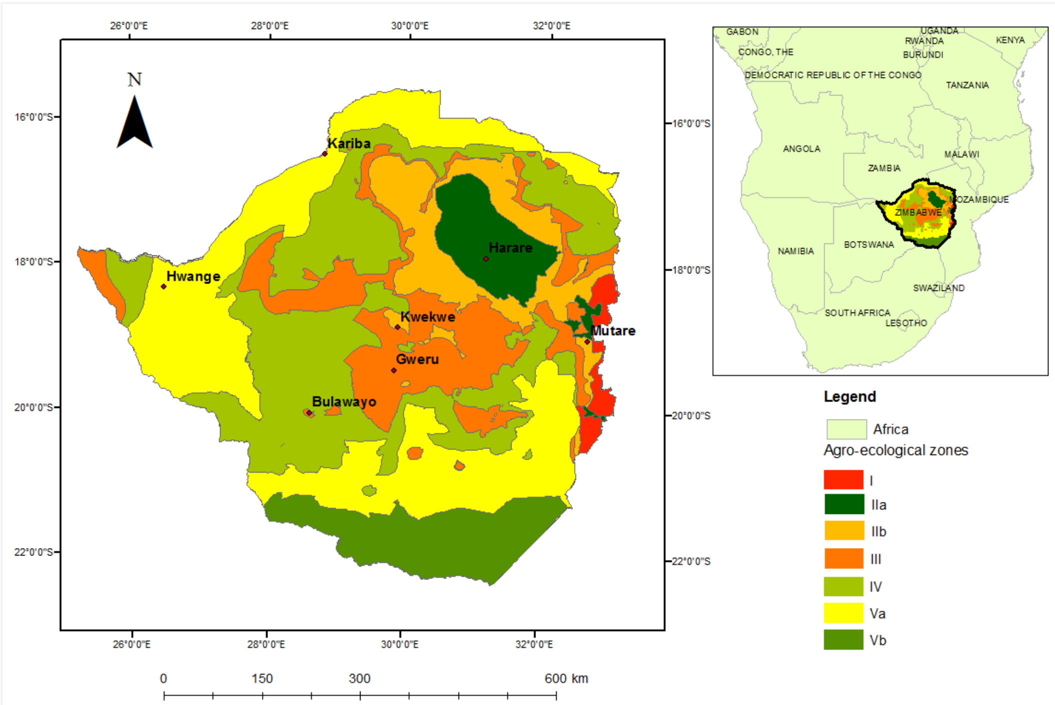


Figure 3.1. Location of study area showing agroecological zones: (*Adapted from Manatsa et al., 2020*)

3.2.2. Satellite Data

The daily active fire product (MCD14DL) from MODIS was used. MODIS Terra and Aqua satellites have a 1 to 2-day revisit time and pass over the equator at around 1030 am and 1.30 pm. The data has a spatial resolution of 1 km at the nadir, but it is worth noting that the MODIS sensor tends to detect fires as small as 50 m^2 (Vadrevu *et al.*, 2012; Vadrevu and Lasko, 2018). Each detected active fire depicts the center of a 1 km pixel where one or more fires are burning during the time the satellite overpasses (Giglio, Randerson and van der Werf, 2013). In this context, an active fire is defined as any fire identified by the MODIS satellite sensor while burning is still active (Soro *et al.*, 2021). The factors that determine the probability of a fire being detected include the temperature of the fire, the area covered by the fire spread, the satellite's angle, and the prevailing weather conditions (Giglio *et al.*, 2003).

Data for the daily active fires detected by the MODIS sensor from January to December 2019 were freely downloaded from the Fire Information Management System (FIRMS) website (https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/active-fire-data (accessed on 10 March 2022)) in shapefile (*shp) format. The geographic coordinates (latitude and longitude) of the fire, brightness temperature (Kelvin), acquisition date and time, confidence (0–100%), and fire radiative power are all included in the MODIS active fire data (FRP). A description by (Giglio *et al.*, 2003) provides details on the acquisition of MODIS data. MODIS active fire data was chosen for analysis in this study because it is free and covers a large area (Chen and Yang, 2018; Mpakairi *et al.*, 2018). Several studies have used MODIS active fire data in fire studies (Giglio, Csiszar and Justice, 2006; Ichoku *et al.*, 2008; Vadrevu *et al.*, 2012). To date, the MODIS sensors have been extensively utilized in the detection of fire because of the presence of channels specifically designed for fire monitoring and their high temporal resolution.

3.2.3 Pre-Processing of Data

The active fires utilized in the analysis had a confidence level greater than 30% (Giglio *et al.*, 2003; Cizungu *et al.*, 2021) to minimize false alarms (Giglio, Schroeder and Justice, 2018). Fire points of less than a 30% confidence level are considered unreliable (Giglio, Schroeder and Justice, 2018; Cizungu *et al.*, 2021). Using ArcMap 9.5's Projection and Transformations tool, all the datasets in Table 1 were projected to the UTM coordinate system using the Project tool in a GIS environment to ensure compatibility.

Table 3.1. Datasets used in the study.

Dataset	Source
MODIS (MCD14DL) active fire data	https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/active-fire-data (accessed on 10 March 2022)
Digital Elevation Model (DEM)	https://earthexplorer.usgs.gov/ (accessed on 15 March 2022)
Land cover map	https://viewer.esa-worldcover.org/worldcover/ (accessed on 27 March 2022)

3.2.4 Data Analysis: Spatial Clustering of Fire Intensity

The presence or absence of spatial clustering in the fires detected by the MODIS sensor was tested using Moran's I (Anselin, 1995) spatial autocorrelation statistic, which was computed using the Spatial Statistics tool in a GIS environment. The fire radiative power extracted from the MODIS fire data was used as a measure of fire intensity (Giglio, Csiszar and Justice, 2006). The FRP, in this context, refers to the rate of radiative energy emitted by the fire at the time of the observation (Giglio, Csiszar and Justice, 2006). It is a good approximation of the total amount of energy released during burning and can be used to assess the destructive power of the detected fire (Giglio, Csiszar and Justice, 2006).

Fire intensity cold spots and hot spots were computed using Getis-Ord (Gi*) (Getis and Ord, 1992) statistic based on Equation (1):

$$Gi^* = \frac{\sum_{j=1}^{n} w_{i,j}\bar{x}_{,} - \bar{X}\sum_{j=1}^{n} w_{i,j}}{s\sqrt{\frac{[n\sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})]}{n-1}}}$$

(1)

Where,

x_j is the attribute value for feature j, w_{ij} is the spatial weight between feature i and j, and n is the total number of features in the dataset. This spatial autocorrelation statistic assessed the extent to which fires exhibit spatial patterns in space as high-intensity hot spots or cold spots, which are areas of statistically high or low fire intensity concentration, respectively. The Gi* statistic identifies spatial clusters of high and low values which are statistically significant hence creating hot spots and cold spots. Hot spots form when points of high values are surrounded by high values, while cold spots form when points of low values are surrounded by low values (Getis and Ord, 1992). This study utilized the default distance thresholds of the Gi* statistic because the specific details on the spatial relationships within the fire dataset were not clear (Getis and Ord, 1992).

In this study, the fire radiative power extracted from the MODIS fire data was utilized in the analysis to detect fire intensity clusters in the form of low fire intensity (cold spots) and high fire intensity (hot spots). MODIS active fire data is globally accessible and can be used at various scales, which is beneficial to data-poor regions such as southern Africa (Shekede, Gwitira and Mamvura, 2021). The Hot spot Analysis tool in ArcMap 10.5 was utilized in the identification of fire intensity clusters. The derived Getis-Ord (Gi*) values were classified into hot spots and cold spots where high values of the Z-score in association with low p-values indicate a hot spot (Zúñiga-Vásquez *et al.*, 2017). In this context, fire-intensity hotspots were formed when points of high FRP were surrounded by high FRP values, while fire-intensity cold spots were formed when points of low FRP values were surrounded by low FRP values. The spatial distribution of high-fire-intensity (hot spots) and low-fire-intensity (cold spots) areas in the study area were presented in the form of a map.

3.2.5 Data Analysis: Analysis of Fire Intensity within Clusters

The number of active fire points within the fire intensity clusters (hot spots and cold spots) was calculated. The paired t-test was calculated using the GraphPad Prism version 6.04 for Windows (www.graphpad.com: accessed on 27 March 2022) to test for the difference in the mean FRP within the fire intensity clusters.

3.2.6 Data Analysis: Correlation of Fire Intensity Clusters with Topographic Factors

Correlation between topographic variables (elevation, slope, aspect) given in Table 2 and FRP was done.

Table 3.2. Topographic variables.

Variable	Source
Slope	Extracted from the Digital Elevation Model using Spatial Analyst tool in ArcMap 10.6
Aspect	Extracted from the Digital Elevation Model using Spatial Analyst tool in ArcMap 10.6
Elevation	Digital Elevation Model

Elevation explains the changes in temperature while aspect determines the amount of solar radiation available for the fuel, hence affects the moisture content of the fuel. Steep slopes are associated with greater preheating of fuels. Topographic derivatives such as aspect, slope, and elevation also influence the amount of solar radiation reaching any location (Ruecker, Leimbach and Tiemann, 2021). The vegetation type is also influenced by slope and altitude and hence affects the fire intensity. To test for the significant difference in topographic variables within fire intensity clusters, the paired t-test was utilized.

3.2.7 Data Analysis: Association between Fire Intensity and Vegetation Cover Types

The association between fire intensity and vegetation cover types was also examined to assess the susceptibility of the various vegetation types to burning. The 10 m resolution land cover map from the European Space Agency (ESA) initiated WorldCover project was downloaded from https://viewer.esa-worldcover.org/worldcover/ (accessed on 27 March 2022) as indicated in Table 1. The specific vegetation cover type for each fire point data was extracted using the Extract tool in ArcMap 10.5, and the FRP for each fire point was determined.

3.2.8 Data Analysis: Association between Fire Intensity and Agroecological Zones

The association between FRP and the agroecological zones was examined to determine which agroecological zones are characterized by hot or cold fires. The agroecological zone map produced by Manatsa et al., 2020 was utilized. The Zimbabwe agroecological zones were delineated based on mean annual precipitation and temperature. The Extract tool in ArcMap

10.5 was utilized to determine the agroecological zone for each fire point. The chi-square test was used to test for the association between fire intensity clusters and agroecological regions.

3.3 Results

3.3.1. Spatial Distribution of Active Fires

A total of 35,342 active fires were detected in 2019 in the study area (Figure 3.2). High fire activity was detected in agroecological regions IIa, IIb, and IV (Figure 3.3), which are characterized by high rainfall and increasing temperatures (Manatsa et al., 2020). The highest fire activity was detected in Mashonaland West province (Figure 3.2), while low activity was recorded in the southern and south-western districts. Nyanga, Mutasa, Chimanimani, and Chipinge districts in Manicaland province also experienced a considerable number of fire incidences.

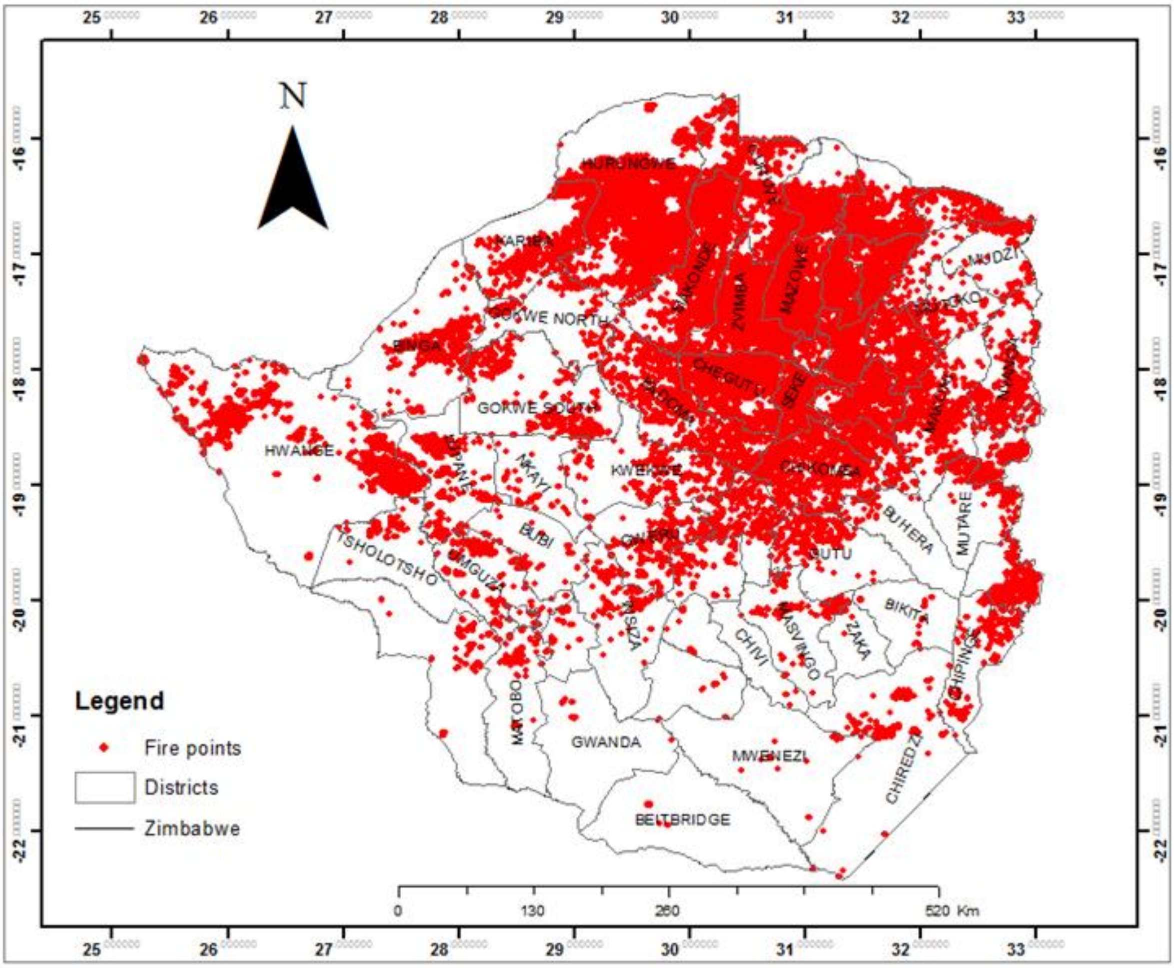


Figure 3.2 Spatial distribution of active fires in 2019

3.3.2. Spatial Distribution of fire Intensity

The test for clustering using the Moran's I statistic revealed that the occurrence of active fire clusters in the study area was statistically significant ($p < 0.05$; z-score = 35.17). The map showing the spatial occurrence of high and low fire intensity clusters (Figure 3.3) shows that most of the fires under study were of low intensity. Based on the results shown in Figures 3.3 and 3.4, agroecological zones I and IIA and parts of agroecological zones III, IV, and VA are significantly ($p < 0.05$) associated with high-intensity fires. Although these zones are associated with lower temperatures than other regions, they are characterized by higher altitudes which could result in high-intensity fires. Agroecological zone I is characterized by plantations that burn intensely. High fire intensity clusters (hot spots), as detected using the Getis-Ord statistic (Gi*), have shown to be distributed in parts of the eastern (Mutasa, Nyanga, Chimanimani), northern (Centenary), and western (Tsholotsho, Hwange) districts as shown in Figure 3.3. The research findings also show that fires of low-intensity (cold spots) occur mostly in the northern districts such as Hurungwe, Kariba, Rushinga, Guruve, and others shown in Figure 3.3.

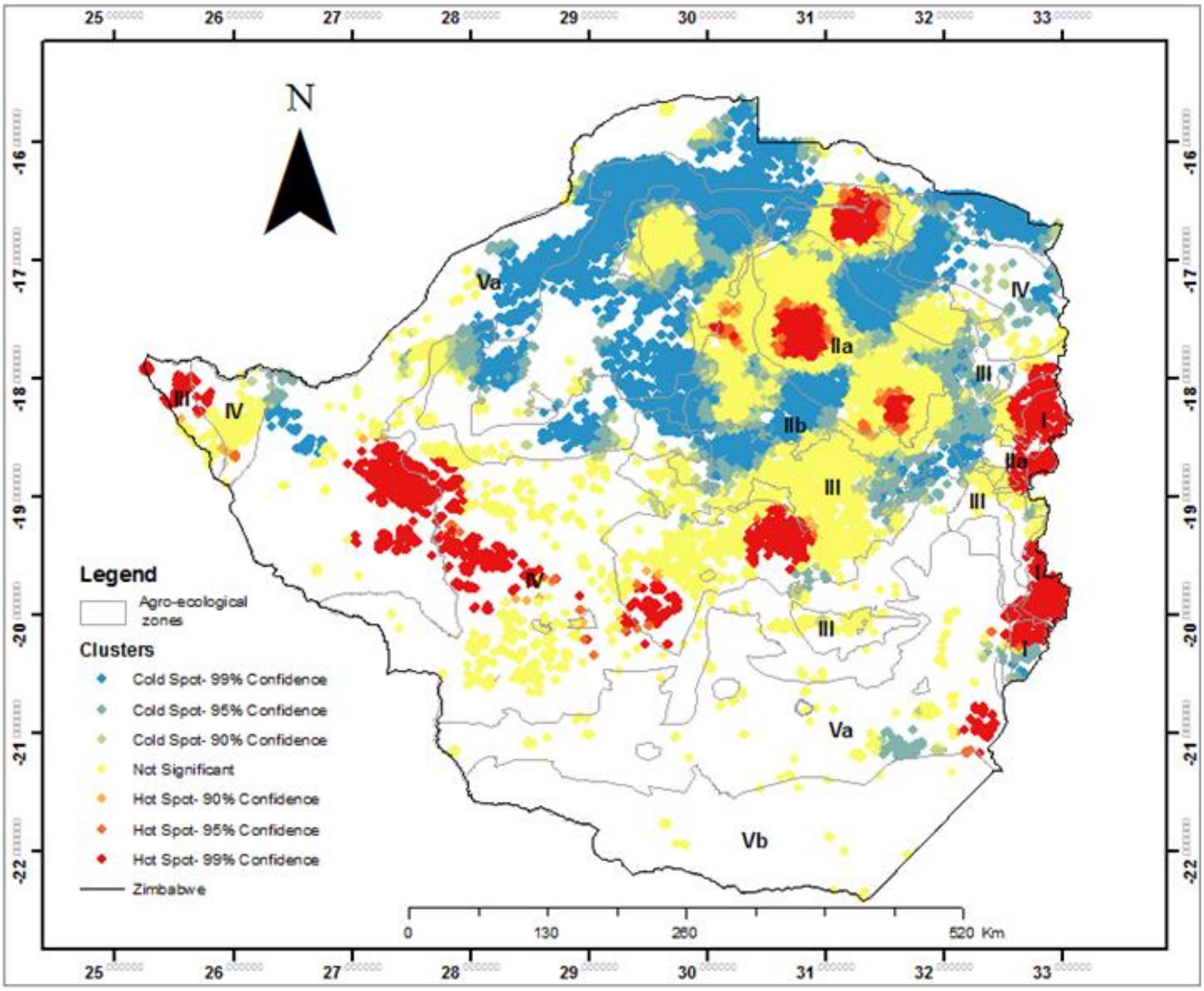


Figure 3.3. Spatial distribution of fire intensity clusters

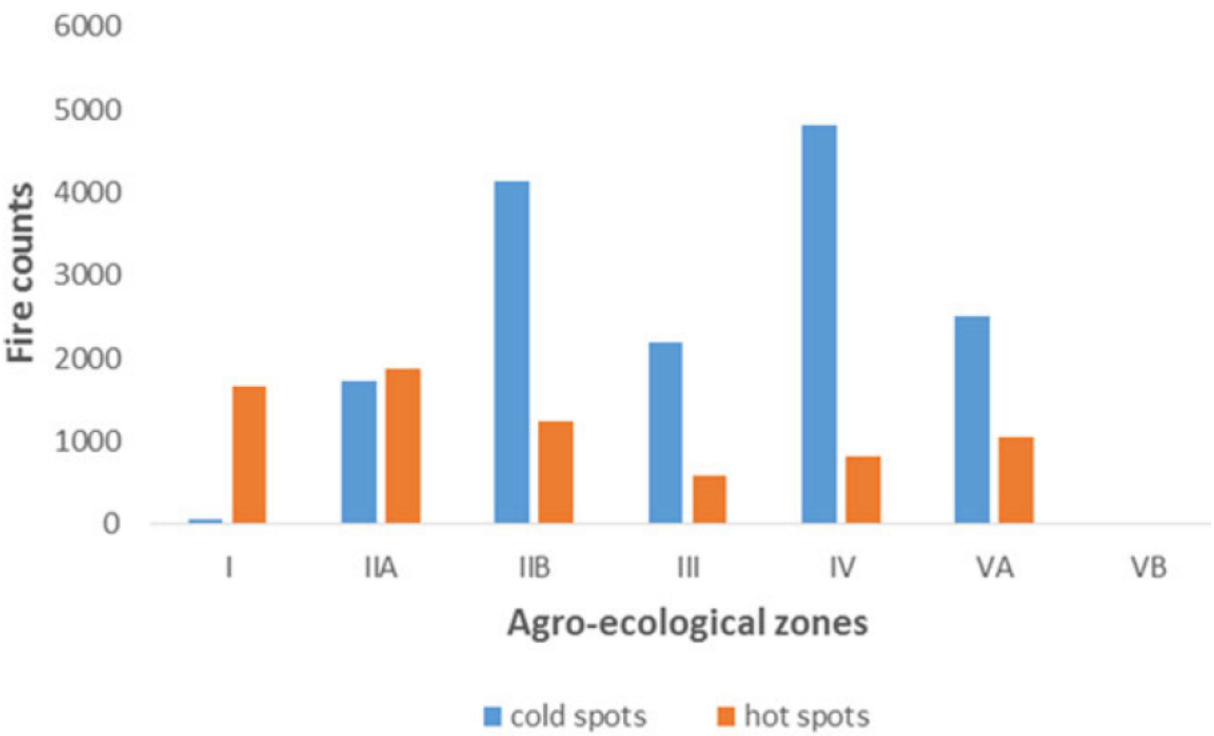


Figure 3.4. Fire intensity clusters in agroecological zones.

According to Giglio et al., 2006, the mean FRP in hot spot clusters is generally around 40 MW, indicating moderate to high fire intensity. This fire intensity class accounted for 20% of all the fire points detected by the MODIS satellite sensor in the study area in 2019. Table 3.3 shows that 44% of the detected fires had low fire intensity (cold spots), describing the majority of fires detected in Zimbabwe as cold fires. The fire intensity within cold spots ranges from 26 to 35 MW. Table 3.3 also shows that 36% of the active fires detected do not show significant clustering, indicating spatial randomness.

Table 3.3. Characteristics of fire intensity clusters.

Class	Number of Fire Counts	Percentage %	Mean FRP (MW)	Fire Intensity class [49]
Cold spot (99% CI)	10,309	29	26.33	Low
Cold spot (95% CI)	3503	10	28.93	Low
Cold spot (90% CI)	1657	5	34.49	Moderate
Not significant	12,580	36		
Hot spot (90% CI)	427	1	40.39	High
Hot spot (95% CI)	805	2	39.10	Moderate
Hot spot (99% CI)	6035	17	40.39	High

The statistical distribution of fire intensity (FRP) in the study area is shown in the box plots in Figure 3.5. The fire intensity as approximated by FRP is significantly ($p < 0.05$) higher within the hot spots than in the cold spots. This implies that although the greater proportion of fires under study was characterized by low fire intensity, the difference in the FRP between the fire intensity clusters is significant. It is important to note that most fires had fire intensity (FRP) of less than 50 MW although there exist outliers with FRP higher than 80 MW.

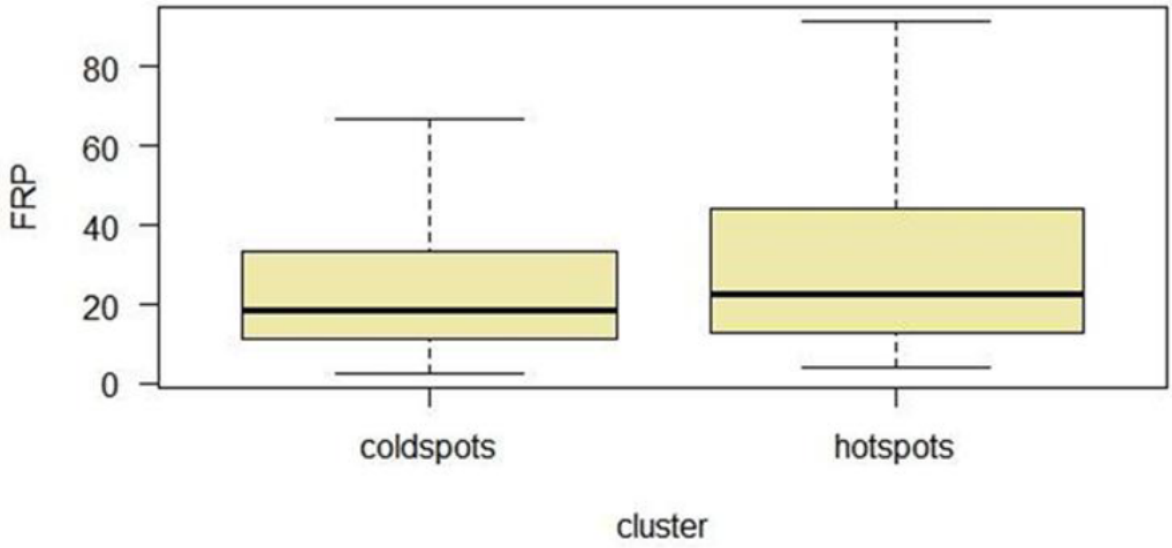


Figure 3.5. The distribution of FRP within fire intensity clusters.

3.3.3. Correlation of Fire Intensity with Topographic Variables

The results of the correlation analysis (Table 3.4) show a significant weak negative correlation between fire intensity (FRP) and slope, while a weak positive correlation exists between fire intensity and elevation. This is shown in Figure 3.3, where high-intensity fires occur in the eastern region (agroecological zone I) of Zimbabwe, which is characterized by high elevation and mountainous terrain. The correlation between fire intensity and aspect was not significant.

Table 3.4. Correlation between FRP and topographic variables.

	FRP vs. Slope	*FRP vs. Aspect*	*FRP vs. Elevation*
r	−0.0186	−0.0008	0.0718
p value	0.0005	0.8843	<0.0001
Significant? (alpha = 0.05)	Yes	No	Yes

Findings from the t-test show that high fire intensity (hot spots) are associated with higher elevation, as illustrated in Table 3.4.

3.3.4. Association between Fire Intensity and Vegetation Type

Analysis of the association between vegetation type and the burning intensity is shown in Table 3.5, which shows that shrubland is affected by fire more than the other vegetation types. The highest proportion (49%) of cold fires occurred within shrublands and grasslands, whilst most hot fires were detected in shrublands, forests and grasslands. For example, within the high fire intensity class (hot spots), 12% of the detected fires occurred in the shrubland, while almost half (49.3%) of the fires within the low fire intensity class (cold spots) were detected in this vegetation type. The sparse vegetation was least affected by burning. Grassland, forests, and croplands also experienced burning mostly of low intensity.

Table 3.5. Distribution of fire intensity in vegetation types.

	Hot Spot		**Cold Spots**	
	Number of Fire Counts	**Percentage (%)**	**Number of Fire Counts**	**Percentage (%)**
Forests	1540	7.8	2250	14.5
Grassland	2326	6.6	3275	21.2
Cropland	847	4	1791	11.6
Shrubland	2381	12	7627	49.3
Sparse vegetation	112	0.6	462	3

3.4. Discussion

This study demonstrates the heterogeneity of fire intensity as affected by various factors. It is the first time that clusters of fire intensity have been characterized using remotely sensed fire data in Zimbabwe. The highest fire activity was detected in northern districts, while low activity was recorded in the southern and southwestern districts. Eastern districts such as Nyanga, Mutasa, Chimanimani, and Chipinge districts also experienced a considerable number of fire incidences. These findings agree with findings from a study by Shekede et al., (2021), where high fire activity was observed in similar areas. The positive relationship between slope and fire occurrence has been observed in rugged terrains, such as those found in the eastern districts.

High fire incidences were detected in agroecological regions IIa, IIb, and IV (Figure 3), which are characterized by moderate rainfall and increasing temperatures (Manatsa *et al.*, 2020).

The FRP derived from satellites is an indicator of the strength of fire which is directly related to the amount of biomass consumed by the fire (Kganyago and Shikwambana, 2019). The majority (44%) of the fires detected in 2019 were classified as cold spots meaning that they were of low to moderate intensity with mean FRP ranging from 26 to 34 MW. This observation corroborates with findings from Cizungu et al., 2021, who observed low fire intensity fires within dense forest and agricultural areas. A study by Agata (2014) in Poland also observed mean FRP of 36.3 and 35.1 in grasslands and forests, respectively. Zimbabwe is largely characterized by savannah grasslands, so the findings from this study are not surprising. A very small proportion (20%) of the clusters of high-intensity fires were mainly concentrated in the eastern regions of Zimbabwe. However, even though high-intensity fires are few, they possess great destructive power (Cizungu *et al.*, 2021), so appropriate precautions should be taken in such areas.

The study also assessed the association between fire intensity clusters and the various vegetation types and agroecological zones within the study area. Low fire intensity was detected in sparse vegetation and cropland, which is agrees with findings by Giglio et al., 2006, who observed low FRP in croplands. On the other hand, Agata (2014) observed highly intense fires in arable lands and grasslands. Zimbabwe is largely characterized by savannah grasslands hence general findings of low fire intensity (Scholes and Archer, 1997; Archibald, Scholes, *et al.*, 2010a; Nyamadzawo *et al.*, 2013). The least effect of burning on the sparse vegetation could have resulted from low fuel loads since the vegetation is sparsely distributed.

High fire activity was detected in agroecological regions IIa, IIb, and IV, which are characterized by moderate rainfall and increasing temperatures (Global Forest Watch, 2023). High fire occurrence and intensity were observed in several districts in Manicaland province. This observation agrees with the findings mentioned in (*Zimbabwe Climate, Weather By Month,* *Average Temperature - Weather Spark*, no date), where from 2001 to 2021, Manicaland had the highest rate of tree cover loss due to fires. The study shows that agroecological zones I and IIA and parts of agroecological zones III, IV, and VA are associated with high-intensity fires. Although agroecological zone I is associated with lower temperatures than other regions, the area is characterized by higher elevation and rugged terrain, which can contribute to high fire intensity (Zhang and Kondragunta, 2008; Cizungu *et al.*, 2021; Shekede, Gwitira and Mamvura, 2021). High fire intensity clusters detected in parts of agroecological zone I could also be associated with plantations of fire-prone eucalyptus-related vegetation and heavy fuel load (Cizungu *et al.*, 2021), which burn intensely and result in hot fires. High-intensity fires in the other regions could be attributed to warmer temperatures and the presence of flammable biomass (Manatsa *et al.*, 2020).

The Gi* statistic was utilized to characterize both the type of clustering and its location and uses probability to determine fire intensity clusters (Peeters *et al.*, 2015) which is imperative for the reliable and informed delineation of fire management zones. Although MODIS fire data does not show the source of ignition, this study has shown its utility in detecting fire intensity clusters in the study area. The dense canopy of forests also affects the detection of fire intensity by satellites. The study, however, did not account for the effect of spatial dependence. Future studies should consider applying tests such as Bonferroni corrections or False Discovery Rate (FDR) to account for the problem of multiple testing and effect of spatial dependence on the data. This is important for the Getis-Ord Gi* local indicator of spatial autocorrelation.

Future studies should also assess burn severity which is positively correlated with fire intensity (Keeley, 2009). This is critical because it gives information on the effects of fire intensity levels on vegetation. In this research, fire intensity was analysed at a larger scale; hence future studies should additionally look at a local scale to gain more finely-tuned information, which will improve fire management. Future studies should also utilize higher spatial resolution satellite data considering that the level of detection of active fires is highly determined by sensor differences such as resolution, swath width, and along scan aggregation (Liu *et al.*, 2012, 2018; Ruecker, Leimbach and Tiemann, 2021). The temporal distribution of fire intensity clustering as a function of climatic drivers should be prioritized in future studies. More variables should be considered to explain the spatial distribution of fire intensity. Since global climate warming may result in the increasing impact of fires on ecosystems (Brotons *et al.*, 2013), more fire studies have become relevant.

3.5 Conclusions

The research findings have shown the utility of a combination of MODIS fire data and spatial autocorrelation methods in mapping spatial patterns of fire intensity in Zimbabwe. The results suggest that most fires detected by the MODIS satellite in the study area were of low intensity (cold spots), while high-intensity fires (hot spots) were associated with mountainous areas of the study area. The study has, therefore, produced critical information which can be used in the management of fires in Zimbabwe. This information will assist fire management agencies to better allocate the limited resources to high-fire-intensity areas and hence plan appropriate fire management activities. Measures should be taken in areas where high fire intensity was observed, such as strict monitoring of fires. Information on fire intensity clusters will assist authorities responsible for fire management to intervene before (for prevention), during (for detection of fire intensity levels), and after the occurrence of fire (for mapping fire intensity). For example, real-time fire monitoring of fire intensity can be implemented by the fire managers to minimize damage by fire on various vegetation types. Areas with similar vegetation characteristics as in areas where high-intensity fires were detected will be given high priority. In addition, areas with high fire intensity clusters will receive the appropriate fire suppression during the fire. Well-equipped firefighting teams can also be set up when a fire occurs in fire-intensity hotspot areas. The research findings, therefore, show extended knowledge about the association between fire intensity and agroclimatic zones, topographic factors, and vegetation types. The global accessibility of MODIS active fire data has enabled the analysis of fire intensity at a broad spatial scale which is beneficial for data-poor regions like Zimbabwe.

3.6 Summary and link to next chapter

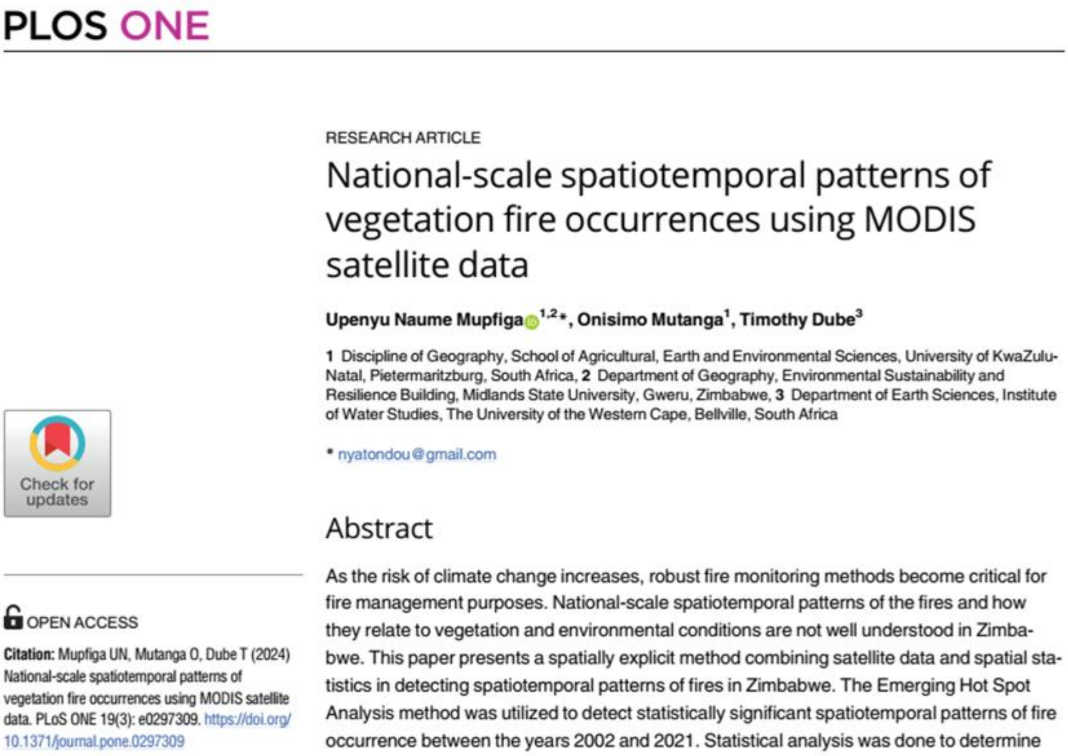
In this chapter spatial statistics was used to detect the spatial clusters of vegetation fire intensity in Zimbabwe. The historic MODIS satellite-derived fire data was used in the analysis. Additionally, the environmental and vegetation characteristics associated with low and high-intensity fires were also detected. The mapping of areas of low and high fire intensity is critical for fire management in Zimbabwe. For instance, stricter fire management strategies would be implemented in regions where high-intensity fires were detected. This novel information unveiled in this chapter determines the appropriate allocation of fire management resources.

The objective addressed in this chapter covers one important fire descriptor, the fire intensity (hotness or coldness), and gives room to the analysis of the spatiotemporal distribution of fire occurrence which is covered in the next chapter.

CHAPTER 4: NATIONAL-SCALE SPATIOTEMPORAL PATTERNS OF VEGETATION FIRE OCCURRENCES USING MODIS SATELLITE DATA

This chapter is based on:

Mupfiga, U.N., Mutanga, O., Dube, T., 2024. National-scale spatiotemporal patterns of vegetation fire occurrences using MODIS satellite data. PLOS ONE 19, e0297309. https://doi.org/10.1371/journal.pone.0297309



PLOS ONE

RESEARCH ARTICLE

National-scale spatiotemporal patterns of vegetation fire occurrences using MODIS satellite data

Upenyu Naume Mupfiga[1,2]*, Onisimo Mutanga[1], Timothy Dube[3]

1 Discipline of Geography, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, 2 Department of Geography, Environmental Sustainability and Resilience Building, Midlands State University, Gweru, Zimbabwe, 3 Department of Earth Sciences, Institute of Water Studies, The University of the Western Cape, Bellville, South Africa

* nyatondou@gmail.com

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Abstract

As the risk of climate change increases, robust fire monitoring methods become critical for fire management purposes. National-scale spatiotemporal patterns of the fires and how they relate to vegetation and environmental conditions are not well understood in Zimbabwe. This paper presents a spatially explicit method combining satellite data and spatial statistics in detecting spatiotemporal patterns of fires in Zimbabwe. The Emerging Hot Spot Analysis method was utilized to detect statistically significant spatiotemporal patterns of fire occurrence between the years 2002 and 2021. Statistical analysis was done to determine

Abstract

As the risk of climate change increases, robust fire monitoring methods become critical for fire management purposes. National-scale spatiotemporal patterns of the fires and how they relate to vegetation and environmental conditions are not well understood in Zimbabwe. This paper presents a spatially explicit method combining satellite data and spatial statistics in detecting spatiotemporal patterns of fires in Zimbabwe. The Emerging Hot Spot Analysis method was utilized to detect statistically significant spatiotemporal patterns of fire occurrence between the years 2002 and 2021. Statistical analysis was done to determine the association between the spatiotemporal patterns and some environmental variables such as topography, land cover, land

use, ecoregions and precipitation. The highest number of fires occurred in September, coinciding with Zimbabwe's observed fire season. The number of fires significantly varied among seasons, with the hot and dry season (August to October) recording the highest fire counts. Additionally, although June, July and November are not part of the official fire season in Zimbabwe, the fire counts recorded for these months were relatively high. This new information has therefore shown the need for revision of the fire season in Zimbabwe. The northern regions were characterized by persistent, oscillating, diminishing and historical spatiotemporal fire hotspots. Agroecological regions IIa and IIb and the Southern Miombo bushveld ecoregion were the most fire-prone areas. The research findings also revealed new critical information about the spatiotemporal fire patterns in various terrestrial ecoregions, land cover, land use, precipitation and topography and highlighted potential areas for effective fire management strategies.

Key words: climate change; emerging hot spot analysis; fire management; hot spot; fire occurrence

4.1 Introduction

In semi-arid savannas of Southern Africa, veld fires have maintained the balance between grassy and woody vegetation (Archibald, Scholes, *et al.*, 2010a; Pricope *et al.*, 2015). While distinct wet and dry seasons in sub-Saharan Africa influence fire activity, the occurrence of fires is affected by several factors including anthropogenic activities and climate variability (Mbanze *et al.*, 2013). Although fire is vital in the existence of savanna ecosystems, the effect of anthropogenic activities has altered the natural fire regimes, threatening biodiversity (Reddy *et al.*, 2016, 2019). While the release of greenhouse gases (GHG) by forest fires significantly contributes to climate change, the higher temperatures associated with climate change influence the drying of forests, increasing their vulnerability to fires (Brivio *et al.*, 2013). Air pollution associated with persistent fires poses a health risk to both humans and ecosystems (Chen *et al.*, 2022; Cobelo *et al.*, 2023).

Due to the recurrent nature of fires in the savanna ecosystems, monitoring their spatiotemporal patterns is inevitable for effective fire management (Argibay, Sparacino and Espindola, 2020). Fire monitoring systems should produce timely and accurate information about the spatiotemporal behaviour of fires. Sustainable management of fire activity requires access to information not only on the location of historical fires but also information on spatiotemporal trends detected early enough to influence future fire trajectory. Remotely sensed data has been useful in fire monitoring (Marsha and Larkin, 2022). The Moderate Resolution Spectral Radiometer (MODIS) active fire product, for example, has greatly enhanced the analysis of fire occurrence in the landscape by providing spatially detailed, timely and cost-effective information on fire dynamics of global and local importance (Adab *et al.*, 2018). The patterns of recorded fire data can be difficult to visually evaluate at different spatiotemporal scales. In addition, a critical bottleneck exists in an attempt to unveil the patterns and trends in the available large and complex fire datasets obtained from remote sensing platforms. There is, therefore, a need for methods to explore and interpret spatiotemporal patterns of fire data for effective fire management and policy decision-making. Spatiotemporal pattern analysis has the potential to rapidly and accurately identify areas where specific fire management interventions should be prioritized (Harris *et al.*, 2017). Spatial statistics greatly assist in the quick identification of spatiotemporal trends of fire activity without the need for pre-existing information on the underlying causal factors (Harris *et al.*, 2017).

Emerging hotspot analysis is an approach used for statistical spatiotemporal analysis of phenomena. Recently, the approach has been used to detect spatiotemporal patterns of COVID-19 cases (Tabarej and Minz, 2022), landslides (Wu, 2022), invasive species (Pasha and Reddy, 2022) and forest loss (Harris *et al.*, 2017; Tran *et al.*, 2020; Singh and Yan, 2021; Boubekraoui *et al.*, 2023). A few studies were done in Australia (Visner, Shirowzhan and Pettit, 2021) and southeast Asia (Reddy *et al.*, 2019, 2020), utilizing the emerging hotspot analysis method to understand the spatiotemporal patterns of fires. In Zimbabwe, limited studies have analysed the spatial distribution of fire occurrence (Shekede, Gwitira and Mamvura, 2021) and its intensity (Mupfiga, Mutanga and Dube, 2024) at a national scale. Shekede et al., (2021) assessed the spatial clustering of remotely sensed fire points while Mupfiga et al., 2022 utilized the Getis-Ord (Gi*), a spatial autocorrelation method, to detect the spatial hotspots of fire intensity in Zimbabwe. With the few studies done, mainly focusing on the spatial nature of fire occurrence, little is still known about the spatiotemporal patterns of the fires occurring in the study area. Fire management in the study area observes a distinct fire season from 31 July to 31 October, as gazetted in the national statutory instrument of Zimbabwe (Government of Zimbabwe, 2007). It, however, remains unclear whether there have been changes in the fire season over the years. The occurrence of fires largely depends on the physical characteristics of the fuel load and the vegetation type (Strydom and Savage, 2016). The characteristics of vegetation determine the fuel load and its flammability. Succulent vegetation, for example, is less likely to burn due to moisture content and less leaf litter. Topography and land use/land cover are also important factors contributing to fire occurrence (Graham, Dube and Mpakairi, 2023).

This study utilized a combination of remotely sensed data and spatial statistics, enabling the solving of complex location-based fire monitoring problems (Younas *et al.*, 2022). Specifically, the objective of this study was to detect both the spatial and temporal patterns of forest fire occurrence in Zimbabwe. The study utilized both the Getis-Ord (Gi*) (Getis and Ord, 1992) statistic, which determines spatial clustering, and the Mann-Kendall trend test which detects the temporal trends across the timeseries (Harris *et al.*, 2017). This more robust approach improves on the traditional hotspot analysis methods which usually analyse the spatial dimension (space-based hotspot analysis) without incorporating the temporal dimension into the hotspot analysis of fire occurrence.

4.2 Materials and Methods

4.2.1 Study area

The study was done in Zimbabwe which is located between 15˚3000 to 22˚3000 S and 25˚3000 to 33˚3000 E in Southern Africa as indicated in Fig 4.1. The mean sea level of the study area ranges from below 300 m for Southern regions to above 2500 m for the Eastern parts. Zimbabwe is generally characterized by three main seasons, hot and wet (November to April), cool and dry (May to August) and hot and dry (August to November). The mean annual rainfall in Zimbabwe varies from below 400 mm to above 1500 mm (Shekede, Mupandira and Gwitira, 2021). Zimbabwe is classified into seven agroecological zones which are characterized by decreasing mean annual rainfall from agroecological zone 1 (about 1250mm) to zone Vb (below 400mm). Temperatures in the study area increase from agroecological zones I to Vb while elevation decreases. About 95% of the study area's forest cover is covered by savannah woodlands where there is a mixture of trees and grasses which offer fuel for fires. Fire is a major forest ecosystem disturbing factor in Zimbabwe and contributes to deforestation and land degradation (Global Forest Watch, 2023).

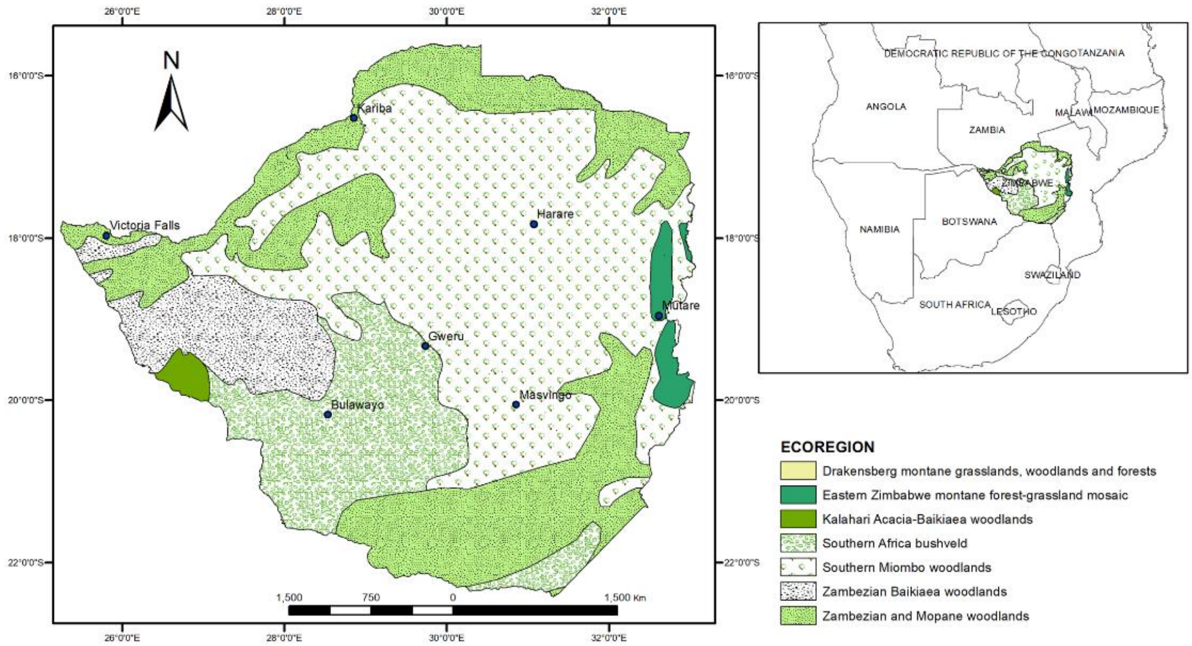


Fig 4.1. Location of the study area and ecoregions (*Adapted from Olson et al., 2001*)

4.2.2 Datasets used for fire occurrence assessment

The MODIS daily active fire data product (MCD14ML) was utilized due to its free accessibility, large area coverage and effectiveness in fire monitoring (Graham, Dube and Mpakairi, 2023). The MODIS Terra and Aqua satellite, with a revisit period of 1 to 2 days, detect active fires at 1 km spatial resolution at nadir but can also detect fires smaller than 1 km2. The detection of a fire is dependent on the fire temperature, the angle of the satellite and the prevailing weather conditions during the detection time (Giglio *et al.*, 2003). Despite the course spatial resolution, fire data from the MODIS sensor was preferred in this study because of the channels on the MODIS sensor that are specifically designed for fire monitoring (Ying *et al.*, 2019). In addition, the MODIS sensor has long-term fire records, high temporal resolution as well as high precision of the fire points (Wei *et al.*, 2019). The MODIS collection 6 (MODIS C6.1) fire product, used in this study, has been improved to give low commission and omission errors (Wei *et al.*, 2019).

The fire events (between 2002 and 2021) utilized in the study were downloaded for free from Fire Information Management System (FIRMS) website (https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/active-fire-data) (accessed on 4 March 2023) as a shapefile (*shp). Attributes associated with the dataset include location (latitude and longitude), date and time of data acquisition, fire radiative power and the confidence level. The acquisition of MODIS data is clearly described in Giglio and Justice (2003). Additionally, based on the fire data attributes, only presumed vegetation fire points were utilized in the data analysis. The variables shown in Table 4.1 were also utilized in the analysis based on their association with fire occurrence (Guo *et al.*, 2017; Piralilou *et al.*, 2022).

Table 4.1: Datasets used in the study

Data	Source	Resolution
Modis (MCD14DL) active fire data	https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/active-fire-data (accessed on 4 March 2023))	1 km
Land cover map	https://viewer.esa-worldcover.org/worldcover/ (accessed on 27 March 2022)	10m
Land use map	Environmental Management Agency	N/A
Agroecological zones	Zimbabwe National Geospatial and Space Agency (ZINGSA) (Manatsa et al., 2020)	N/A
Topography	https://earthexplorer.usgs.gov/ (accessed on 15 March 2022)	30m
Precipitation	https://climateknowledgeportal.worldbank.org (accessed on 24 March 2023)	N/A
Ecoregions/ biomes	https://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world (accessed on 15 March 2023)	N/A

4.2.3 Satellite data pre-processing

All the data (Table 4.1) used in this study was projected to the UTM coordinate system in ArcMap 10.5 using the Projection and Transformation tool. To minimize false fire alarms and maximize reliability, only fire points with a confidence level greater than 30%, were utilized in the analysis (Giglio, Schroeder and Justice, 2018; Cizungu *et al.*, 2021).

4.2.4 Data analysis: Annual, monthly and seasonal fire trends.

The fire counts were extracted from the fire point map and the total number of fires detected for each year was calculated. To test whether fire data was normally distributed, the Shapiro-Wilk test of normality (Royston, 1982) was performed using the "shapiro.test" function in the R programming software. The normality test results indicated that the fire data utilized in this study did not follow a normal distribution hence non-parametric statistical methods were used. To test whether total annual fire counts were statistically different over the 20-year study period, the Kruskal-Wallis rank sum test, a non-parametric test, was applied to the data, using the "kruskal.test" function in R studio. To determine the correlation between the annual fires and annual rainfall acquired from https:// climateknowledgeportal.worldbank.org (accessed on 24 March 2023), the Spearman's rank correlation method was utilized using the "cor.test()" function in the R studio programming package.

The monthly average fire counts detected in the study area from 2002 to 2021 were calculated. The Kruskal-Wallis rank sum test was used to test whether the monthly fire counts were significantly different over the study period. The "kruskal.test" function in R studio was used to calculate the number of fire counts detected during the three seasons (wet and dry, cool and dry, hot and dry) and to analyse the seasonal variation of fire occurrence in the study area, the Kruskal Wallis rank sum test was also applied to the fire data.

4.2.5 Data analysis: Emerging hot spot analysis

The emerging hotspot analysis was used to identify spatial and temporal trends and patterns of fire occurrence in the study area. The spatial statistic method combines the utilization of the Getis-Ord (Gi*) (Getis and Ord, 1992) statistic to determine the location and level of clustering and the Mann-Kendall trend test to evaluate the temporal trends across the time series (Harris *et al.*, 2017). The Mann-Kendall test, a rank correlation method, analyses whether there is a decreasing or increasing trend in a given time series data.

One important component of the emerging hotspot analysis method is the space-time cube, which is a descriptive statistic contained in bins, where the geographic location (x and y) is represented by the base of every bin while the height (z) represents time (Singh and Yan, 2021; Younas *et al.*, 2022). Before running the emerging hotspot analysis, the Space Time Pattern Mining Tool in a GIS environment was used to create the space-time cube, using the MODIS fire data from 2002 to 2021. This tool utilizes the non-parametric Mann-Kendall (Mann, 1945; Kendall and Gibbons, 1990) trend test to estimate the temporal trends for each fire location. The trend analysis is based on a comparison of the assumed result of having no significant trend over time against the observed result. The trend for each bin is shown by a z-score where a positive and negative z-score indicates an increasing or decreasing trend respectively.

The space-time cube was then used as an input into the emergence hotspot analysis to determine the spatiotemporal pattern of the fires from 2002 to 2021. The Getis-Ord Gi* (Getis and Ord, 1992) statistic analyses spatial clustering and determines variability within clusters, assigning z scores for all bins. The neighbourhood distance and neighbourhood time step parameters define how many surrounding bins in space and time are considered during the calculation of the statistic for a specific bin. For this study, the neighbourhood distance was set at 1km and the neighbourhood time step interval was set at one year.

For every feature in the input feature file, the emerging hotspot analysis makes a new output feature class with a z-score, p-value and the significance of the trend is shown by the p-value. A statistically significant hotspot, for example, with a z-score greater than 1.96 and p-value less than 0.05 has a higher clustering intensity. The emerging hotspot analysis results in seventeen categories (Harris *et al.*, 2017). In this study, an emerging hotspot refers to locations where the observed spatiotemporal patterns are not due to random, but represent areas where underlying spatiotemporal processes are at play (Getis and Ord 1992). The emerging hotspot analysis method, using the Mann-Kendall statistic, tests whether there exists a significant temporal trend within the 20-year fire data.

4.2.6 Data analysis: Association between spatiotemporal patterns of fire and agroecological regions.

The fire spatiotemporal patterns map was overlaid with the agroecological regions map to analyse their association. The agroecological zone map utilized in the analysis was developed based on the spatial distribution of temperature and rainfall conditions in the study area (Manatsa *et al.*, 2020). The association between the spatiotemporal patterns of fire and the agroecological regions was statistically tested using the chi-square test in R programming.

4.2.7 Data analysis: Association between spatiotemporal patterns of fire and terrestrial ecoregions.

The occurrence of fires largely depends on the physical characteristics of the fuel load and the vegetation type (Strydom and Savage, 2016). Terrestrial ecoregions data from the World Wildlife Fund (WWF) (Olson *et al.*, 2001) was therefore included in the analysis to determine the association between the fire occurrence pattern and vegetation types. The ecoregions data showing distinct biotas was downloaded from http://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world (accessed 15 March 2023). The association between the terrestrial ecoregions and the spatiotemporal fire patterns was analysed using overlay analysis in a GIS environment and a chi-square test was used to statistically test the significance of the association.

4.2.8 Data analysis: Association between spatiotemporal patterns of fire and land use and land cover types.

Land cover types derived from the land cover map acquired from https://viewer.esaworldcover.org/worldcover/ (accessed on 27 March 2022) shown in Table 4.1 were used in this study to analyse their association between the spatiotemporal fire patterns. The land use and the land cover maps were each overlaid with the spatiotemporal fire patterns in a GIS. The chi-square test was used to analyse the association between the spatiotemporal patterns of fire and the landcover types in the study area.

4.2.9 Data analysis: Association between spatiotemporal patterns of fire and topography.

The association between the spatiotemporal patterns of fire and topographic variables was analysed. Topographic variables, slope and aspect were derived from the digital elevation model downloaded from https://earthexplorer.usgs.gov/ (accessed on 15 March 2022). Overlay analysis in a GIS was done to relate topography and the spatiotemporal fire patterns in Zimbabwe. The statistical significance of the association was analysed using the chi-square test. The methods used in the study are outlined in Fig 4.2.

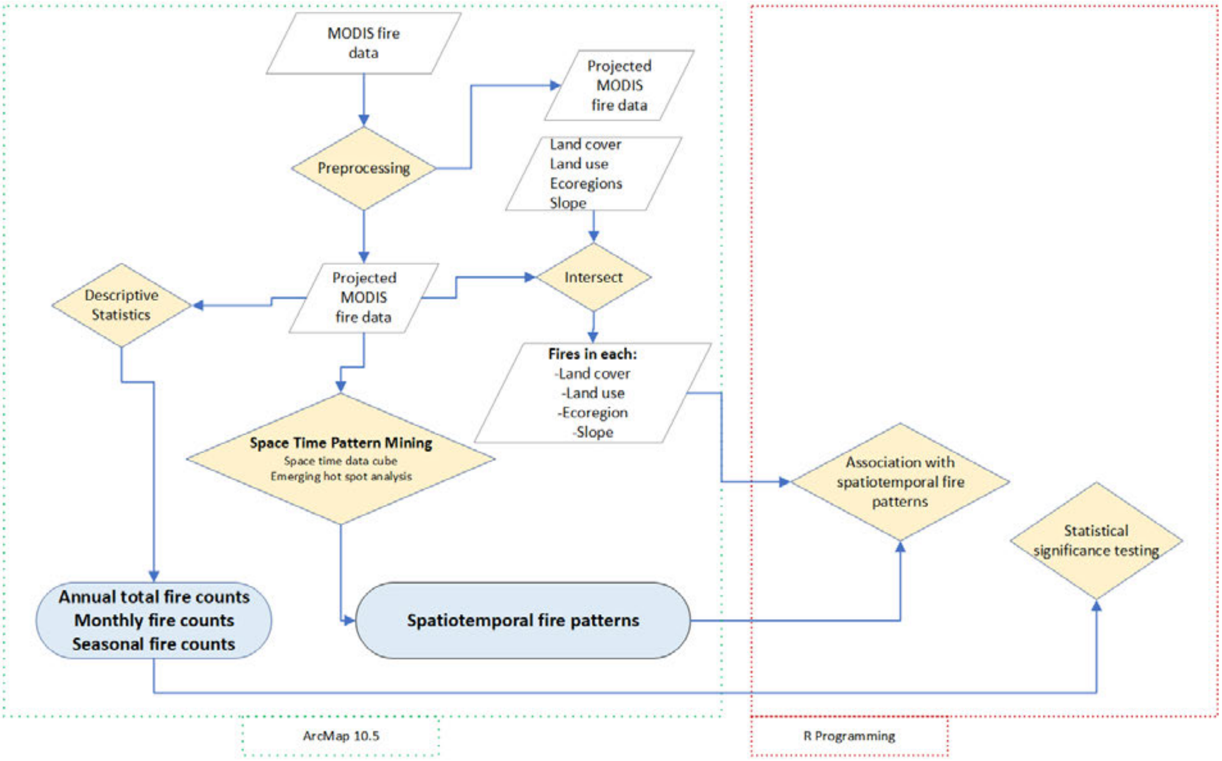


Fig 4.2. Outline of the methods for data processing and analysis used in the study

4.3. Results

4.3.1 Annual, monthly and seasonal fire trends

The results from the analysis of the MODIS fire data from the study area have shown (Fig 4.3a) that fires were detected every year during the study period. Each box plot in Fig 4.3a shows the summary of all the fires that occurred in the respective year. The highest total number of fires was detected in 2008, while the lowest total fire incidents occurred in 2020. There was an upward trend in the total annual fire counts from 2002 to 2010, while from 2011 to 2021 there was a general downward trend as clearly shown in Fig 4.3a and 4.3b. The Mann-Kendall trend test revealed a downward trend (tau = -0.2) which was, however, not statistically significant ($p>0.05$). The results of the Spearman's rank correlation test revealed that in the first 10 years of the study period, there was a weak non-significant correlation (rho = 0.224 and $p>0.05$) between total annual fire occurrence and rainfall. On the other hand, in the last 10 years of the study period, the correlation between total annual fire occurrence and annual rainfall was negative (rho = 0.44) and not statistically significant ($p>0.05$).

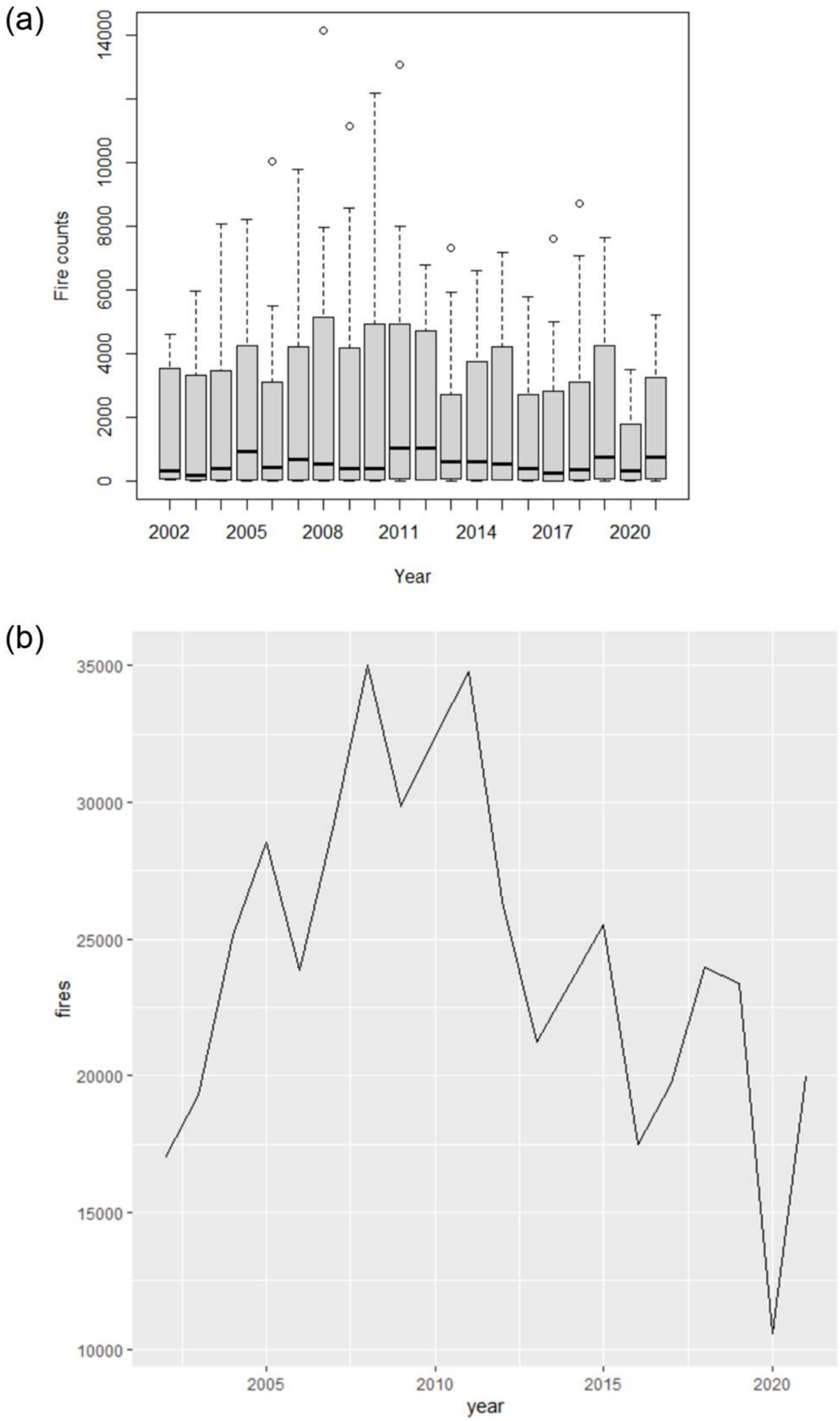


Fig 4.3. a. Annual distribution of the fire counts from 2002-2021 b. Total annual fire trend from 2002-2021

Table 4.2: Kruskal-Wallis rank test results

	Kruskal-Wallis chi^2 statistic	p-value	Significance
Mean annual fire counts	2.698	1	*
Mean monthly fire counts	219.84	< 2.2e-16	**
Mean seasonal fire counts	46.974	6.305e-11	**

NB asterisks * depicts not significant ** depicts significant fires

Fig 4.4 clearly shows the average monthly fire counts over the 20-year study period based on the detection of fires by the MODIS sensor. Each box plot represents a summary of all the fires that occurred in each month over the 20 years. It is evident from Fig 4.4 that over the study period fire activity was experienced in every month of the year. Fire activity significantly increases from June, with a peak in September, then declines from October as shown in Fig 4.4. The higher monthly fire counts coincide with the legally defined fire season which spans from 31 July to 31 October (Government of Zimbabwe, 2007) in Zimbabwe. Although June, July and November are not included in the official fire season, the fire activity during these months is relatively high.

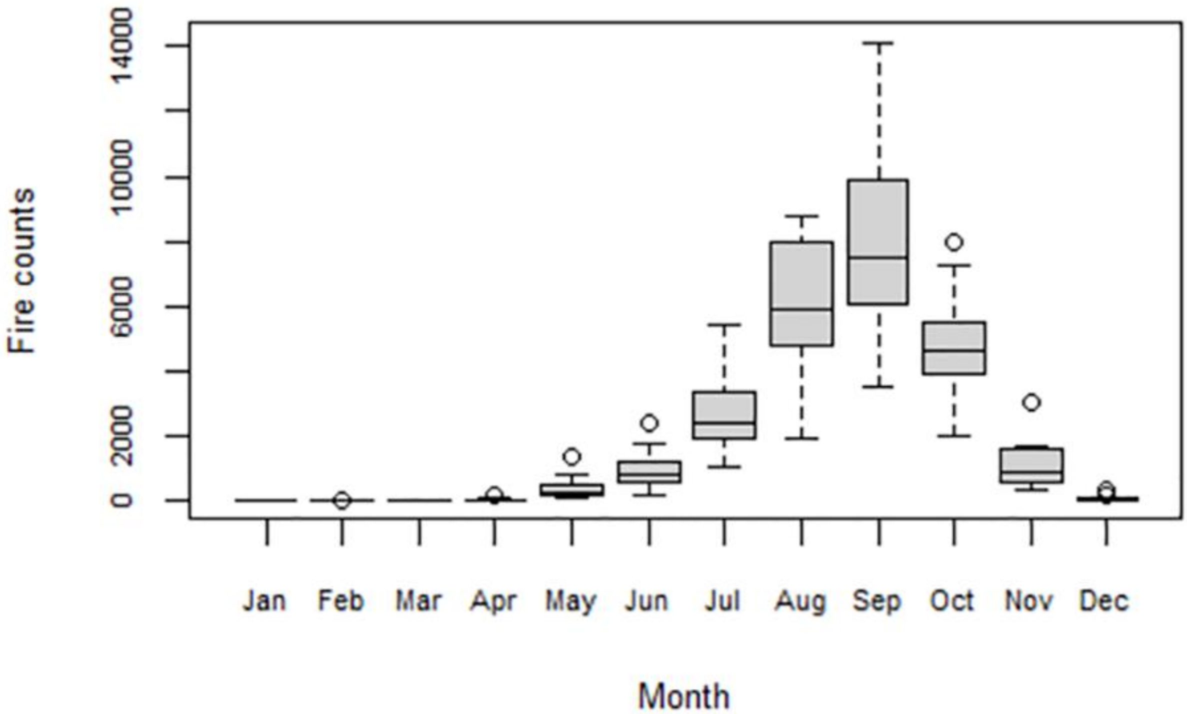


Fig 4.4. Monthly distribution of fire counts from 2002–2021

The temporal distribution of fire counts based on climatic seasons in Zimbabwe during the study period is clearly illustrated in Fig 4.5. The hot and dry season is characterized by significantly higher fire activity than the other seasons. During the hot and wet season, the fire counts detected in the study area were generally below 2000. The least number of fires were detected during the cool and dry season. The Kruskal Wallis rank test results showed a significant difference (Table 4.2) in the number of fire counts among seasons.

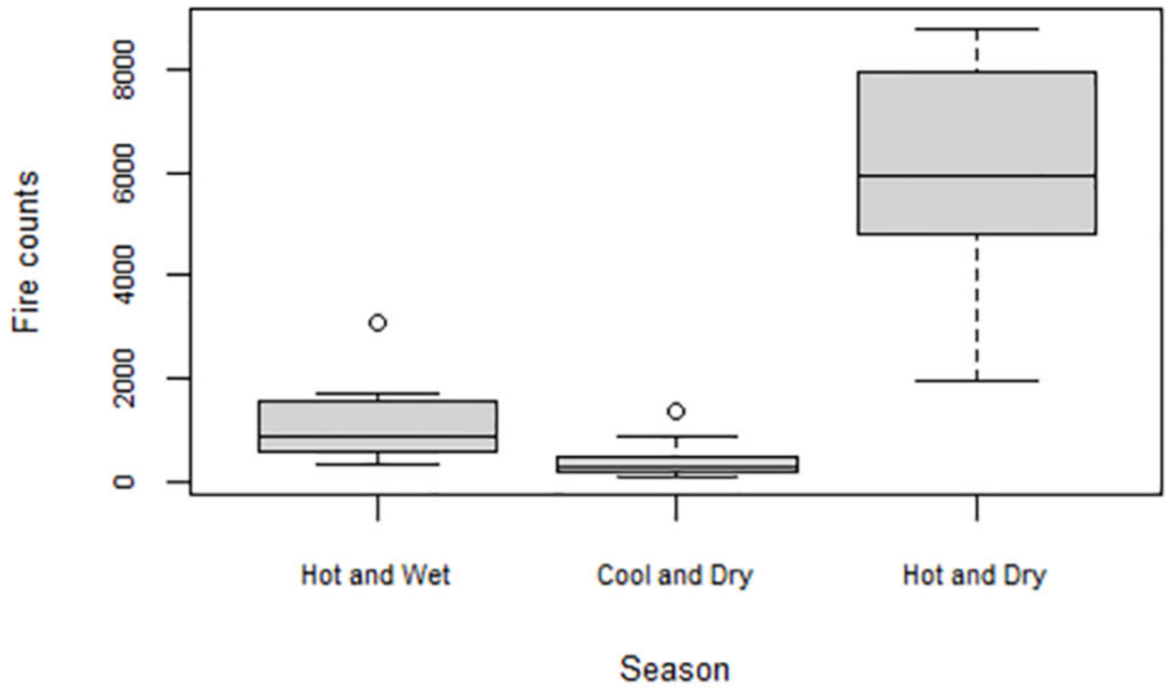


Fig 4.5. Number of fires occurring during the hot and wet (November to April), cool and dry (May to July) and hot and dry (August to October) seasons from 2002 to 2021

4.3.2 Spatiotemporal fire pattern analysis

4.3.2.1 Emerging hotspot analysis.

The analysis of the spatiotemporal pattern of fire incidents which occurred in Zimbabwe during the study period is illustrated in Figs 4.6 and 4.7 with over 60% of the fires showing an oscillating cold spots pattern. Only 10% of the fires did not show any spatiotemporal pattern. The oscillating fire cold spots are dominant in the central and north-western parts of the study area. The fire hot spots detected in the northern districts such as Bindura, Chinhoyi, Kariba, Karoi and Muzarabani, exhibited oscillating, sporadic and persistent patterns.

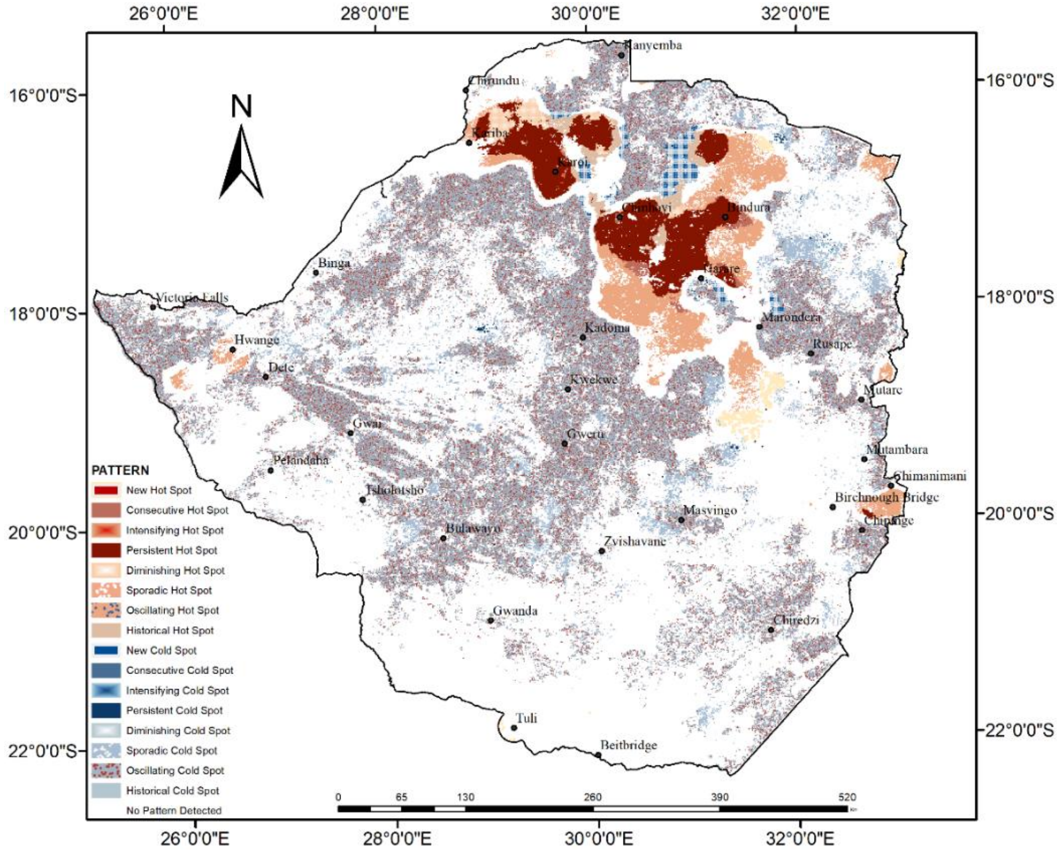


Fig 4.6: The spatiotemporal pattern of fire occurrence from 2002 to 2021

Interestingly some of the spatiotemporal fire hot spots detected in the northern parts of the study area exhibited historical and diminishing spatiotemporal patterns. A few fire incidents were classified into sporadic fire hot spot pattern in the eastern and western parts of the study area. The proportions of the various spatiotemporal fire patterns detected in the study area are illustrated in Fig 4.7. Generally, most of the fires detected in Zimbabwe during the study period are characterized by an oscillating pattern.

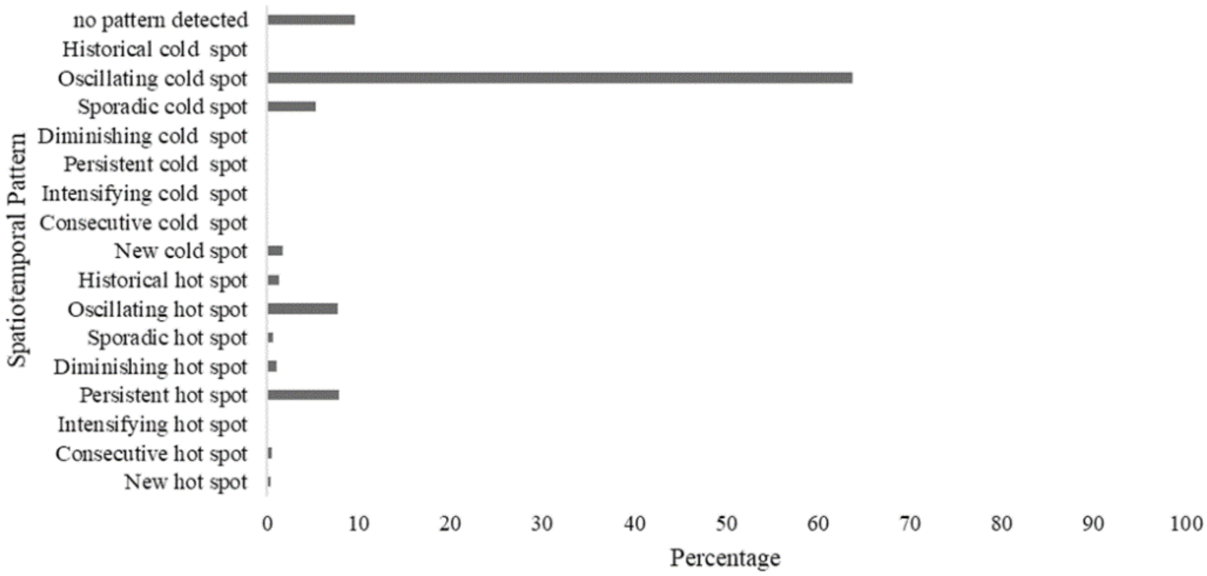


Fig 4.7: The proportions of the spatiotemporal fire patterns

To give a clear visualization of the distribution of only the spatiotemporal hotspots detected in the study area Fig 4.8 has been presented. The map shows that besides the distribution of the different patterns of hotspots in the northern parts of the study area, there were patches of oscillating hotspots in the eastern and western parts of the study area specifically in Chipinge and Hwange areas.

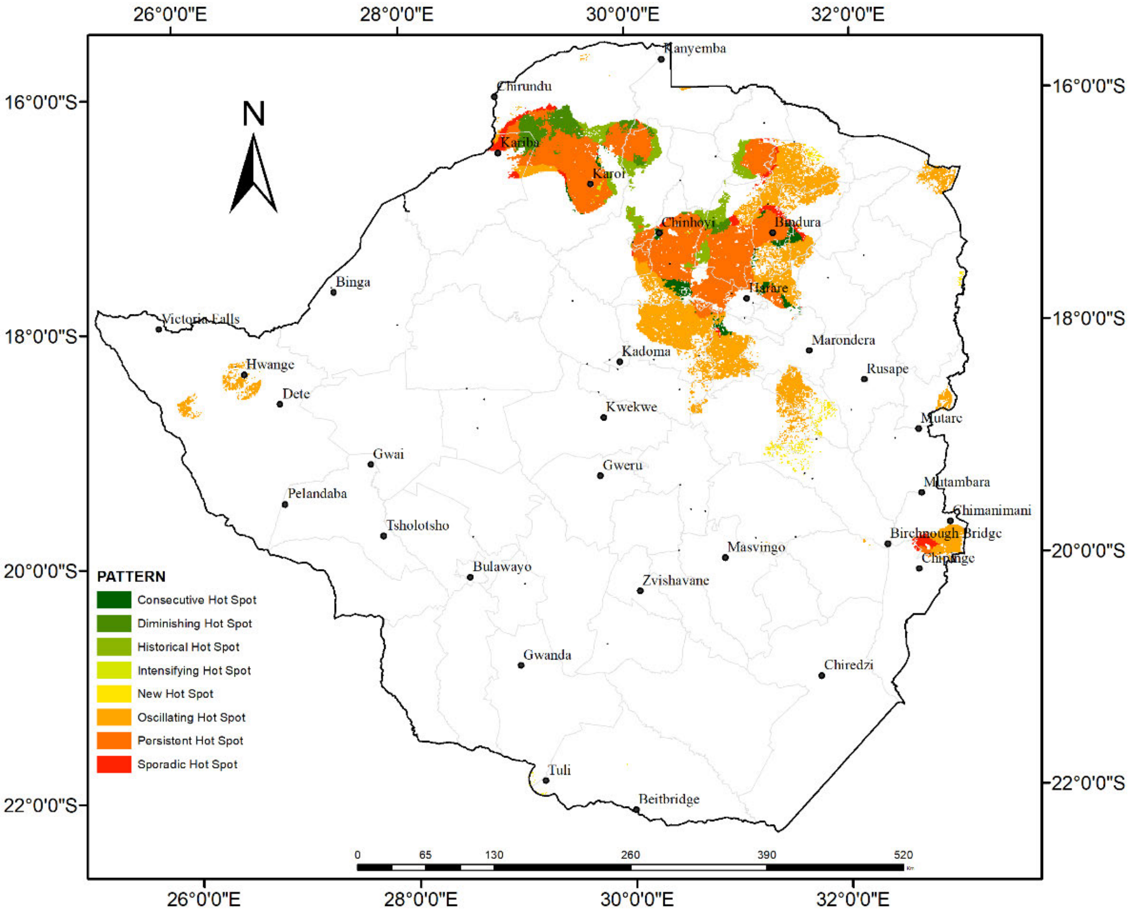
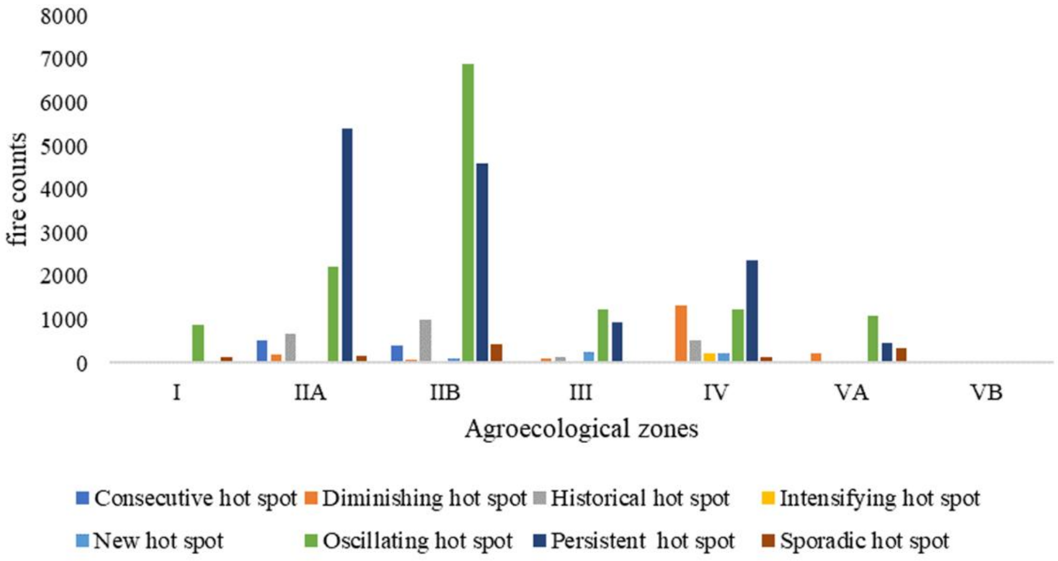


Fig 4.8: The spatiotemporal patterns of hot spots only from 2002 to 2019

4.3.2.2 Association between spatiotemporal fire hotspots with agroecological zones.

The oscillating and the persistent hotspots are the most prevalent patterns of temporal fire clusters in the study area as shown in Fig 4.9a. Regions IIa and IIb are the most fire-prone areas in the study area. The oscillating spatiotemporal pattern was exhibited by the fire hotspots observed in the agroecological zone I which lies in the eastern mountainous part of Zimbabwe. Fig 4.9b shows that the Southern Miombo bushveld is the most fire-prone ecoregion in Zimbabwe as shown by the prevalence of persistent and oscillating hotspots. Historical, diminishing and sporadic spatiotemporal patterns of fires were also observed in the Southern Miombo woodlands. There was also fire activity observed in the Zambezian Mopane woodlands and the Eastern Montane Forest ecoregions over the study area as evidenced by the detection of oscillating, persistent and sporadic fire hot spots.

(a)



(b)

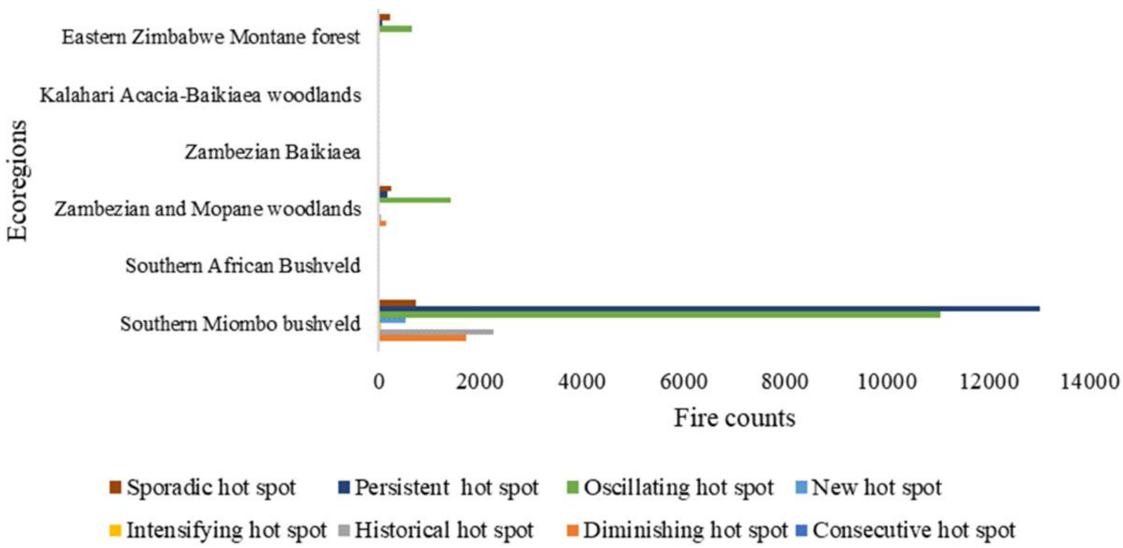


Fig 4.9: Spatiotemporal patterns of fire in a) agroecological zones and b) terrestrial ecoregions

4.3.2.3 Association between spatiotemporal patterns of fire and land use types and topography.

The spatiotemporal patterns of the detected fires and their association with the various land use types are shown in Fig 4.10. It is evident that the large-scale commercial areas were highly affected by fire over the 20-year study period with the oscillating fire hotspot pattern being most prevalent. Persistent and historical fire hot spots were also detected in the study area. Interestingly, there is evidence of persistent, diminishing and oscillating hot spots within protected areas which is highly unexpected. The association between the spatiotemporal patterns of fire occurrence and land use types and topography was statistically significant.

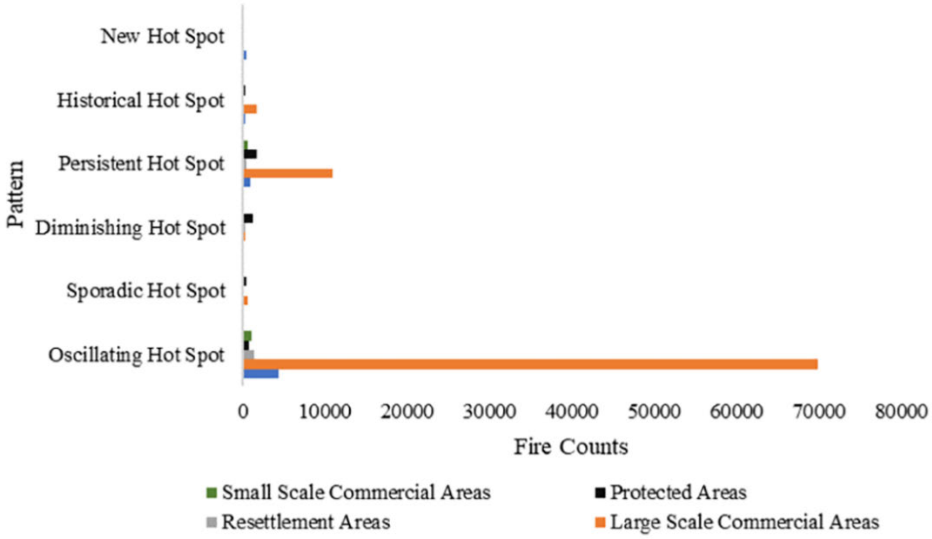


Fig 4.10. Association between spatiotemporal patterns of fire and land use types

The spatiotemporal pattern of fires and their occurrence in different slope conditions shown in Fig 4.11 significantly ($p<0.05$) show that most fires in Zimbabwe occur in areas on gentle slope with persistent and oscillating fire hotspots constituting 45% and 28% of the fire hot spots respectively. There was also a small proportion of the persistent and oscillating fire pattern occurring in areas lying on moderately steep slopes. There were no fires detected in very steep areas (>45˚).

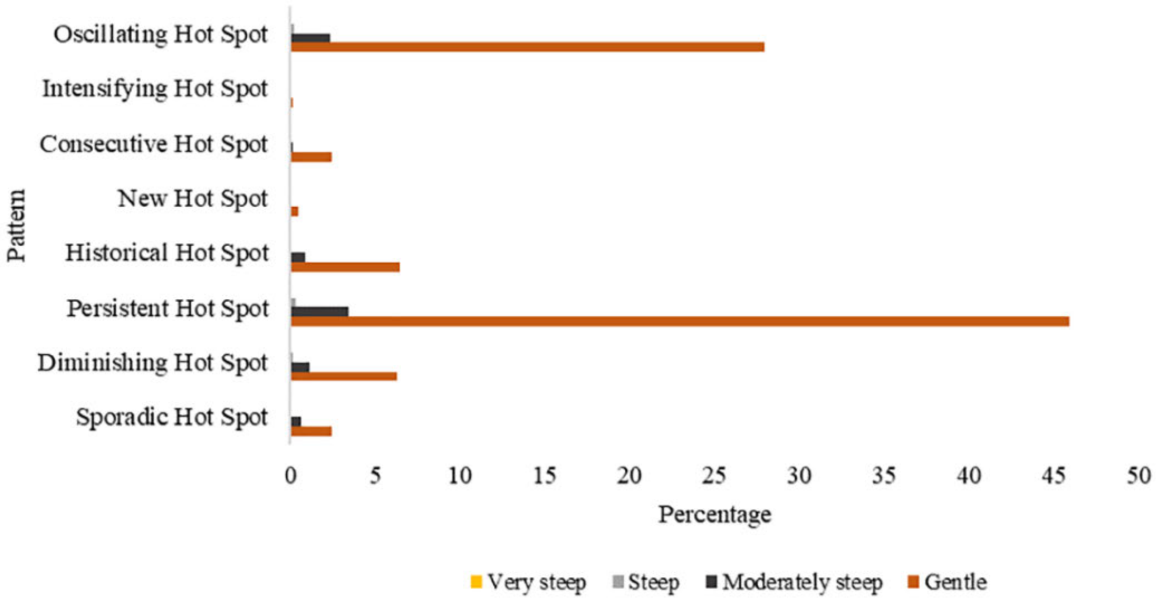


Fig 4.11. Association between spatiotemporal patterns of fire and slope

4.3 Discussion

The study assessed the utility of satellite data and emerging hot spot analysis to detect the spatiotemporal patterns of fires that were detected by the MODIS satellite sensor from 2000–2019. The general analysis of the average annual fire occurrence data reveals that there was a slight non-significant downward trend (Kendall Tau = -0.2 and $p>0.05$) in the fire activity in the study area over the 20-year study period. The study findings show an upward trend in the occurrence of fires from 2002 to around 2010 while a downward trend in fire occurrence was observed from 2010 to 2021. The upward trend in fire occurrence observed in this study however agrees with findings by (Maponga, Ahmed and Mushore, 2018) who observed an increasing trend in fire occurrence in one district of Zimbabwe from 2001 to 2009. The research findings however contrast with findings from Shekede et al., 2021 where an increasing trend in fire counts was observed over Zimbabwe but within a different period (2000 to 2019). This variation could be due to the differing start and end times of the fire data analysis. The downward trend observed in this study from 2000 to 2019 could be associated with improved fire management strategies being implemented by responsible authorities.

This study has shown that high fire activity predominantly occurs during the dry and hot season. The seasonality of fire occurrence in Zimbabwe is influenced by the country's two distinct rainfall-related seasonal patterns, the wet season from November to March and the dry season from April to October (Manatsa *et al.*, 2020). During the wet season, for example, vegetation in Zimbabwe grows due to the abundant rainfall, and the susceptibility to fire occurrence is generally low. The dry season coincides with the fire season in Zimbabwe which is associated with the drying up of vegetation due to high temperatures and lack of rainfall and becomes highly combustible. Fire occurrence is significantly (Table 2) high between July and September, which is the driest and windiest of the year. The number of fire incidents tends to decline towards the end of the dry season as the first rains begin to fall, and the vegetation becomes moister and less prone to fires.

The research findings have also shown that although June, July and November are not included in the official fire season, the fire counts recorded for these months are relatively high. This newly unveiled information is critical for fire management decisions which may lead to considering the shifting of the fire season in Zimbabwe. This information from the study findings strengthens the perception highlighted in (Nyakudanga, 2022) to change the fire season dates and the amendment of statutory instrument provisions. A detailed study on the analysis of possible shifts in fire seasonal occurrence over a long period may be required. Understanding the seasonality of fire occurrence is crucial for the development of timely and effective fire management strategies in Zimbabwe.

The study has revealed that, based on the analysis of the 20-year MODIS fire occurrence data, the spatiotemporal patterns vary from oscillating cold spots in the southern and central parts to persistent, oscillating, diminishing and historic hot spots in the northern parts of the study area. Persistent hotspots pattern refers to the occurrence of fire in all the time steps (Harris *et al.*, 2017)]. The sporadic hot / coldspots, for example, represent areas where fires disappear and reappear over time while diminishing hot or cold spots are those areas which have become less of a fire hotspot over the years (Visner, Shirowzhan and Pettit, 2021). The occurrence of diminishing and historical spatiotemporal fire patterns could be associated with changes in the extent and quality of vegetation in these areas. The reduction in vegetation cover results in reduced fuel available for burning hence the potential reduction in fire occurrence. New hotspots are areas which were never hotspots until the final time step which is the 2021 fire season (Harris *et al.*, 2017). These emerging spatiotemporal fire patterns are expected to guide the allocation of resources for fire monitoring and management by responsible authorities in Zimbabwe. Local investigations could also be done in areas where persistent hot spots were observed to determine the drivers of the spatiotemporal pattern. The spatiotemporal fire pattern analysis therefore assists in identifying priority areas for conservation (Harris *et al.*, 2017).

The research findings unveil new information on the patterns of temporal fire clusters in the various ecoregions indicating the risk that fires pose on the ecoregions within the study area. The persistent and oscillating fire hot spot patterns were associated with Southern Miombo Bushveld which has shown to be prone to fire. Ecoregions are characterized by different vegetation and climatic conditions which affect the fire occurrence patterns (Singh, Sood and Collins, 2022). Miombo woodlands are generally susceptible to fire and burn mainly during the dry season. The occurrence of the persistent fire hot spot in the Southern Miombo Bushveld ecoregion is not surprising because the biome is highly associated with persistent fires (Ryan and Williams, 2010). The information on the association between ecoregions and spatiotemporal fire clusters supports the development of effective fire management policies which benefit economic, social and ecological objectives (Nyamadzawo et al., 2013; Maponga, Ahmed and Mushore, 2018).

Agroecological zones IIa and IIb, characterized by moderate rainfall and high temperatures, are the most fire-prone regions with oscillating and persistent hotspots being more prevalent. This concurs with literature which indicates the high occurrence of fires in such regions (Mupfiga *et al.*, 2022; Global Forest Watch, 2023). The oscillating fire hotspots detected in the eastern region (Agroecological zone I) could be associated with burning occurring in forest plantations. While higher elevation may be associated with less probability of fire occurrence due to cool and moist conditions, local factors can influence this relationship. The higher fire activity within the large-scale commercial farms could be associated with the Fast Track Land Reform Program where burning was a common practice as the farmers prepared their new land (Nyamadzawo *et al.*, 2013; Maponga, Ahmed and Mushore, 2018).

The research findings have clearly shown a significant association between fire occurrence and gentle slopes. This can be highly associated with human contribution to fire occurrence where most agricultural activities are done in flat areas (Piralilou *et al.*, 2022). Most farmers utilize fire during land preparation in Zimbabwe (Nyamadzawo *et al.*, 2013; Maponga, Ahmed and Mushore, 2018).

This study has shown the utility of remote sensing in assessing a past fire regime, which is useful in fire management policy formulation. There could however be limitations on the MODIS fire detection where cloud cover, smoke or dense forest canopies could have obscured the detection of some fires (Nieman, van Wilgen and Leslie, 2021). With a spatial resolution of 1km, the MODIS sensor could also have a chance of missing too small fires.

Ground truthing for validation was not possible because of the historical nature of the fire data used in the analysis. The detailed process of validating MODIS active fire data has, however, been provided by (Morisette *et al.*, 2005). To improve the observational accuracy of the data, the techniques used by the Fire Information Resource Management System (FIRMS) to validate the active fire data are provided by Justice et al., 2011.

Although this study analysed how terrestrial ecoregions, agroecological zones and topography are associated with fire occurrence, the causes of fire occurrence were not within the scope of this study as remote sensing methods cannot assess such information. Although the temporal scale of this study was restricted by the availability of the MODIS sensor, the timescale used is adequate to study a fire regime of the study area (Nieman, van Wilgen and Leslie, 2021).

The research findings from this study provide valuable information for the evaluation of the fire management policies and plans implemented in Zimbabwe over the study period. The research findings also add new information for decision-making regarding resource allocation for fire management. The study findings can also assist in identifying areas where incentives should be provided to the responsible communities for improvement in fire management. With the rise in climate warming and population, it is important to understand the long-term spatiotemporal patterns in fire occurrence (Pricope *et al.*, 2015; Argibay, Sparacino and Espindola, 2020).

This study focused on the whole country of Zimbabwe and resulted in a valuable but coarse map of the spatiotemporal fire patterns throughout the study area. The causes and drivers of the spatiotemporal patterns such as persistent and diminishing hotspots, which were out of this study's scope, should be investigated in future studies. The contribution of climate change, land use changes and human activities on the spatiotemporal distribution of fires in the study area could also be explored in future studies.

4.5. Conclusion

This paper has unveiled the utility of the emerging hotspot analysis detecting the spatiotemporal patterns of fire occurrence in Zimbabwe using MODIS fire data over 20 years. The research findings have shown that based on MODIS fire data and emerging hot spot analysis, significant spatiotemporal patterns of fires were detected. In addition, fire occurrence in Zimbabwe is largely seasonal, with the highest frequency of fires occurring during the dry season from April to October. The spatiotemporal fire pattern in Zimbabwe is related to variations in vegetation types and topography. Overall, the study has shown the utility of the emerging hot spot analysis method as a robust tool in detecting spatiotemporal patterns of fires. The results hence provide timely information to fire management decision-makers. Informed fire management strategies such as resource allocation can therefore be implemented. The revision of the current fire season could also improve the effectiveness of the fire management strategies in the study area.

4.6 Summary and link to the next chapter

This chapter focused on the analysis of the spatiotemporal dynamics of fire occurrence in Zimbabwe. The objective addressed in this chapter was to detect how the distribution of vegetation fires varied both spatially and temporally in Zimbabwe from 2002 to 2021. The Emerging hotspot analysis algorithm used to detect the spatiotemporal fire patterns utilizes both the Getis-Ord (Gi) statistic and the Mann-Kendall trend test. This robust spatiotemporal method revealed new information about vegetation fires in Zimbabwe. For example, based on the results the study recommends the review of the fire season observed in Zimbabwe. Following the research findings from this chapter, there is a need to assess the major factors that drive the occurrence of vegetation fires in Zimbabwe. The following chapter therefore utilized the Maxent machine learning model and historical satellite fire data to assess the drivers of vegetation fire occurrence*

CHAPTER 5: ASSESSING DRIVERS OF VEGETATION FIRE OCCURRENCE IN ZIMBABWE - INSIGHTS FROM MAXENT MODELLING AND HISTORICAL DATA ANALYSIS

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REMOTE SENSING APPLICATIONS

Assessing drivers of vegetation fire occurrence in Zimbabwe - Insights from Maxent modelling and historical data analysis

Upenyu Mupfiga [a,c,*], Onisimo Mutanga [a], Timothy Dube [b]

[a] Discipline of Geography, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Private Bag X01, Scottsville, Pietermaritzburg, 3201, South Africa

[b] Institute for Water Studies, Department of Earth Sciences, The University of the Western Cape, Private Bag X17, Bellville, 7535, South Africa

[c] Department of Geography, Environmental Sustainability and Resilience Building, Midlands State University, Gweru, 9055, Zimbabwe

Abstract

Vegetation fires are known to profoundly impact ecosystem structure and composition, posing threats to ecosystem stability and human safety. In Zimbabwe, uncontrolled fires have been recurrent, yet a rigorous analysis of the key drivers is still lacking. Previous studies in Zimbabwe have predominantly focused on spatio-temporal dynamics of the occurrence of vegetation fire, leaving a gap in understanding the underlying drivers. Accurate prediction of fire occurrence and identification of the major drivers is imperative for effective fire management strategies. The study employs the Maxent model, a machine-learning approach, to analyze historical MODIS fire data alongside bioclimatic, topographic, anthropogenic, and vegetation variables, to assess the likelihood of fire occurrence in Zimbabwe. The research also aims to elucidate the major factors that influence fire occurrence within the region. The independent contributions of predictor variables to the model's goodness of fit are evaluated using a jackknife test, while model accuracy is assessed using the AUC (area under the receiver operating characteristic curve). Results indicate that elevation, precipitation seasonality, temperature annual range and human footprint emerge as the major factors influencing fire occurrence in Zimbabwe. The model demonstrates an acceptable accuracy, with an average AUC of 0.77. This study underscores the utility of the Maxent model in elucidating the contributions of various environmental factors to vegetation fire occurrence. Moreover, the ability of the model to predict the probability of fire occurrence offers valuable insights for fire managers, facilitating the assessment of the spatial vulnerability of vegetation to fire occurrence. Overall, this research contributes to an improved understanding of the drivers of vegetation fires in Zimbabwe and provides a practical tool for enhancing fire management efforts in the region and beyond.

Keywords: *fire risk; Maxent; MODIS; probability; vulnerability; Zimbabwe*

5.1 Introduction

Although vegetation fires have greatly shaped the savanna ecosystem, they are a major disturbing factor in global forest ecosystems, contributing to land degradation (Global Forest Watch, 2023). Although many prevention and mitigation strategies have been put in place, fires remain a major global concern, degrading forested areas (Armenteras *et al.*, 2017b; Mishra *et al.*, 2023) and disturbing biodiversity and ecosystem services (Zhang, Lim and Sharples, 2017; Piralilou *et al.*, 2022). Additionally, fires significantly contribute to greenhouse gas emissions, hence, becoming an important contributor to global climate change, which in turn influences the increase in fire occurrence incidents and their severity (Mishra *et al.*, 2023; Wasserman and Mueller, 2023). Uncontrolled fires can result in major disasters and have devastating effects on human lives and may lead to economic losses (Zhang, Lim and Sharples, 2017).

Effective fire management greatly depends on a clear understanding of the dynamic spatiotemporal distribution of and the factors driving fire occurrence in a landscape. Variability in the spatiotemporal distribution of vegetation fire occurrence is greatly controlled by several factors including fuel type, topography, precipitation and temperature (Zhang, Lim and

Sharples, 2017). Anthropogenic factors are also important predictors of fire occurrence. Topography influences the local climatic variations, especially the spatial distribution of precipitation and temperature, hence, controlling fuel type distribution and flammability (Zhang, Lim and Sharples, 2017). Temperature and precipitation control fire occurrence by determining fuel availability and moisture (Graham, Dube and Mpakairi, 2023). Higher precipitation and temperature conditions increase the probability of fire occurrence (Archibald, Nickless, *et al.*, 2010).

Despite being highly accurate, traditional methods of collecting fire data in a landscape, such as mapping burned areas using handheld GPS receivers, have proven to be expensive, labour-intensive, time-consuming and difficult to carry out, especially over large and inaccessible areas (Wang *et al.*, 2023). Earth observation and geospatial methods have proven to offer practical and cheap means to predict and quantify the occurrence of fires both locally and globally. Satellite-borne sensors are widely used in fire monitoring studies, and they utilise the thermal, shortwave, mid-infrared, and visible parts of the electromagnetic spectrum. Fire detection sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS), for example, utilize the brightness temperature in the fire detection algorithm. The free availability of remotely sensed data has allowed the easy generation of topographic derivatives such as aspect and slope, from digital elevation models (DEM). Rainfall and temperature data are also freely available from databases such as the WorldClim which provides bioclimatic data (Fick and Hijmans, 2017). The modelling of fire occurrence with limited ground observations greatly benefits from the availability of satellite-derived variables (Odebiri et al., 2020).

Globally, several studies have assessed the spatiotemporal occurrence of fires in differing ecosystems (Guo *et al.*, 2017; Oliveira *et al.*, 2021; Mishra *et al.*, 2023). In Southern Africa, a few studies (Makhaya et al., 2022; Mishra et al., 2023; Mpakairi et al., 2018) have utilized spatial techniques to determine the factors that drive fire occurrence. For instance, Makhaya et al., 2022, utilized topographic and bioclimatic variables to assess key drivers supporting the occurrence of vegetation fires in Ethekwini Municipality, KwaZulu Natal, South Africa. Studies carried out in Zimbabwe mainly focused on the spatial and temporal occurrence of fires (Mpakairi *et al.*, 2018; Shekede, Gwitira and Mamvura, 2021; Mupfiga *et al.*, 2022) and the influence of tenure systems on areas burned (Maponga, Ahmed and Mushore, 2018). Although the previous studies provided valuable information on fire occurrence using various methods, the main influential environmental and human-related factors which influence the occurrence of vegetation fires in Zimbabwe are still poorly understood. While Mpakairi et al., 2018 predicted the occurrence of vegetation fires as a function of factors such as elevation, air temperature, biomass and population density in a protected area in Zimbabwe, the study was done on a small scale. The current study analyzed the key environmental and anthropogenic factors that influence the occurrence of vegetation fires at a much larger scale such as country level. It also includes a more diverse set of environmental variables, incorporating the human footprint variable, a more robust indicator for anthropogenic effect on fire occurrence and at a larger scale. The study presents new information on predicting the likelihood of vegetation fire occurrence within a landscape.

In the past few decades, a high number of cases of vegetation fires have been experienced in Zimbabwe despite the availability of several legislative frameworks (Shekede, Gwitira and Mamvura, 2021; Mupfiga *et al.*, 2022; Shekede *et al.*, 2024). The temperature rise, the fall in precipitation levels and the recurrence of vegetation fires clearly show the reality of climate change (Mushore *et al.*, 2021; Mupfiga *et al.*, 2022). This study focused on a nationwide analysis of the factors driving the spatiotemporal occurrence of vegetation fires in Zimbabwe, Southern Africa. The study covers a larger area, characterized by diverse climatic, topographic, vegetation, and anthropogenic conditions. The nationwide approach employed in this study offers a wall-to-wall analysis of the predictor variables that drive the occurrence of vegetation fires in Zimbabwe. To fill the research gap, this study employed Maximum Entropy model (Maxent), a widely used species distribution model, in predicting the likelihood of vegetation fire occurrence across the landscape and assessing the relative contribution of the factors to the spatial occurrence of vegetation fires.

The results from the study are important for informed fire management decisions to minimize the impacts of fire. The identification of major drivers that influence the occurrence of vegetation fires and prediction of the likelihood of fire occurrence assists in providing a framework for proactive measures for the reduction of the risk of fire occurrence thereby contributing to the formulation of effective strategies for the prevention and management of vegetation fires. The findings from the study avail valuable insights which assist decisions towards national fire prevention and mitigation strategies.

5.2. Materials and Methods

5.2.1. The study area characteristics

This national scale study covered Zimbabwe (figure 5.1), a country situated in sub-Saharan Africa between 15°30″ to 22°30″ S and 25°30″ to 33°30″ E, covering an area of about 390,757 km^2. Zimbabwe is characterized by topography which varies from below 300 m in southern parts to above 2000 m in Eastern regions. Annual rainfall in Zimbabwe decreases from agroecological zone I to zone Vb with temperatures increasing from zone I to Vb. Most of the precipitation which varies spatially in Zimbabwe, falls during summer from late Nov to April. There is variation in temperature along elevation zones. Being a savanna ecosystem, fire frequently occurs in the study area and contributes to deforestation and land degradation (Global Forest Watch, 2023). About 95% of forest cover in Zimbabwe is characterized by savanna woodlands with a fire season generally occurring from around August to October (Archibald, Scholes, *et al.*, 2010b; Mupfiga *et al.*, 2022).

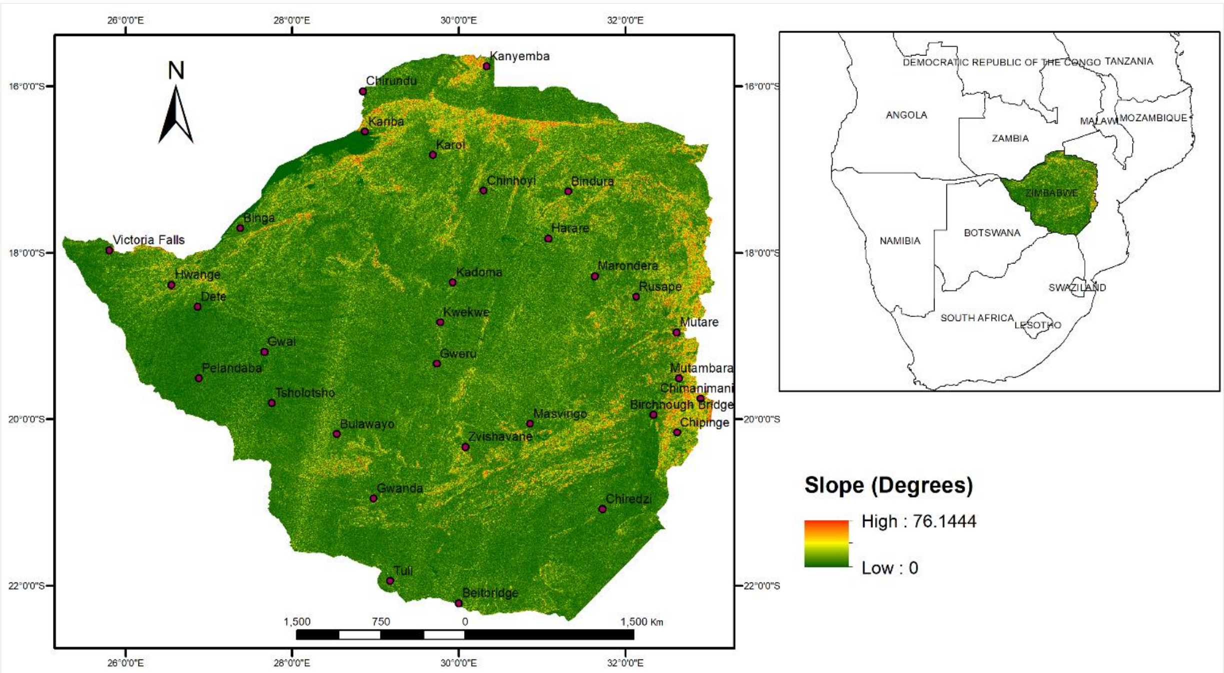


Figure 5.1: Topographic characteristics (slope) which was used to model vegetation fire vulnerability in Zimbabwe

5.2.2 Data

5.2.2.1 Dependent variables: Fire occurrence data

Due to the unavailability of historic field data on fires, MODIS Collection 6 fire data (January to December 2018) was used. The MODIS fire data product (MCD14ML), is recognized as one of the most accurate and effective satellite data systems for fire monitoring (Justice *et al.*, 2011; Zhang, Lim and Sharples, 2017; Graham, Dube and Mpakairi, 2023) and was used in several fire occurrence studies (Zhang, Lim and Sharples, 2017; Mupfiga *et al.*, 2022; Mishra *et al.*, 2023). The presence of a thermal band within the MODIS, specifically developed for fire monitoring, makes the MODIS data the most suitable dataset for fire monitoring studies. The fire data which was acquired from the Fire Information for Resource Management System (FIRMS) platform (https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/active-fire-data) (accessed on 4 March 2023), includes information on the location, the time and the date when the fire data was acquired, the confidence level and the brightness of the fire. The MODIS algorithm identifies pixels containing fires that are actively burning during the satellite's overpass (Justice *et al.*, 2011; Giglio, Schroeder and Justice, 2018). Only fires occurring within vegetated areas and with confidence levels higher than 30% were utilized in the analysis.

5.2.2.2 Predictor Variables

The variables used in the analysis included topographical, climatic, vegetation and anthropogenic, which are the common factors influencing the spatiotemporal distribution of vegetation fires (Makhaya, Odindi and Mutanga, 2022; Graham, Dube and Mpakairi, 2023; Mishra *et al.*, 2023).

Bioclimatic variables

The probability of fire occurrence largely depends on climatic conditions which influence the availability of fuel load and moisture and determine the level of fire fuel such as forest litter, grasses, and leaves. Long-term dry conditions influence the drying of fuels thereby increasing the susceptibility of vegetation to burning. Warmer temperatures between 20ºC and 27ºC result in the drying of fuels in the savanna, thereby increasing the likelihood of fire ignition. Similarly, precipitation influences the amount of moisture available for vegetation growth and eventually determines the amount of dry-season biomass that will be available for burning (Archibald et al., 2010).

The study considered 19 bioclimatic variables (1km spatial resolution), freely extracted from https://www.worldclim.org/data/bioclim.html (accessed on 28 April 2023). Detailed information on the development of the bioclimatic data is found in Fick and Hijmans, 2017 and listed in Table 1. The bioclimatic variables, computed from long-term rainfall and temperature averages, were preferably used in this study compared to raw monthly rainfall and temperature data because they were fine-tuned into more ecologically meaningful variables (Moyo *et al.*, 2019). These 19 variables, which show the annual and seasonal temperature and precipitation, have been successfully used in other studies globally (Makhaya, Odindi and Mutanga, 2022; Mishra *et al.*, 2023) as governing factors for fire occurrence.

Topographic variables

Elevation, slope, and aspect greatly determine the local climate variations, especially the spatial distribution of precipitation and temperature, controlling fuel type distribution and flammability (Zhang, Lim and Sharples, 2017; Graham, Dube and Mpakairi, 2023). The digital elevation model (DEM) utilized in the analysis was extracted from the Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) and downloaded from the www.usgs.gov platform at 30m spatial resolution. The aspect and slope variables were derived from the DEM in ArcGIS 10.5 using the Spatial analyst tool. The topographic variables were resampled to 1km spatial resolution to match the fire data and other predictor variables.

Fuel variables

Due to variability in combustibility and fuel load characteristics, vegetation types are affected differently by fire. Some specific land cover types such as shrubs and conifers tend to be more fire-prone than other land cover types such as wetlands, burned areas, and agricultural areas (Adab *et al.*, 2018). Vegetation flammability is greatly influenced by its moisture content and structure which affect fuel load. Vegetation which is generally dry, woody, and has higher oil content tends to be more flammable compared to other vegetation types. On the other hand, succulent vegetation, with higher moisture content and less litter is less flammable. The highest probability of fire occurrence is associated with high NDVI values ranging from 0.5 to 1 (Mpakairi et al., 2018). The MODIS NDVI product was used in this study as a proxy for biomass and representing the fuel variable.

Anthropogenic variables

There is a close relationship between the occurrence of fire and the presence of humans and their activities. Human activities increase the probability of fire occurrence by providing possible sources of fire ignition (Zhang, Lim and Sharples, 2017). The susceptibility to fire occurrence tends to increase with proximity to populated settlements and accessibility of forests to roads (Armenteras, González and Retana, 2013; Guo *et al.*, 2017; Piralilou *et al.*, 2022). The human footprint map, developed by Venter et al., 2016 was used as a proxy for the environmental disturbance caused by human pressures. This anthropogenic data set was developed based on overlaying of eight anthropogenic factors, population density, built-up area, croplands, pasture land, roads, railways, navigable waterways and electric infrastructure. The details of the variables used in the modelling are given in Table 5.1.

Table 5.1: Predictor variables which were used for modelling fire occurrence

Variable		**Source**
Bioclimatic	Annual mean temperature (Bio1) Mean monthly temperature range (Bio2) Isothermality (Bio3) Temperature seasonality (Bio4) Maximum temperature of warmest month (Bio5) Mean temperature of coldest month (Bio6) Temperature annual range (Bio7) Mean temperature of wettest quarter (Bio8) Mean temperature of driest quarter (Bio9) Mean temperature of warmest quarter (Bio10) Mean temperature of coldest quarter (Bio11) Annual precipitation (Bio12) Precipitation of wettest month (Bio13) Precipitation of driest month (Bio14) Precipitation seasonality (Bio15) Precipitation of wettest quarter (Bio16) Precipitation of driest quarter (Bio17) Precipitation of warmest quarter (Bio18) Precipitation of coldest quarter (Bio19)	https://www.worldclim.org/data/worldclim21.html (Fick and Hijmans, 2017)
Vegetation	NDVI	

Topographic	Elevation Slope Aspect	https://www.worldclim.org/data/worldclim21.html (accessed 15 September 2023) (Fick and Hijmans, 2017)
Anthropogenic	Human footprint map	https://sedac.ciesin.columbia.edu/data/set/wildareas-v2-human-footprint-ighp/data-download (accessed 15 September 2023) (Venter *et al.*, 2016)

5.2.3 Data preparation

The processes done on the collected data are clearly shown in Figure 5.2. The multisource input data was resampled to 1 km spatial resolution to match the resolution of the fire data. The study area map was used to clip the topographic, human footprint, NDVI, bioclimatic and fire data using the spatial analyst tool in ArcMap. After the predictor variables, in raster format, were stacked in R Studio, the fire data was used to extract raster values for each fire point. The values of the predictor variables for each fire point were recorded in a Microsoft Excel csv file.

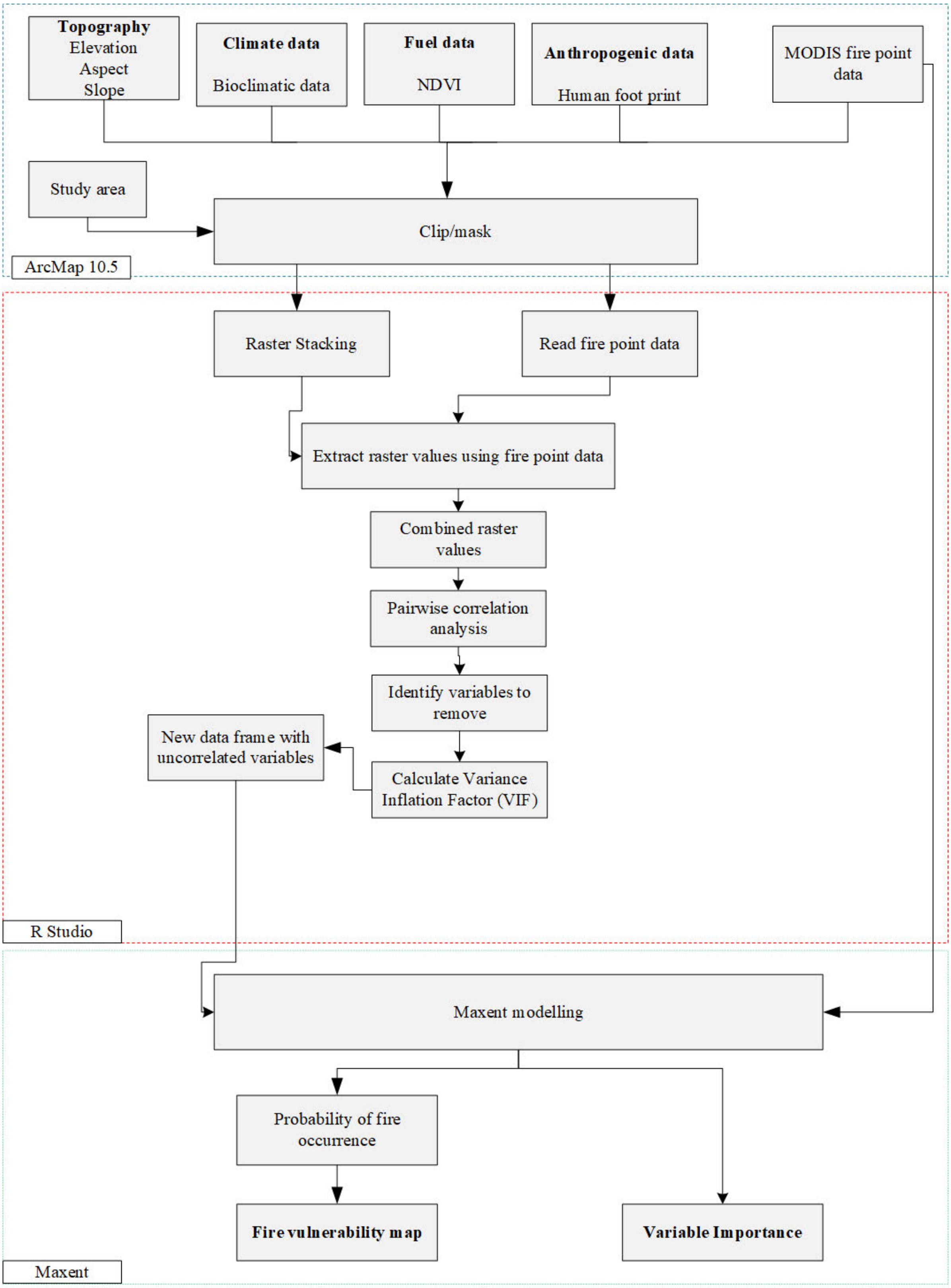


Fig. 5.2: Flow diagram showing the processing of data used in modelling vegetation fire vulnerability of Zimbabwe

5.2.4 Selection of predictor variables

Multicollinearity is detected when two or more predictor variables are highly correlated and negatively affect models. To avoid instability in the Maxent model's performance, testing for multicollinearity among the predictor variables was done using the variance inflation factor (VIF) in R Studio. The predictor variables with VIF less than 10 (Dormann *et al.*, 2013; Makori *et al.*, 2022) were selected for predicting fire occurrence using Maxent (version 3.3.3).

5.2.5 Modeling the likelihood of fire occurrence

The probability of fire occurrence was predicted using the Maxent model (Phillips, Anderson and Schapire, 2006) as a function of topographic, climatic, anthropogenic and vegetation factors. Maxent is a machine learning model broadly applied in suitability and ecology studies. It correlates explanatory variables with the locations of species presence to predict suitability (Fitzgibbon, Pisut and Fleisher, 2022). The model utilizes presence-only data together with raster covariates to predict the suitability of a specific phenomenon and calculates the probability of occurrence ranging from 0 to 1 (Adab *et al.*, 2018). Modelling the suitability of the occurrence of a phenomenon using Maxent does not require verification of the absence-only data which is usually difficult to acquire (Adab et al., 2018). In this study, the MODIS presence-only active fire data was utilized as the dependent variable in modelling the likelihood of fire occurrence using the Maxent model. The contribution of each predictor variable to the model results was determined using the jackknife tool within the Maxent 3.3.3. The Maxent model runs several repetitions until there are no further changes in the spatial estimation of the probability of fire occurrence and identifies the maximum likelihood of fire occurrences within the study area (Rahmati, Pourghasemi and Melesse, 2016). For this study, a map showing the fire risk level was developed by reclassifying the map showing the probability of fire occurrence into 4 classes very low risk (0-0.25, low risk (0.25-0.5), high risk (0.5-0.75), and): very high risk (0.75-1) (Chen *et al.*, 2015).

For best model results, the calibration of the model is essential. In the Maxent model, fire data was divided into training (70%), for building the model and test datasets (30%), for the validation of the model (Phillips, Anderson and Schapire, 2006; Odebiri *et al.*, 2020) using the random test percentage setting. The model was run using the default Maxent settings. To check for overfitting, the difference between values of the training area and the test area under curve (AUC) was assessed. Since overfitting was not detected, the default regularization was utilized in the model. To generate a map showing the likelihood of fire occurrence in Zimbabwe, the 10-percentile limit was utilized in the Maxent model. The threshold assumed that the omission error of the occurrence is less than 10%, and 90% of the fire data was modelled as present (Odebiri *et al.*, 2020).

The Maxent model produces the receiver operating characteristic (ROC) curve as output which gives and AUC (area under curve) as a measure of the model accuracy. The receiver operating characteristic (ROC) curve, which describes the model performance (Rahmati, Pourghasemi and Melesse, 2016), was utilized to evaluate and validate the Maxent model. It shows the probability that fire occurrence (sensitivity) is correctly explained by the predictor variables as compared to the absence (specificity) of fire occurrence. It is generated through the plotting of sensitivity on the y-axis against specificity on the x-axis. For highly accurate models, the AUC value will be close or equal to 1, while, a model performing no better than random will have a value less than or equal to 0.5 (Phillips, Anderson and Schapire, 2006). The ROC curve has been widely used in several previous studies for the evaluation and validation of probability modelling (Odebiri *et al.*, 2020; Makhaya, Odindi and Mutanga, 2022; Mishra *et al.*, 2023). The chi square test was used to assess the association between the resulting fire risk zones and the fire intensity clusters identified in Section 3.32.

5.3. Research Findings

5.3.1 Selection of the Predictor Variables

Multicollinearity test results given in the form of the variance inflation factor (VIF) of the non-collinear predictor variables are shown in Table 5.2. As indicated in Table 5.2, 11 out of 23 predictor variables had VIF values less than 10, implying that they had a low degree of correlation and were therefore selected to be used in the Maxent model. This makes the predictor variables listed in Table 2 the best subset for use in predicting the spatial variability of fire occurrence using Maxent.

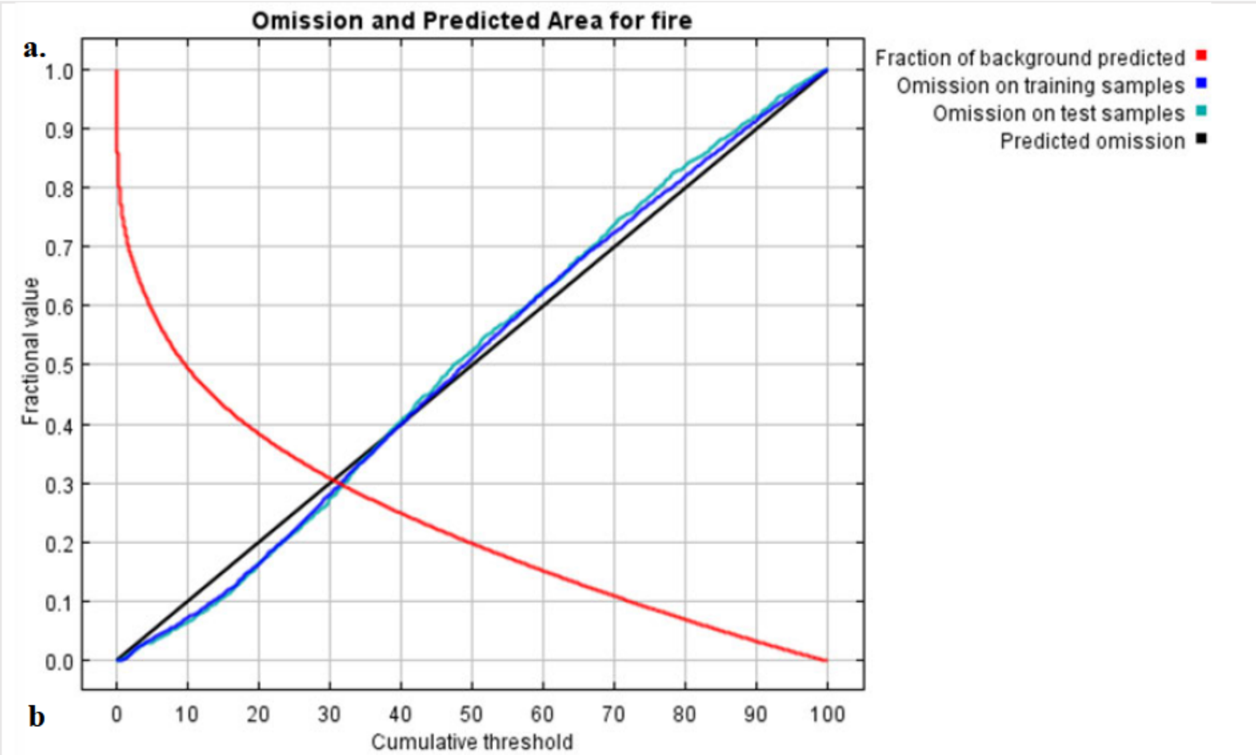
Table 5.2. The VIF value for the selected predictor variable used in the Maxent model

Predictor Variables	VIF
Annual mean temperature (Bio1)	6.5
Isothermality (Bio3)	1.9
Temperature seasonality (Bio4)	3.0
Temperature annual range (Bio7)	5.4
Precipitation seasonality (Bio15)	2.2
Precipitation of warmest quarter (Bio18)	2.1
Elevation	5.0
Aspect	1.0
NDVI	1.2
Human footprint	1.0
Slope	1.5

5.3.2 Maxent model

5.3.2.1 Analysis of Maxent model results

Figure 5.4a shows that the omission on test samples (turquoise is close to the predicted omission rate (black) signifying a good Maxent model. Based on the AUC value of 0.77 (Figure 5.4b), the Maxent model can be said to have performed better in predicting fire occurrence than a random model (Jiang *et al.*, 2018).



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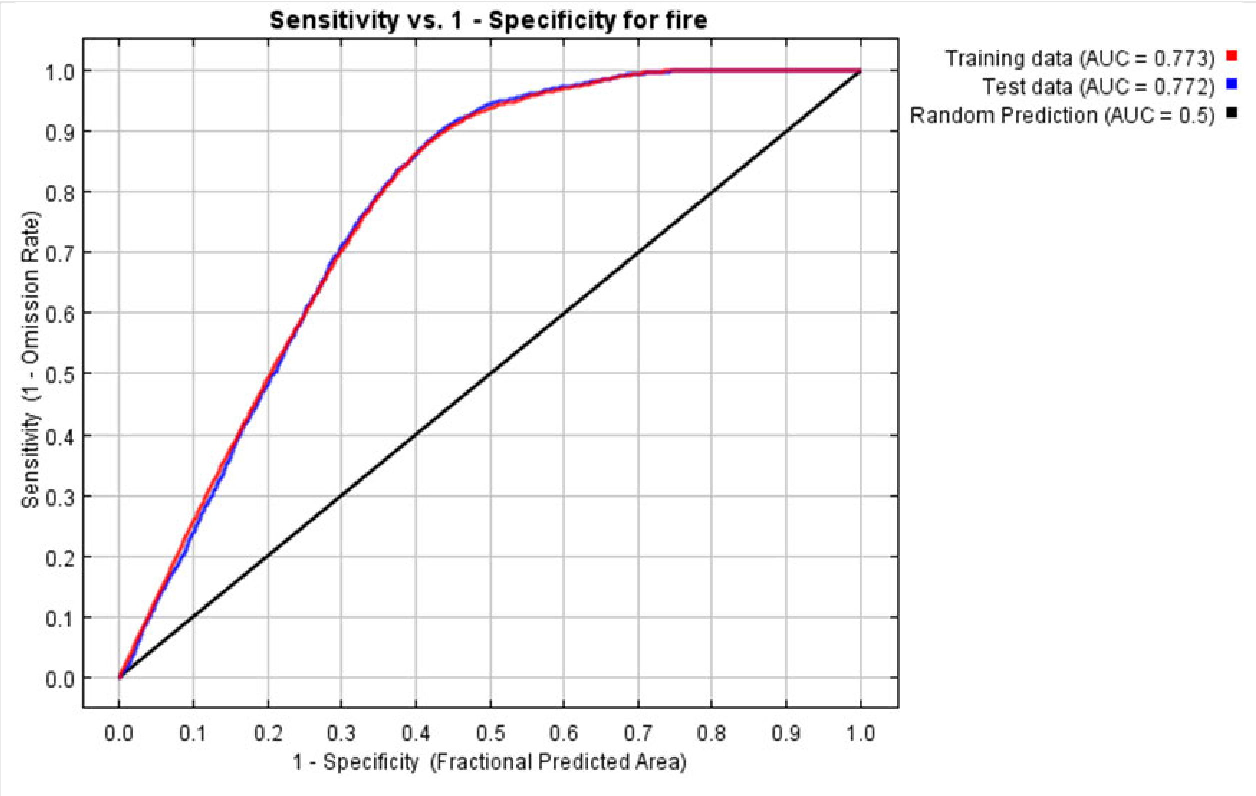

Figure 5.4. a. The omission analysis of the test and training data sets for the Maxent model. b. The ROC curve for training and test data sets as shown by AUC

5.3.2.2 Analysis of Variable Contributions

The Maxent model allows for assessing each variable's influence on the model results. The higher percentage contribution of any predictor variable implies that it has a higher effect on predicting the likelihood of vegetation fires. Table 5.3 shows the ranking of the estimated relative contributions of the variables towards predicting fire occurrence. Predictor variables with higher values tend to present greater importance in model prediction.

Table 5.3: The percentage contribution of the variables towards fire occurrence modelled using the Maxent model.

Predictor variables	**Percentage contribution (%)**
Elevation	31.2
Temperature annual range (Bio7)	26.5
Human footprint	16.4
Precipitation seasonality (Bio15)	13.9
Precipitation of warmest quarter (Bio18)	6.6

NDVI	2.6
Temperature seasonality (Bio4)	1.8
Isothermality (Bio3)	0.5
Slope	0.3
Aspect	0.1

Table 5.3 shows that the predictor variable with the highest percentage contribution (31.5%) towards the occurrence of vegetation fires in Zimbabwe is elevation followed by temperature annual range (Bio7) (26.5%). The human footprint and precipitation seasonality (Bio 15) also had a considerable predictive contribution to fire occurrence with percentage contributions of 16.4% and 13.9% respectively. The total contribution of elevation, temperature annual range, human footprint and precipitation seasonality (Bio 15) to fire occurrence was over 88%. Variables like slope, aspect and isothermality (Bio 3) had very low contribution to fire occurrence in Zimbabwe as shown in Table 5.3.

Findings from the assessment of the contribution of predictor variables towards the occurrence of vegetation fires using Maxent's jackknife test are shown in Figure 5.5. The bars in turquoise colour reveal the Maxent model's overall accuracy excluding the individual predictor variable. On the other hand, the blue bars illustrate the individual predictor variable's performance and accuracy if applied in isolation. The model's overall gain, calculated when all the predictor variables are used, is shown by the red bar.

Figure 5.5 shows that when applied alone, the annual mean temperature (Bio 1) variable, has the highest gain implying that this predictor variable contains the most important information which is independent of the other variables. Temperature annual range (Bio 7) is the predictor variable which caused the reduction of the model's overall gain if it is excluded. This, therefore, implies that the 'temperature annual range' variable contains more information which is absent in the other variables.

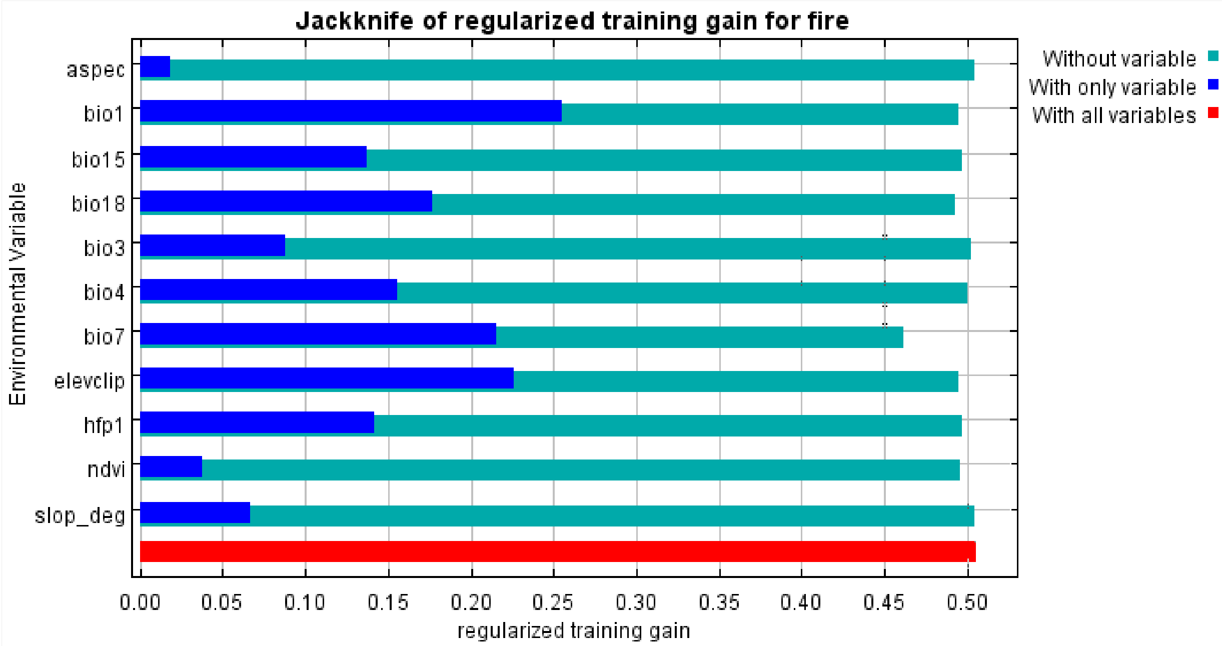

Figure 5.5: The results of the analysis of the importance of the variable using the jackknife test.

5.3.2.3. Spatial Distribution of Fire Risk

The map in Figure 5.6 showing the spatial distribution of fire occurrence in Zimbabwe was generated from the Maxent prediction model. The map shows the probability of fire occurrence, reclassified into fire risk levels, based on MODIS fire points as a function of bioclimatic, topographic, fuel and anthropogenic factors as predictor variables. As shown in Figure 5.6, areas with a very high probability of fire occurrence are presented in red colour, while areas with a very low likelihood of fire occurrence are shown in darker green. Areas of low and high risk of fire occurrence are shown in light green and orange colours, respectively. The areas characterized by a high to very high probability of fire occurrence cover more than 50% of Zimbabwe.

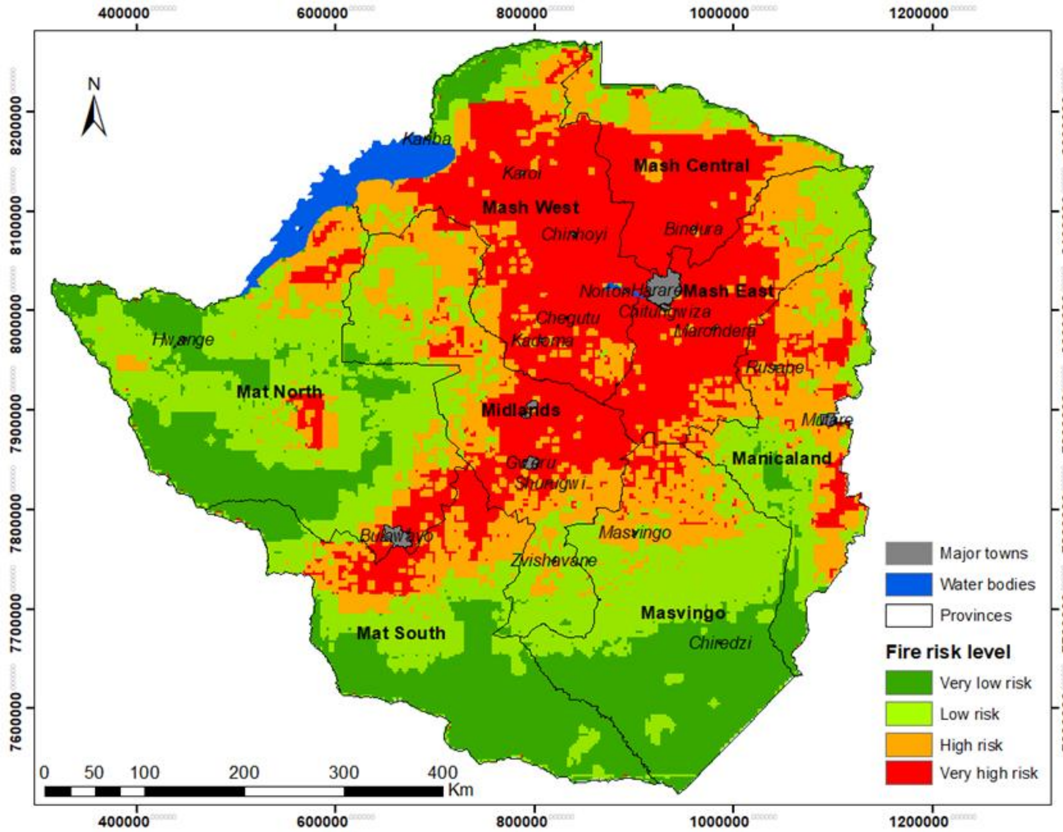

Figure 5.6. Spatial distribution of predicted fire occurrence risk level for each province in Zimbabwe. (*The two metropolitan provinces (Harare and Bulawayo) and other major towns were masked as these a mostly urban*).

Based on the Maxent probability model results, the very high risk of fire occurrence characterizes the central, northern and eastern regions which generally include the Mashonaland west, east and central provinces of Zimbabwe as shown in figures 6 and 7. Figure 7 clearly shows the percentage area covered by the predicted fire risk levels for each province in Zimbabwe where 63% of the area covered by Mashonaland West province presents a very high fire risk. The southern regions and some western parts characterized by the low-lying areas of Gonarezhou (Masvingo province) and parts of Hwange National Parks (Matabeleland North province), respectively had over 40% area characterized by a very low risk of fire occurrence. There was a significant ($p<0.05$) association between the fire risk zones and the fire intensity clusters presented in Section 3.3.2. The high fire risk zones, for instance, were generally identified within areas where the fire was of high intensity.

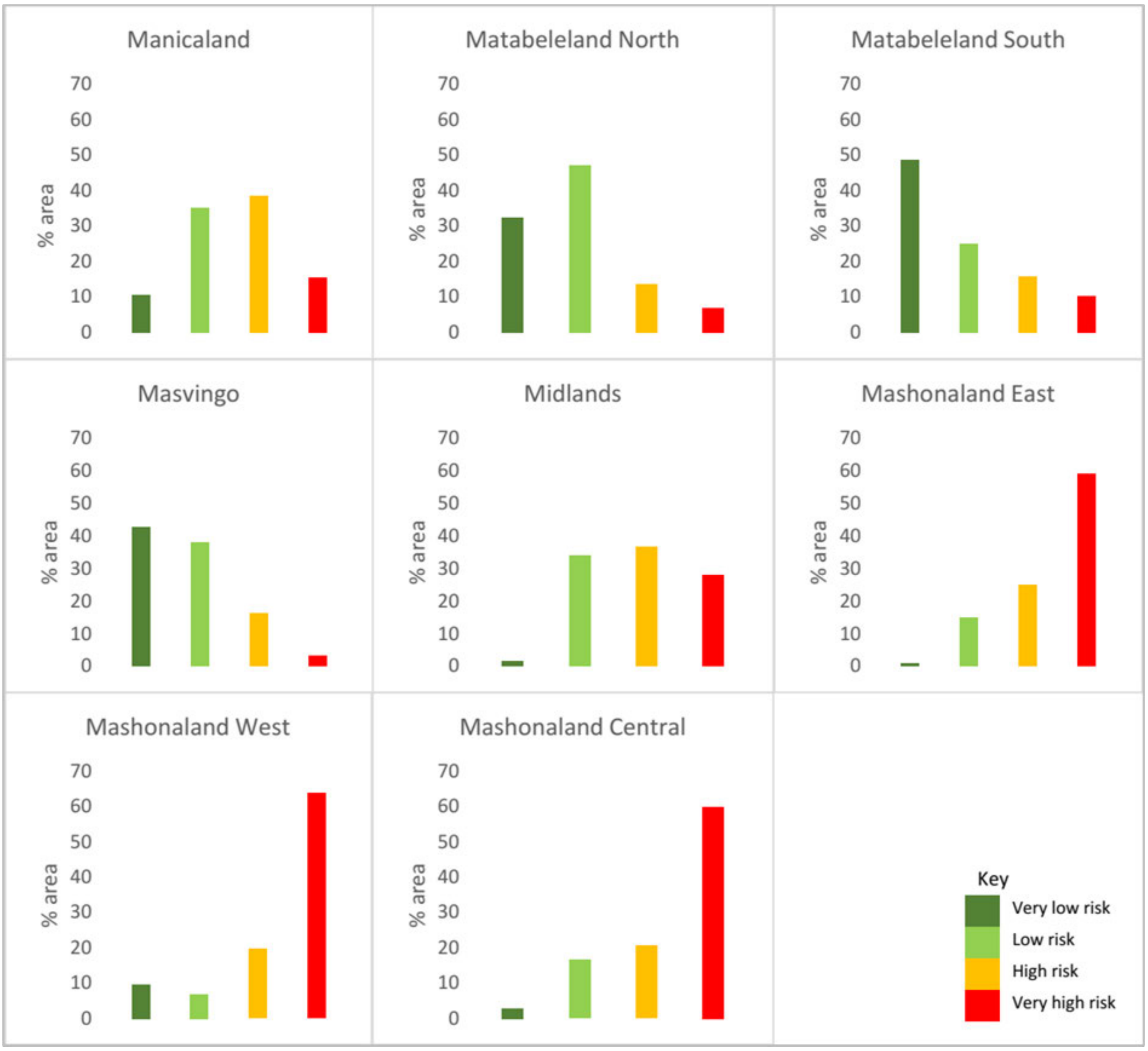

Figure 5.7. Percentage level of the fire risk for each province based on MaxEnt modelling

5.4. Discussion

Although fire is an intrinsic phenomenon within the savanna ecosystem, understanding the various factors driving the occurrence of vegetation fires is vital for sustainable fire management within ecosystems. The study reveals the utility of geospatial and earth observation tools in predicting and mapping the heterogeneity of fire occurrence as determined by fuel, topographic, climatic and anthropogenic factors. The study also determined the contribution of the various predictor variables to fire occurrence. Findings from the study have revealed that the variability in fire occurrence can be effectively predicted using fuel, topographic, climatic and anthropogenic factors in a Maxent environment with a satisfactory accuracy of 0.77 (Lissovsky and Dudov, 2021).

The study findings show the utility of the widely used Maxent as a rigorous fire prediction model. Fire occurrence data is generally presented as presence-only data and Maxent is highly suitable for handling such data (Mlambo *et al.*, 2024). The strength of the method utilized in the study is that we managed to exclude highly correlated predictor variables from the model fitting which greatly improved the model performance (Dormann *et al.*, 2013). This key step removes mutually dependent predictor variables from other model inputs. The multicollinearity test revealed that 11 out of 23, shown in Table 2 proposed predictor variables were not collinear and were therefore the best set of variables to be used in predicting the occurrence of vegetation fires using the Maxent model. The excluded variables were considered to be useful but similar information was contained in other variables.

Fire occurrence is largely influenced by topographic, vegetation, climatic and anthropogenic characteristics of a landscape. Topographic and climatic conditions which influence fuel load were the major contributing variables towards fire occurrence. Areas with higher precipitation and temperature are characterized by a higher probability of fire occurrence. Fires have been observed to occur largely in areas of precipitation ranging between 500 mm and 700 mm (Archibald, Scholes, *et al.*, 2010b). While high precipitation influences the level of fuel moisture during the fire season thereby decreasing fire ignition probability, high precipitation levels promote the accumulation of biomass during the pre-fire season, which increases the likelihood of burning during the fire season (Guo *et al.*, 2017). In this study, elevation had the highest percentage contribution (31.5%) towards the occurrence of vegetation fires in Zimbabwe followed by temperature annual range (Bio7) (26.5%). In this context, the temperature annual range shows the difference between the maximum and minimum temperatures over the year and gives the seasonal variation in temperatures over an area. The research findings are not surprising because Makhaya et al., 2022 in KwaZulu Natal, South Africa also indicated that a correlation between rainfall and temperature affects biomass and hence fuel characteristics which generally influence the occurrence of vegetation fires. The study findings also corroborate findings by Guo et al., 2017 where temperature was also identified as an important factor in influencing fire occurrence by increasing evaporation from vegetation and decreasing the moisture content of potential fire fuels.

Moreso, the observation of the association between elevation and fire occurrence agrees with findings from several studies (Guo *et al.*, 2017; Mupfiga *et al.*, 2022; Mishra *et al.*, 2023) where fire occurrence was high in regions of higher elevation. Contrary to a study by Guo et al., 2017, in this study, high fire risk was associated with areas of higher elevation. The eastern regions characterized by high elevation and exotic forest plantations were also predicted as having a high risk of fire occurrence. This observation agrees with previous studies (Makhaya et al., 2022; Mpakairi et al., 2018; Mupfiga et al., 2022; Strydom and Savage, 2016) where fire occurrence was observed to be highly correlated with elevation where there is an association between higher elevation and higher probability of fire occurrence (Graham et al., 2023). The research findings are not surprising because topographic factors such as elevation determine the local climate variations, especially the spatial distribution of precipitation and temperature, hence, controlling fuel type distribution and flammability (Graham et al., 2023; Zhang et al., 2017).

The human footprint variable was utilized in this study as a proxy for the contribution of human activities to vegetation fire occurrence. This anthropogenic data set was developed based on overlaying eight factors, built-up environment, population density, pasture land, croplands, railways, roads, waterways and electric infrastructure. The combination of all these factors makes the human footprint, a more robust measure of human activities. This predictor variable had a considerable contribution (16.4%) to fire occurrence, showing the significant contribution of human activities to the occurrence of vegetation fires in the study area. This agrees with previous research (Armenteras et al., 2013; Guo et al., 2017; Piralilou et al., 2022) where anthropogenic factors were highlighted as highly contributing to fire occurrence. Related studies have also emphasized that the likelihood of occurrence of vegetation fires increases when human activities are common in a landscape (Guo *et al.*, 2017; Piao *et al.*, 2022). The strength of this research lies in the use of a more robust measure of human activities and their association with fire occurrence. This is also the first study in Zimbabwe which incorporates anthropogenic factors in modelling fire occurrence at a national scale.

The Normalized Difference Vegetation Index (NDVI), applied as a proxy for biomass, and an indicator of the fuel amount had low predictive power (2.6%). This finding is consistent with previous studies which indicated a lack of linear relationship between NDVI and fire occurrence in most ecoregions (Zhang et al., 2017). Research by Mishra et al., 2023 in Nepal, also highlighted that vegetation-related predictor variables had a lower contribution to fire occurrence. In a study by Guo, et al., 2017, vegetation which had a positive influence on fire occurrence gives an indication of the available fuel for fire ignition.

Based on the Maxent probability modelling, the study findings show that the central, eastern and northern regions of Zimbabwe had a very high risk of fire occurrence. The northern and central regions of the study area are characterized by resettlement areas which are associated with burning activities (Mupfiga *et al.*, 2022). This region of high likelihood of fire occurrence also coincides with tobacco-producing farming areas where timber from the miombo woodlands is used for tobacco curing (Zinyowera, Ndagurwa, and Muvengwi, Justice, 2021). The southern region and western parts, characterized by protected areas such as Gonarezhou and Hwange National Parks, respectively had a very low fire risk. Although these areas are characterized by high temperatures and high biomass content, protected areas are also associated with strict fire management strategies which minimize fire ignition as observed in the study. (Guo *et al.*, 2017).

The study findings contribute to the improved understanding of fire patterns and the drivers of fire occurrence. This valuable information assists fire managers and communities in decision-making related to fire management strategies. For sustainable fire management, the spatially varying fire risk zoning may result in the development of fire management strategies which are specific to local areas.

Although Maxent is a valuable model for predicting the occurrence of phenomena using presence-only data, the performance of Maxent may be limited by the difficulties associated with defining true/false fire during model fitting. This is because fires do not always occur in every fire-prone area. This, therefore, implies that there are chances of classifying highly vulnerable areas as characterised by low vulnerability to fire occurrence if no fire is detected in areas of high vulnerability (Mishra *et al.*, 2023). Further studies should also assess the importance of predictor variables under varying conditions such as agroecological zones, seasons and vegetation types. Future studies should also compare the prediction capacity of Maxent to other presence only models.

5.4. Conclusion

Uncontrolled fires disturb vegetation and threaten biodiversity. This national-scale fire prediction study has unveiled the interaction between climatic, topographic, vegetation and anthropogenic variables to predict the potential fire vulnerability at a national scale in Zimbabwe using the maximum entropy method (Maxent). The model evaluation, with a good level of accuracy (AUC of 0.77), shows the utility of the Maxent model in predicting the probability of fire occurrence. The most important variables influencing the occurrence of vegetation fires in the study area included elevation, precipitation seasonality, temperature annual range and human footprint. The research findings are critical for understanding the major driving factors of vegetation fire occurrence in Zimbabwe and, hence, provide valuable information for the fire managers' decision-making. The availability of MODIS remotely sensed data at no cost enables cheap and highly accurate fire prediction. Additionally, mapping fire risk levels produces critical information for vegetation fire management in Zimbabwe. The identification of the key factors driving fire occurrence is important for the implementation of proactive strategies aimed at minimizing future fire incidents. Fire management authorities can, for example, allocate resources to 'very high hazard' zones. This study has unveiled the utility of remotely sensed fire data coupled with spatial modelling in the prediction of fire vulnerability and can be upscaled in other landscapes. The detrimental socioeconomic and environmental effects of fire occurrence can therefore be minimized.

5.5 Summary and link to the next chapter

This chapter has shown the utility of Maxent, a machine learning model, and historical satellite fire data to model vegetation fire occurrence and identify the major factors driving the occurrence of fires across Zimbabwe. Bioclimatic, topographic and anthropogenic variables were utilised as predictor variables in the Maxent model while the MODIS satellite-derived fire data was used as the dependent variables. The novelty of this study involves the inclusion of the *robust anthropogenic variable, the human footprint, in the model and generally the identification of major predictors of vegetation fire occurrence in Zimbabwe. The findings from the study revealed that elevation, temperature annual range, precipitation seasonality, and human footprint greatly influence the distribution of vegetation fires in the Zimbabwean landscape. Furthermore, the Maxent modelling resulted in the prediction and mapping of fire hazard zones across Zimbabwe based on the topographic, bioclimatic, vegetation and anthropogenic factors. The research results for this objective are critical for the development and implementation of fire management strategies in Zimbabwe. The next chapter of this thesis synthesises all the research results from the study objectives and makes conclusions based on the research results. Recommendations for further research are also made in the final chapter.*

CHAPTER 6: SPATIOTEMPORAL ANALYSIS OF VEGETATION FIRES USING SATELLITE DATA: A SYNTHESIS

6.1 Introduction and Synthesis

Fire occurrence is common in biomes such as the savanna and the Mediterranean and has been responsible for their structure (Semeraro *et al.*, 2019; Pereira *et al.*, 2021). The increased occurrence of uncontrolled fires threatens such ecosystems resulting in biodiversity loss, alien species invasion and bush encroachment (Molaudzi and Adelabu, 2019). The global climate change projections predict a doubling of the impacts of vegetation fires in fire-prone regions threatening several ecosystem services (Bowman *et al.*, 2017; Qiu *et al.*, 2023). Consequently, the occurrence of vegetation fires greatly threatens public health, economies and human life (Bin Hao *et al.*, 2022; Chen *et al.*, 2023).

Earth observation methods enable the low-cost analysis of large-scale spatiotemporal fire analysis (Graham, Dube and Mpakairi, 2023). For example, the MODIS sensor utilises the thermal and mid-infrared spectral bands in detecting fires. The effective monitoring of vegetation fires requires repetitive and synoptic measurements of fire locations, which is greatly offered by remote sensing methods. The utilisation of the satellite-derived fire data coupled with spatial autocorrelation methods enables the detection of spatiotemporal fire patterns across landscapes (Harris *et al.*, 2017).

6.2 Conclusions

The development of effective fire management strategies requires accurate, up-to-date and large-scale fire data and use of robust spatiotemporal analysis algorithms. This thesis was based on a retrospective analysis of spatiotemporal vegetation fire dynamics utilising the historical MODIS satellite fire data. The main essence of the research was to analyse the spatiotemporal dynamics of vegetation fires across Zimbabwe's landscape through the utilisation of spatial autocorrelation methods. The study also utilised machine learning methods, the Maxent model, to predict the spatial variation in the fire risk levels across Zimbabwe. The modelling in Maxent also assessed the contribution of topographical, bioclimatic, vegetation and anthropogenic factors towards vegetation fire occurrence in Zimbabwe. The key drivers of fire occurrence in Zimbabwe were identified from the analysis.

Based on the research findings for each objective, the study concluded that:

1. The impacts of vegetation fires on various ecosystems were assessed based on a systematic literature review utilising the PRISMA approach. The research findings from the systematic literature review revealed the utility of earth observation methods in analysing the impacts of vegetation fires on the flow of various ecosystem services. Specifically, vegetation indices such as NDVI and NBR were widely used in the reviewed literature to assess the vegetation condition before and after burning. The review also revealed that most studies were biased towards the Asian and American continents while Africa has been understudied. While the review showed that vegetation fires are a threat to grassland, forests, soil, wetlands and the atmosphere ecosystems, most studies were carried out in forest ecosystems.

2. Spatial autocorrelation methods, specifically the Getis-Ord (Gi*), applied on MODIS fire data are useful in detecting the spatial distribution of fire intensity hence identifying cold- and hotspots across Zimbabwe. The information generated by this study is useful for fire management in Zimbabwe. The fire management agencies in Zimbabwe, may utilize the available resources in high fire intensity areas for planning fire management activities appropriately. The results are important for fire management authorities for intervention measures before, during and after fire occurrence. The real-time monitoring of fire intensity, for example, may be useful in minimizing the damage by fire in various ecosystems.

3. The results for the third objective elucidated the utility of the spatial autocorrelation method, the emerging hotspot analysis, in mapping the spatiotemporal fire occurrence patterns in Zimbabwe. Using the MODIS satellite fire data, fire occurrence was observed to be seasonal, occurring mostly from April to October. The emerging hotspot analysis algorithm was successfully used for the detection of spatiotemporal patterns of fire occurrence. The research findings offer valuable information relevant to developing and implementing fire management strategies. The redefinition of the fire season from the analysis is imperative for the reconsideration of Zimbabwe's current fire season which may enhance fire management decision-making.

4. The research findings for the fourth objective unveiled the incorporation of climatic, anthropogenic, topographic and anthropogenic factors into predicting fire occurrence using the Maxent model with a good model accuracy (AUC=0.77). The fire risk model developed based on the Maxent model results together with the information about the key drivers is critical to fire management decision-making. For example, areas which are highly prone to fire occurrence can be identified and appropriate measures put in place.

6.3 Limitations, Recommendations and Future Possibilities

- This study was based on a retrospective analysis of spatiotemporal vegetation fire dynamics utilising the historical MODIS satellite fire data. The study revealed that the African continent has been understudied in terms of assessing the utilisation of remote sensing methods in detecting the impacts of fires on ecosystems and the flow of ecosystem services. Furthermore, the study unveiled the importance of spatial clustering in mapping the spatial clusters of fire occurrence in Zimbabwean landscapes. The MODIS daily active fire data offers an opportunity for monitoring fire occurrence across local, regional and global landscapes. Additionally, the capability of the MODIS sensor to measure the fire intensity in the form of fire radiative power (FRP) provides key information for fire monitoring. Overall, the combination of spatial clustering techniques and spatial modelling results in generation of important information for fire management decisions. While the MODIS data provides critical fire monitoring information, its coarse spatial resolution (1km) limits its accuracy for local applications. There was also limited incorporation of anthropogenic factors in the analysis. In this regard, the study therefore recommends the following for future research. While remote sensing allows for the analysis of spatial and temporal dynamics of fire occurrence, there is a need for further explanation which can be enhanced by incorporating the socio-economic factors. Remote sensing methods fail to detect the political, socioeconomic and cultural influence on fire occurrence. There is therefore need for further investigation based on approaches that integrate earth observation and field survey data to enhance the understanding of the spatiotemporal fire dynamics.

- While this thesis focused on analysing the spatiotemporal fire dynamics at the national scale, there is a need for local-scale future studies to better understand the factors governing fire occurrence. For instance, future studies should focus on understanding the drivers contributing to the occurrence of high-intensity fires observed in the Eastern highlands of Zimbabwe and the very high fire risk zones detected in the Mashonaland provinces. More spatially detailed studies will provide more useful information for local-scale fire management decision-making

- Due to the free availability of the MODIS fire occurrence data and the Maxent model, further research can explore the prediction of fire hazard zones at a smaller scale, for example, district of ecoregion level. This will provide finer-scale information which may be useful to the local fire management teams in their decisions for local fire management.

- New studies should focus beyond just the prediction of the spatial and temporal occurrence of vegetation fires and also assess the impacts of fires on ecosystem services within the predicted fire hazard zones.

REFERENCES

Adab, H. *et al.* (2018) 'Assessing fire hazard potential and its main drivers in Mazandaran province, Iran: a data-driven approach', *Environmental Monitoring and Assessment*, 190. Available at: https://doi.org/10.1007/s10661-018-7052-1.

Agata, H. and Konrad, T. (2014) 'Use of satellite data for monitoring fire events in Poland', in *Dig Int Geosci Remote Sens Symp (IGARSS)*. Institute of Electrical and Electronics Engineers Inc., pp. 828–831. Available at: https://doi.org/10.1109/IGARSS.2014.6946552.

Alamanos, A. *et al.* (2024) 'Representation of a Post-Fire Flash-Flood Event Combining Meteorological Simulations, Remote Sensing, and Hydraulic Modeling', *Land*, 13(1). Available at: https://doi.org/10.3390/land13010047.

Andela, N. and Van Der Werf, G.R. (2014) 'Recent trends in African fires driven by cropland expansion and El Niño to la Niña transition', *Nature Climate Change*, 4(9), pp. 791–795. Available at: https://doi.org/10.1038/nclimate2313.

Anselin, L. (1995) 'Local indicators of spatial association—LISA', *Geographical analysis*, 27(2), pp. 93–115.

Archibald, S., Nickless, A., *et al.* (2010) 'Methods to determine the impact of rainfall on fuels and burned area in southern Africa savannas', *International Journal of Wildland Fire*, 19, pp. 774–782. Available at: https://doi.org/10.1071/WF08207.

Archibald, S., Scholes, R., *et al.* (2010a) 'Southern African fire regimes as revealed by remote sensing', *International Journal of Wildland Fire*, 19, pp. 861–878. Available at: https://doi.org/10.1071/WF10008.

Archibald, S., Scholes, R., *et al.* (2010b) 'Southern African fire regimes as revealed by remote sensing', *International Journal of Wildland Fire*, 19, pp. 861–878. Available at: https://doi.org/10.1071/WF10008.

Argibay, D.S., Sparacino, J. and Espindola, G.M. (2020) 'A long-term assessment of fire regimes in a Brazilian ecotone between seasonally dry tropical forests and savannah', *Ecological Indicators*, 113. Available at: https://doi.org/10.1016/j.ecolind.2020.106151.

Armenteras, D. *et al.* (2017a) 'Changing patterns of fire occurrence in proximity to forest edges, roads and rivers between NW Amazonian countries', *Biogeosciences*, 14(11), pp. 2755–2765. Available at: https://doi.org/10.5194/bg-14-2755-2017.

Armenteras, D. *et al.* (2017b) 'Changing patterns of fire occurrence in proximity to forest edges, roads and rivers between NW Amazonian countries', *Biogeosciences*, 14(11), pp. 2755–2765. Available at: https://doi.org/10.5194/bg-14-2755-2017.

Armenteras, D., González, T.M. and Retana, J. (2013) 'Forest fragmentation and edge influence on fire occurrence and intensity under different management types in Amazon forests', *Biological Conservation*, 159, pp. 73–79. Available at: https://doi.org/10.1016/j.biocon.2012.10.026.

Barrera, de la *et al.* (2018) 'Megafires in Chile 2017: Monitoring multiscale environmental impacts of burned ecosystems', *Science of the Total Environment*, 637–638, pp. 1526–1536. Available at: https://doi.org/10.1016/j.scitotenv.2018.05.119.

Benali, A. *et al.* (2017) 'Bimodal fire regimes unveil a global-scale anthropogenic fingerprint', *Global Ecology and Biogeography*, 26(7), pp. 799–811.

Boubekraoui, H. *et al.* (2023) 'Spatio-temporal analysis and identification of deforestation hotspots in the Moroccan western Rif', *Trees, Forests and People*, 12. Available at: https://doi.org/10.1016/j.tfp.2023.100388.

Bowman, D.M.J.S. *et al.* (2017) 'Human exposure and sensitivity to globally extreme wildfire events', *Nature Ecology and Evolution*, 1(3). Available at: https://doi.org/10.1038/s41559-016-0058.

Brivio, P. *et al.* (2013) 'Techniques for spatio-temporal analysis of vegetation fires in the tropical belt of Africa', *Proc SPIE*, Proc. SPIE 2586, pp. 162–171. Available at: https://doi.org/10.1117/12.228619.

Brogan, D.J., Nelson, P.A. and MacDonald, L.H. (2017) 'Reconstructing extreme post-wildfire floods: a comparison of convective and mesoscale events', *Earth Surface Processes and Landforms*, 42(15), pp. 2505–2522. Available at: https://doi.org/10.1002/esp.4194.

Brotons, L. *et al.* (2013) 'How Fire History, Fire Suppression Practices and Climate Change Affect Wildfire Regimes in Mediterranean Landscapes', *PLOS ONE*, 8(5), p. e62392. Available at: https://doi.org/10.1371/journal.pone.0062392.

Chainey, S., Tompson, L. and Uhlig, S. (2008) 'The utility of hotspot mapping for predicting spatial patterns of crime', *Security journal*, 21, pp. 4–28.

Chen, C.Y. and Yang, Q.-H. (2018) 'Hotspot Analysis of the Spatial and Temporal Distribution of Fires', in *International Conference on Geographical Information Systems Theory, Applications and Management*. Available at: https://api.semanticscholar.org/CorpusID:14038846.

Chen, D. *et al.* (2023) 'Simulating spatio-temporal dynamics of surface PM2.5 emitted from Alaskan wildfires', *Science of The Total Environment*, 898, p. 165594. Available at: https://doi.org/10.1016/j.scitotenv.2023.165594.

Chen, F. *et al.* (2015) 'Modeling Forest Lightning Fire Occurrence in the Daxinganling Mountains of Northeastern China with MAXENT', *Forests*, 6(5), pp. 1422–1438. Available at: https://doi.org/10.3390/f6051422.

Chen, S. *et al.* (2022) 'Sources, characteristics and climate impact of light-absorbing aerosols over the Tibetan Plateau', *Earth-Science Reviews*, 232. Available at: https://doi.org/10.1016/j.earscirev.2022.104111.

Chu, T. and Guo, X. (2014) 'Remote Sensing Techniques in Monitoring Post-Fire Effects and Patterns of Forest Recovery in Boreal Forest Regions: A Review', *Remote Sensing*, 6(1), pp. 470–520. Available at: https://doi.org/10.3390/rs6010470.

Chuvieco, E. (2019) 'Global analysis of burned areas for climate assessment: Experiences from the Fire-CCI project', in *Dig Int Geosci Remote Sens Symp (IGARSS)*. Institute of Electrical and Electronics Engineers Inc., pp. 9950–9952. Available at: https://doi.org/10.1109/IGARSS.2019.8899046.

Cizungu, N.C. *et al.* (2021) 'Fire risk assessment, spatiotemporal clustering and hotspot analysis in the Luki biosphere reserve region, western DR Congo', *Trees, Forests and People*, 5, p. 100104. Available at: https://doi.org/10.1016/j.tfp.2021.100104.

Cobelo, I. *et al.* (2023) 'The impact of wildfires on air pollution and health across land use categories in Brazil over a 16-year period', *Environmental Research*, 224, p. 115522. Available at: https://doi.org/10.1016/j.envres.2023.115522.

Dormann, C.F. *et al.* (2013) 'Collinearity: a review of methods to deal with it and a simulation study evaluating their performance', *Ecography*, 36(1), pp. 27–46. Available at: https://doi.org/10.1111/j.1600-0587.2012.07348.x.

Drewa, P.B. (2003) 'Effects of fire season and intensity on Prosopis glandulosa Torr. var. glandulosa', *International Journal of Wildland Fire*, 12(2), pp. 147–157.

Dwyer, E. *et al.* (2000) 'Characterization of the spatio-temporal patterns of global fire activity using satellite imagery for the period April 1992 to March 1993', *Journal of Biogeography*, 27(1), pp. 57–69. Available at: https://doi.org/10.1046/j.1365-2699.2000.00339.x.

Emmerton, C.A. *et al.* (2020) 'Severe western Canadian wildfire affects water quality even at large basin scales', *Water Research*, 183, p. 116071. Available at: https://doi.org/10.1016/j.watres.2020.116071.

Eskandari, S., Miesel, J.R. and Pourghasemi, H.R. (2020) 'The temporal and spatial relationships between climatic parameters and fire occurrence in northeastern Iran', *Ecological Indicators*, 118, p. 106720.

Fick, S.E. and Hijmans, R.J. (2017) 'WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas', *International Journal of Climatology*, 37(12), pp. 4302–4315. Available at: https://doi.org/10.1002/joc.5086.

Filipponi, F. (2019) 'Exploitation of sentinel-2 time series to map burned areas at the national level: A case study on the 2017 italy wildfires', *Remote Sensing*, 11(6), p. 622.

Fitzgibbon, A., Pisut, D. and Fleisher, D. (2022) 'Evaluation of Maximum Entropy (Maxent) Machine Learning Model to Assess Relationships between Climate and Corn Suitability', *Land*, 11(9). Available at: https://doi.org/10.3390/land11091382.

Gambiza, J. *et al.* (2005) 'Fire behaviour in a semi-arid Baikiaea plurijuga savanna woodland on Kalahari sands in western Zimbabwe', *South African Journal of Science*, 101(5), pp. 239–244.

Getis, A. (2007) 'Reflections on spatial autocorrelation', *Regional Science and Urban Economics*, 37(4), pp. 491–496.

Getis, A. and Ord, J.K. (1992) 'The Analysis of Spatial Association by Use of Distance Statistics', *Geographical Analysis*, 24(3), pp. 189–206. Available at: https://doi.org/10.1111/j.1538-4632.1992.tb00261.x.

Giglio, L. *et al.* (2003) 'An Enhanced Contextual Fire Detection Algorithm for MODIS', *Remote Sensing of Environment*, 87(2), pp. 273–282. Available at: https://doi.org/10.1016/S0034-4257(03)00184-6.

Giglio, L., Csiszar, I. and Justice, C.O. (2006) 'Global distribution and seasonality of active fires as observed with the Terra and Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) sensors', *Journal of Geophysical Research: Biogeosciences*, 111(G2), pp. 1–12. Available at: https://doi.org/10.1029/2005JG000142.

Giglio, L., Randerson, J.T. and van der Werf, G.R. (2013) 'Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4)', *Journal of Geophysical Research: Biogeosciences*, 118(1), pp. 317–328. Available at: https://doi.org/10.1002/jgrg.20042.

Giglio, L., Schroeder, W. and Justice, C.O. (2018) 'MODIS Collection 6 Active Fire Product User's Guide Revision B'. NASA.

Gleim, E.R. *et al.* (2019) 'Frequent Prescribed Fires Can Reduce Risk of Tick-borne Diseases', *Scientific Reports*, 9(1). Available at: https://doi.org/10.1038/s41598-019-46377-4.

Global Forest Watch (2023) *Zimbabwe Deforestation Rates & Statistics | GFW*. Available at: https://globalforestwatch.org/dashboards/country/ZWE/?burnedAreaRanked=eyJoaWdobGlnaHRlZCI6ZmFsc2V9&category=fires&dashboardPrompts=eyJzaG93UHJvbXB0cyI6dHJ1ZSwicHJvbXB0c1ZpZXdlZCI6WyJkb3dubG9hZERhc2hib2FyZFN0YXRzIiwiZGFzaGJvYXJkQW5hbHlzZXMiLCJ3aWRnZXRTZXR0aW5ncyJdLCJzZXR0aW5ncyI6eyJzaG93UHJvbXB0cyI6dHJ1ZSwicHJvbXB0c1ZpZXdlZCI6WyJkb3dubG9hZERhc2hib2FyZFN0YXRzIiwiZGFzaGJvYXJkQW5hbHlzZXMiLCJ3aWRnZXRTZXR0aW5ncyJdLCJzZXR0aW5ncyI6eyJzaG93UHJvbXB0cyI6dHJ1ZSwicHJvbXB0c1ZpZXdlZCI6WyJkb3dubG9hZERhc2hib2FyZFN0YXRzIiwiZGFzaGJvYXJkQW5hbHlzZXMiXSwic2V0dGluZ3MiOnsic2hvd1Byb21wdHMiOnRydWUsInByb21wdHNWaWV3ZWQiOltdLCJzZXR0aW5ncyI6eyJvcGVuIjpmYWxzZSwic3RlcEluZGV4IjowLCJzdGVwc0tleSI6IiJ9LCJvcGVuIjp0cnVlLCJzdGVwc0tleSI6ImRvd25sb2FkRGFzaGJvYXJkU3RhdHMifSwib3BlbiI6dHJ1ZSwic3RlcEluZGV4IjowLCJzdGVwc0tleSI6IndpZGdldFNldHRpbmdzIn0sInN0ZXBzS2V5Ijoid2lkZ2V0U2V0dGluZ3MiLCJzdGVwSW5kZXgiOi0xLCJmb3JjZSI6dHJ1ZX0sIm9wZW4iOnRydWUsInN0ZXBzS2V5Ijoic2hhcmVXaWRnZXQifQ%3D%3D&location=WyJjb3VudHJ5IiwiWldFIl0%3D&map=eyJjZW50ZXIiOnsibGF0IjotMTkuMDMzNTgzNTkzNjY5NzUsImxuZyI6MjkuMTU5MDU5NTI1MDA1MDEzfSwiem9vbSI6NC44MTA2NDUwNTQ4NzQ0MjMsImNhbkJvdW5kIjpmYWxzZSwiZGF0YXNldHMiOlt7ImRhdGFzZXQiOiJwb2xpdGljYWwtYm91bmRhcmllcyIsImxheWVycyI6WyJkaXNwdXRlZC1wb2xpdGljYWwtYm91bmRhcmllcyIsInBvbGl0aWNhbC1ib3VuZGFyaWVzIl0sImJvdW5kYXJ5Ijp0cnVlLCJvcGFjaXR5IjoxLCJ2aXNpYmlsaXR5Ijp0cnVlfSx7ImRhdGFzZXQiOiJmaXJlLWFsZXJ0cy12aWlycyIsImxheWVycyI6WyJmaXJlLWFsZXJ0cy12aWlycyJdLCJvcGFjaXR5IjoxLCJ2aXNpYmlsaXR5Ijp0cnVlLCJwYXJhbXMiOnsidmlzaWJpbGl0eSI6dHJ1ZSwiYWRtX2xldmVsIjoiYWRtMCJ9LCJ0aW1lbGluZVBhcmFtcyI6eyJzdGFydERhdGVBYnNvbHV0ZSI6IjIwMjItMDctMjMiLCJlbmREYXRlQWJzb2x1dGUiOiIyMDIyLTEwLTIxIiwic3RhcnREYXRlIjoiMjAyMi0wNy0yMyIsImVuZERhdGUiOiIyMDIyLTEwLTIxIiwidHJpbUVuZERhdGUiOiIyMDIyLTEwLTIxIn19XX0%3D&showMap=true (Accessed: 21 October 2022).

Government of Zimbabwe (2007) *Environmental Management (Environmetal Impact Assessment and Ecosystems Protection) Regulations SI 7 of 2002*, *Statutory Instrument 7*.

Graham, E., Dube, T. and Mpakairi, K.S. (2023) 'Progress in the remote sensing of veld fire occurrence and detection: A review', *African Journal of Ecology*, n/a(n/a). Available at: https://doi.org/10.1111/aje.13147.

Guo, F. *et al.* (2017) 'Spatial modelling of fire drivers in urban-forest ecosystems in China', *Forests*, 8(6). Available at: https://doi.org/10.3390/f8060180.

Haines, A. *et al.* (2017) 'Short-lived climate pollutant mitigation and the Sustainable Development Goals', *Nature Climate Change*, 7. Available at: https://doi.org/10.1038/s41558-017-0012-x.

Han, J. *et al.* (2020) 'Mapping the intellectual structure of research on surgery with mixed reality: Bibliometric network analysis (2000–2019)', *Journal of Biomedical Informatics*, 109, p. 103516. Available at: https://doi.org/10.1016/j.jbi.2020.103516.

Hao, Bin *et al.* (2022) 'Long-Term Effects of Fire Severity and Climatic Factors on Post-Forest-Fire Vegetation Recovery', *Forests*, 13(6). Available at: https://doi.org/10.3390/f13060883.

Hao, B. *et al.* (2022) 'Long-Term Effects of Fire Severity and Climatic Factors on Post-Forest-Fire Vegetation Recovery', *Forests*, 13(6). Available at: https://doi.org/10.3390/f13060883.

Harris, N.L. *et al.* (2017) 'Using spatial statistics to identify emerging hot spots of forest loss', *Environmental Research Letters*, 12(2), p. 024012. Available at: https://doi.org/10.1088/1748-9326/aa5a2f.

Hartung, M. *et al.* (2021a) 'Tropical Dry Forest Resilience to Fire Depends on Fire Frequency and Climate', *Frontiers in Forests and Global Change*, 4. Available at: https://doi.org/10.3389/ffgc.2021.755104.

Hartung, M. *et al.* (2021b) 'Tropical Dry Forest Resilience to Fire Depends on Fire Frequency and Climate', *Frontiers in Forests and Global Change*, 4. Available at: https://doi.org/10.3389/ffgc.2021.755104.

He, W., Shirowzhan, S. and Pettit, C.J. (2022) 'GIS and Machine Learning for Analysing Influencing Factors of Bushfires Using 40-Year Spatio-Temporal Bushfire Data', *ISPRS International Journal of Geo-Information*, 11(6). Available at: https://doi.org/10.3390/ijgi11060336.

He, Y. *et al.* (2021) 'Forest landscape patterns shaped by interactions between wildfire and sudden oak death disease', *Forest Ecology and Management*, 486, p. 118987. Available at: https://doi.org/10.1016/j.foreco.2021.118987.

Herawati, H. *et al.* (2015) 'Tools for assessing the impacts of climate variability and change on wildfire regimes in forests', *Forests*, 6(5), pp. 1476–1499. Available at: https://doi.org/10.3390/f6051476.

Ichoku, C. *et al.* (2008) 'Global characterization of biomass-burning patterns using satellite measurements of fire radiative energy', *Remote Sensing of Environment*, 112(6), pp. 2950–2962. Available at: https://doi.org/10.1016/j.rse.2008.02.009.

Ivo, I.O. *et al.* (2020) 'Effect of fires on biophysical parameters, energy balance and evapotranspiration in a protected area in the Brazilian Cerrado', *Remote Sensing Applications: Society and Environment*, 19, p. 100342. Available at: https://doi.org/10.1016/j.rsase.2020.100342.

Jiang, D. *et al.* (2018) 'Mapping the Potential Global Codling Moth (Cydia pomonella L.) Distribution Based on a Machine Learning Method', *Scientific Reports*, 8. Available at: https://doi.org/10.1038/s41598-018-31478-3.

Justice, C.O. *et al.* (2011) 'MODIS-Derived Global Fire Products', in B. Ramachandran, C.O. Justice, and M.J. Abrams (eds) *Land Remote Sensing and Global Environmental Change: NASA's Earth Observing System and the Science of ASTER and MODIS*. New York, NY: Springer New York, pp. 661–679. Available at: https://doi.org/10.1007/978-1-4419-6749-7_29.

Keeley, J.E. (2009) 'Fire intensity, fire severity and burn severity: A brief review and suggested usage', *International Journal of Wildland Fire*, 18(1), pp. 116–126. Available at: https://doi.org/10.1071/WF07049.

Kendall, M. and Gibbons, J.D. (1990) *Rank Correlation Methods.* 5th edn. London: Edward Arnold.

Kganyago, M. and Shikwambana, L. (2019) 'Assessing spatio-temporal variability of wildfires and their impact on sub-Saharan ecosystems and air quality using multisource remotely sensed data and trend analysis', *Sustainability (Switzerland)*, 11(23). Available at: https://doi.org/10.3390/su11236811.

Kganyago, M. and Shikwambana, L. (2020) 'Assessment of the characteristics of recent major wildfires in the USA, Australia and Brazil in 2018–2019 using multi-source satellite products', *Remote Sensing*, 12(11), p. 1803.

Kowe, P. *et al.* (2019) 'Exploring the spatial patterns of vegetation fragmentation using local spatial autocorrelation indices', *Journal of Applied Remote Sensing*, 13(2), pp. 024523–024523.

Kowe, P. *et al.* (2020) 'A quantitative framework for analysing long term spatial clustering and vegetation fragmentation in an urban landscape using multi-temporal landsat data', *International Journal of Applied Earth Observation and Geoinformation*, 88, p. 102057.

Kugbe, J.X. *et al.* (2012) 'Annual vegetation burns across the northern savanna region of Ghana: period of occurrence, area burns, nutrient losses and emissions', *Nutrient Cycling in Agroecosystems*, 93(3), pp. 265–284. Available at: https://doi.org/10.1007/s10705-012-9514-0.

Kurbanov, E. *et al.* (2022) 'Remote Sensing of Forest Burnt Area, Burn Severity, and Post-Fire Recovery: A Review', *Remote Sensing*, 14(19). Available at: https://doi.org/10.3390/rs14194714.

Lentile, L.B. *et al.* (2006) 'Remote sensing techniques to assess active fire characteristics and post-fire effects', *International Journal of Wildland Fire*, 15(3), pp. 319–345. Available at: https://doi.org/10.1071/WF05097.

Li, F. *et al.* (2018) 'Comparison of fire radiative power estimates from VIIRS and MODIS observations', *Journal of Geophysical Research: Atmospheres*, 123(9), pp. 4545–4563.

Lissovsky, A. and Dudov, S. (2021) 'Species-Distribution Modeling: Advantages and Limitations of Its Application. 2. MaxEnt', *Biology Bulletin Reviews*, 11, pp. 265–275. Available at: https://doi.org/10.1134/S2079086421030087.

Liu, X. *et al.* (2012) 'GIS-based multi-dimensional risk assessment of the grassland fire in northern China', *Natural Hazards*, 64(1), pp. 381–395. Available at: https://doi.org/10.1007/s11069-012-0244-z.

Liu, Y. *et al.* (2018) 'Synchronous satellite wide area monitoring for overhead transmission line wildfire and tower location', *Dianwang Jishu/Power System Technology*, 42(4), pp. 1322–1327. Available at: https://doi.org/10.13335/j.1000-3673.pst.2017.1812.

Makhaya, Z., Odindi, J. and Mutanga, O. (2022) 'The influence of bioclimatic and topographic variables on grassland fire occurrence within an urbanized landscape', *Scientific African*, 15, p. e01127. Available at: https://doi.org/10.1016/j.sciaf.2022.e01127.

Makori, D.M. *et al.* (2022) 'The use of multisource spatial data for determining the proliferation of stingless bees in Kenya', *GIScience & Remote Sensing*, 59(1), pp. 648–669. Available at: https://doi.org/10.1080/15481603.2022.2049536.

Manatsa, D. *et al.* (2020) *Report on Revised Agroecological Zones of Zimbabwe (in press)*. Government of Zimbabwe.

Mancilla-Ruiz, D. *et al.* (2021) ‘The Effects of a Megafire on Ecosystem Services and the Pace of Landscape Recovery’, *Land*, 10(12). Available at: https://doi.org/10.3390/land10121388.

Mann, H.B. (1945) ‘Non-Parametric Test against Trend’, *Econometrica*, 13, pp. 245–259. Available at: http://dx.doi.org/10.2307/1907187.

Maponga, R., Ahmed, F. and Mushore, T.D. (2018) ‘Remote sensing-based assessment of veld fire trends in multiple interwoven land tenure systems in Zimbabwe’, *Geocarto International*, 33(6), pp. 612–626. Available at: https://doi.org/10.1080/10106049.2017.1289557.

Marambanyika, T. *et al.* (2021) ‘Local Perceptions on the Impact of Drought on Wetland Ecosystem Services and Associated Household Livelihood Benefits: The Case of the Driefontein Ramsar Site in Zimbabwe’, *Land*, 10(6). Available at: https://doi.org/10.3390/land10060587.

Marsha, A.L. and Larkin, N.K. (2022) ‘Evaluating Satellite Fire Detection Products and an Ensemble Approach for Estimating Burned Area in the United States’, *Fire*, 5(5). Available at: https://doi.org/10.3390/fire5050147.

Martin, D. (2018) ‘Linking fire and the United Nations Sustainable Development Goals’, *Science of The Total Environment*, 662. Available at: https://doi.org/10.1016/j.scitotenv.2018.12.393.

Matz, C.J. *et al.* (2020) ‘Health impact analysis of PM2.5 from wildfire smoke in Canada (2013–2015, 2017–2018)’, *Science of The Total Environment*, 725, p. 138506. Available at: https://doi.org/10.1016/j.scitotenv.2020.138506.

Mbanze, A. *et al.* (2013) ‘Assessment of causes that contribute to the occurrence of plantations forests fires in Niassa Province, North of Mozambique’, *African Journal of Agricultural Research*, 8, pp. 5684–5691. Available at: https://doi.org/10.5897/AJAR12.1969.

Michael, Y. *et al.* (2018) ‘Economic Assessment of Fire Damage to Urban Forest in the Wildland–Urban Interface Using Planet Satellites Constellation Images’, *Remote Sensing*, 10(9). Available at: https://doi.org/10.3390/rs10091479.

Millennium Ecosystem Assessment (2005) *ECOSYSTEMS AND HUMAN WELL-BEING: WETLANDS AND WATER Synthesis*. Washington, DC, USA: World Resources Institut.

Mishra, B. *et al.* (2023) ‘Forest fire pattern and vulnerability mapping using deep learning in Nepal’, *Fire Ecology*, 19(1), p. 3. Available at: https://doi.org/10.1186/s42408-022-00162-3.

Mlambo, L. *et al.* (2024) ‘The influence of biophysical characteristics on elephant space use in an African savanna’, *Ecological Informatics*, 82, p. 102724. Available at: https://doi.org/10.1016/j.ecoinf.2024.102724.

Molaudzi, O. and Adelabu, S. (2019) ‘Review of the use of remote sensing for monitoring wildfire risk conditions to support fire risk assessment in protected areas’, *South African Journal of Geomatics*, 7, p. 222. Available at: https://doi.org/10.4314/sajg.v7i3.2.

Montorio, R. *et al.* (2020) ‘Unitemporal approach to fire severity mapping using multispectral synthetic databases and Random Forests’, *Remote Sensing of Environment*, 249. Available at: https://doi.org/10.1016/j.rse.2020.112025.

Morisette, J.T. *et al.* (2005) ‘Validation of the MODIS active fire product over Southern Africa with ASTER data’, *International Journal of Remote Sensing*, 26(19), pp. 4239–4264. Available at: https://doi.org/10.1080/01431160500113526.

Moyo, S. *et al.* (2019) ‘Spatial distribution and abundance of the African baobab (Adansonia digitata) in Zimbabwe’, *Transactions of the Royal Society of South Africa*, 74(3), pp. 213–218. Available at: https://doi.org/10.1080/0035919X.2019.1650309.

Mpakairi, K. *et al.* (2018) ‘Distribution of wildland fires and possible hotspots for the Zimbabwean component of Kavango-Zambezi Transfrontier Conservation Area’, *South African Geographical Journal*, 101, pp. 1–11. Available at: https://doi.org/10.1080/03736245.2018.1541023.

Mupangwa, W., Walker, S. and Twomlow, S. (2011) ‘Start, end and dry spells of the growing season in semi-arid southern Zimbabwe’, *Journal of Arid Environments*, 75(11), pp. 1097–1104.

Mupfiga, U.N. *et al.* (2022) ‘Spatial Clustering of Vegetation Fire Intensity Using MODIS Satellite Data’, *Atmosphere*, 13(12). Available at: https://doi.org/10.3390/atmos13121972.

Mupfiga, U.N., Mutanga, O. and Dube, T. (2024) ‘National-scale spatiotemporal patterns of vegetation fire occurrences using MODIS satellite data’, *PLOS ONE*, 19(3), p. e0297309. Available at: https://doi.org/10.1371/journal.pone.0297309.

Mushore, T.D. *et al.* (2021) ‘Climate Change Adaptation and Mitigation Strategies for Small Holder Farmers: A Case of Nyanga District in Zimbabwe’, *Frontiers in Climate*, 3, p. 676495. Available at: https://doi.org/10.3389/fclim.2021.676495.

Niccoli, F. *et al.* (2023) ‘Fire Affects Tree Growth, Water Use Efficiency and Carbon Sequestration Ecosystem Service of Pinus nigra Arnold: A Combined Satellite and Ground-Based Study in Central Italy’, *Forests*, 14(10). Available at: https://doi.org/10.3390/f14102033.

Nieman, W.A., van Wilgen, B. and Leslie, A. (2021) ‘A review of fire management practices in African savanna-protected areas’, *KOEDOE - African Protected Area Conservation and Science*, 63. Available at: https://doi.org/10.4102/koedoe.v63i1.1655.

Nowell, H.K. *et al.* (2018) ‘A New Picture of Fire Extent, Variability, and Drought Interaction in Prescribed Fire Landscapes: Insights From Florida Government Records’, *Geophysical Research Letters*, 45(15), pp. 7874–7884. Available at: https://doi.org/10.1029/2018GL078679.

Nyakudanga, J. (2022) ‘Zimbabwe’s forestry industry fire season calendar set to change’, 15 June. Available at: https://www.zimbabweforestrymagazine.com.

Nyamadzawo, G. *et al.* (2013) ‘Understanding the causes, socio-economic and environmental impacts, and management of veld fires in tropical Zimbabwe’, *Fire Science reviews (SpringerOpen)*, 2.2. Available at: https://doi.org/10.1186/2193-0414-2-2.

Odebiri, O. *et al.* (2020) ‘Estimating soil organic carbon stocks under commercial forestry using topo-climate variables in KwaZulu-Natal, South Africa’, *South African Journal of Science*, 116. Available at: https://doi.org/10.17159/sajs.2020/6339.

Oliveira, U. *et al.* (2021) ‘Modeling fuel loads dynamics and fire spread probability in the Brazilian Cerrado’, *Forest Ecology and Management*, 482. Available at: https://doi.org/10.1016/j.foreco.2020.118889.

Olson, D.M. *et al.* (2001) ‘Terrestrial Ecoregions of the World: A New Map of Life on Earth: A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity’, *BioScience*, 51(11), pp. 933–938. Available at: https://doi.org/10.1641/0006-3568(2001)051[0933:TEOTWA]2.0.CO;2.

Page, M.J. *et al.* (2021) 'The PRISMA 2020 statement: an updated guideline for reporting systematic reviews', *BMJ*, 372, p. n71. Available at: https://doi.org/10.1136/bmj.n71.

Pandit, K., Dashti, H., Hudak, A.T., *et al.* (2021) 'Understanding the effect of fire on vegetation composition and gross primary production in a semi-arid shrubland ecosystem using the Ecosystem Demography (EDv2.2) model', *Biogeosciences*, 18(6), pp. 2027–2045. Available at: https://doi.org/10.5194/bg-18-2027-2021.

Pandit, K., Dashti, H., Hudak, A. T., *et al.* (2021) 'Understanding the effect of fire on vegetation composition and gross primary production in a semi-arid shrubland ecosystem using the Ecosystem Demography (EDv2.2) model', *Biogeosciences*, 18(6), pp. 2027–2045. Available at: https://doi.org/10.5194/bg-18-2027-2021.

Pasha, S.V. and Reddy, C.S. (2022) 'Trends in Hotspots of Alien Plant Invasion in Kachchh Biosphere Reserve, India Using Spatial Pattern Mining Tool', *Journal of the Indian Society of Remote Sensing* [Preprint]. Available at: https://doi.org/10.1007/s12524-022-01637-1.

Paula, A. *et al.* (2023) 'Could spaceborne multispectral data be used as SMART proxies' indicators for agroforestry ecosystem services? - A systematic review', *ECOLOGICAL INDICATORS*, 156. Available at: https://doi.org/10.1016/j.ecolind.2023.111162.

Peeters, A. *et al.* (2015) 'Getis–Ord's hot- and cold-spot statistics as a basis for multivariate spatial clustering of orchard tree data', *Computers and Electronics in Agriculture*, 111, pp. 140–150. Available at: https://doi.org/10.1016/j.compag.2014.12.011.

Percival, J.E.H. *et al.* (2024) 'Non fire-adapted dry forest of Northwestern Madagascar: Escalating and devastating trends revealed by Landsat timeseries and GEDI lidar data', *PLOS ONE*, 19(2), p. e0290203. Available at: https://doi.org/10.1371/journal.pone.0290203.

Pereira, P. *et al.* (2021) 'Short-term effect of wildfires and prescribed fires on ecosystem services', *Current Opinion in Environmental Science & Health*, 22, p. 100266. Available at: https://doi.org/10.1016/j.coesh.2021.100266.

Pérez-Cabello, F., Montorio, R. and Alves, D.B. (2021) 'Remote sensing techniques to assess post-fire vegetation recovery', *Current Opinion in Environmental Science & Health*, 21, p. 100251. Available at: https://doi.org/10.1016/j.coesh.2021.100251.

Perianes-Rodriguez, A., Waltman, L. and van Eck, N.J. (2016) 'Constructing bibliometric networks: A comparison between full and fractional counting', *Journal of Informetrics*, 10(4), pp. 1178–1195. Available at: https://doi.org/10.1016/j.joi.2016.10.006.

Phillips, S.J., Anderson, R.P. and Schapire, R.E. (2006) 'Maximum entropy modeling of species geographic distributions', *Ecological Modelling*, 190(3), pp. 231–259. Available at: https://doi.org/10.1016/j.ecolmodel.2005.03.026.

Piao, Y. *et al.* (2022) 'Forest fire susceptibility assessment using google earth engine in Gangwon-do, Republic of Korea', *Geomatics, Natural Hazards and Risk*, 13(1), pp. 432–450. Available at: https://doi.org/10.1080/19475705.2022.2030808.

Piralilou, S.T. *et al.* (2022) 'A Google Earth Engine Approach for Wildfire Susceptibility Prediction Fusion with Remote Sensing Data of Different Spatial Resolutions', *Remote Sensing*, 14(3). Available at: https://doi.org/10.3390/rs14030672.

Pricope, N.G. *et al.* (2015) 'Spatio-temporal analysis of vegetation dynamics in relation to shifting inundation and fire regimes: Disentangling environmental variability from land management decisions in a Southern African transboundary watershed', *Land*, 4(3), pp. 627–655. Available at: https://doi.org/10.3390/land4030627.

Qiu, L. *et al.* (2023) 'Higher burn severity stimulates postfire vegetation and carbon recovery in California', *Agricultural and Forest Meteorology*, 342, p. 109750. Available at: https://doi.org/10.1016/j.agrformet.2023.109750.

Rahmati, O., Pourghasemi, H.R. and Melesse, A.M. (2016) 'Application of GIS-based data driven random forest and maximum entropy models for groundwater potential mapping: A case study at Mehran Region, Iran', *CATENA*, 137, pp. 360–372. Available at: https://doi.org/10.1016/j.catena.2015.10.010.

Ratajczak, Z. *et al.* (2016) 'Assessing the Potential for Transitions from Tallgrass Prairie to Woodlands: Are We Operating Beyond Critical Fire Thresholds?', *Rangeland Ecology & Management*, 69(4), pp. 280–287. Available at: https://doi.org/10.1016/j.rama.2016.03.004.

Reddy, C.S. *et al.* (2016) 'Conservation priorities of forest ecosystems: Evaluation of deforestation and degradation hotspots using geospatial techniques', *Ecological Engineering*, 91, pp. 333–342. Available at: https://doi.org/10.1016/j.ecoleng.2016.03.007.

Reddy, C.S. *et al.* (2019) 'Identification and characterization of spatio-temporal hotspots of forest fires in South Asia', *Environmental Monitoring and Assessment*, 191. Available at: https://doi.org/10.1007/s10661-019-7695-6.

Reddy, C.S. *et al.* (2020) 'Characterizing Vegetation Fire dynamics in Myanmar and South Asian Countries', *Journal of the Indian Society of Remote Sensing*, 48(12), pp. 1829–1843. Available at: https://doi.org/10.1007/s12524-020-01205-5.

Ribeiro-Kumara, C. *et al.* (2020) 'How do forest fires affect soil greenhouse gas emissions in upland boreal forests? A review', *Environmental Research*, 184, p. 109328. Available at: https://doi.org/10.1016/j.envres.2020.109328.

Roberts, G. and Wooster, M.J. (2021) 'Global impact of landscape fire emissions on surface level PM2. 5 concentrations, air quality exposure and population mortality', *Atmospheric Environment*, 252, p. 118210.

Rouget, M. *et al.* (2016) 'A spatial and temporal assessment of fire regimes on different vegetation types using MODIS burnt area products', *Bothalia-African Biodiversity & Conservation*, 46(2), pp. 1–9.

Royston, J.P. (1982) 'Algorithm AS 181: The W Test for Normality', *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 31(2), pp. 176–180. Available at: https://doi.org/10.2307/2347986.

Ruecker, G., Leimbach, D. and Tiemann, J. (2021) 'Estimation of byram's fire intensity and rate of spread from spaceborne remote sensing data in a savanna landscape', *Fire*, 4(4). Available at: https://doi.org/10.3390/fire4040065.

Ryan, C. and Williams, M. (2010) 'How does fire intensity and frequency affect miombo woodland tree populations and biomass?', *Ecological Applications*, 21, pp. 48–60. Available at: https://doi.org/10.1890/09-1489.

Said, S.N.B.M., Zahran, E.-S.M.M. and Shams, S. (2017) 'Forest fire risk assessment using hotspot analysis in GIS', *The Open Civil Engineering Journal*, 11(1).

Sankey, J.B. *et al.* (2017) ‘Climate, wildfire, and erosion ensemble foretells more sediment in western USA watersheds’, *Geophysical Research Letters*, 44(17), pp. 8884–8892. Available at: https://doi.org/10.1002/2017GL073979.

Scholes, R.J. and Archer, S.R. (1997) ‘Tree-Grass Interactions in Savannas’, *Annual Review of Ecology and Systematics*, 28(1), pp. 517–544. Available at: https://doi.org/10.1146/annurev.ecolsys.28.1.517.

Semeraro, T. *et al.* (2019) ‘Application of vegetation index time series to value fire effect on primary production in a Southern European rare wetland’, *Ecological Engineering*, 134, pp. 9–17. Available at: https://doi.org/10.1016/j.ecoleng.2019.04.004.

Shekede, M. *et al.* (2024) ‘A two-decade analysis of the spatial and temporal variations in burned areas across Zimbabwe’, *PLOS Climate*, 3, p. e0000201. Available at: https://doi.org/10.1371/journal.pclm.0000201.

Shekede, M.D., Gwitira, I. and Mamvura, C. (2021) ‘Spatial modelling of wildfire hotspots and their key drivers across districts of Zimbabwe, Southern Africa’, *Geocarto International*, 36(8), pp. 874–887. Available at: https://doi.org/10.1080/10106049.2019.1629642.

Shekede, M.D., Mupandira, I. and Gwitira, I. (2021) ‘Spatio-temporal clustering of active wildfire pixels over a 19-year period in a southern African savanna ecosystem of Zimbabwe’, *South African Geographical Journal*, 103(3), pp. 283–302. Available at: https://doi.org/10.1080/03736245.2020.1786442.

Shoko, C., Masocha, M. and Dube, T. (2015) ‘A new potential method to estimate abundance of small game species’, *African journal of ecology*, 53(4), pp. 406–412.

Simler-Williamson, A.B. *et al.* (2021) ‘Wildfire alters the disturbance impacts of an emerging forest disease via changes to host occurrence and demographic structure’, *Journal of Ecology*, 109(2), pp. 676–691. Available at: https://doi.org/10.1111/1365-2745.13495.

Singh, M., Sood, S. and Collins, C.M. (2022) ‘Fire Dynamics of the Bolivian Amazon’, *Land*, 11(9). Available at: https://doi.org/10.3390/land11091436.

Singh, M. and Yan, S. (2021) ‘Spatial–temporal variations in deforestation hotspots in Sumatra and Kalimantan from 2001–2018’, *Ecology and Evolution*, 11(12), pp. 7302–7314. Available at: https://doi.org/10.1002/ece3.7562.

Soro, T.D. *et al.* (2021) ‘Identified main fire hotspots and seasons in Côte d’Ivoire (West Africa) using MODIS fire data’, *South African Journal of Science*, 117(1–2). Available at: https://doi.org/10.17159/SAJS.2021/7659.

Souto-Oliveira, C.E. *et al.* (2023) ‘Impact of extreme wildfires from the Brazilian Forests and sugarcane burning on the air quality of the biggest megacity on South America’, *Science of The Total Environment*, 888, p. 163439. Available at: https://doi.org/10.1016/j.scitotenv.2023.163439.

Srivastava, A. *et al.* (2023) ‘FCCC: Forest Cover Change Calculator User Interface for Identifying Fire Incidents in Forest Region using Satellite Data’, *International Journal of Advanced Computer Science and Applications*, 14. Available at: https://doi.org/10.14569/IJACSA.2023.01407103.

Stavi, I. (2019) ‘Wildfires in Grasslands and Shrublands: A Review of Impacts on Vegetation, Soil, Hydrology, and Geomorphology’, *Water*, 11(5). Available at: https://doi.org/10.3390/w11051042.

Stefanidis, S. *et al.* (2022) ‘Wildfire Effects on Soil Erosion Dynamics: The Case of 2021 Megafires in Greece’, *Agriculture & Forestry*, 68(2), pp. 49–63.

Stefanidis, Stefanos, Alexandridis, V. and Mallinis, G. (2022) ‘A cloud-based mapping approach for assessing spatiotemporal changes in erosion dynamics due to biotic and abiotic disturbances in a Mediterranean Peri-Urban forest’, *CATENA*, 218, p. 106564. Available at: https://doi.org/10.1016/j.catena.2022.106564.

Stefanidis, S., Alexandridis, V. and Mallinis, G. (2022) ‘A cloud-based mapping approach for assessing spatiotemporal changes in erosion dynamics due to biotic and abiotic disturbances in a Mediterranean Peri-Urban forest’, *Catena*, 218. Available at: https://doi.org/10.1016/j.catena.2022.106564.

Stephens, C.W., Collins, B.M. and Rogan, J. (2020) ‘Land ownership impacts post-wildfire forest regeneration in Sierra Nevada mixed-conifer forests’, *Forest Ecology and Management*, 468, p. 118161. Available at: https://doi.org/10.1016/j.foreco.2020.118161.

Strydom, S. and Savage, M.J. (2016) ‘A spatio-temporal analysis of fires in South Africa’, *South African Journal of Science*, 112(11–12). Available at: https://doi.org/10.17159/sajs.2016/20150489.

Sudhakar Reddy, C. *et al.* (2015) ‘Geospatial characterization of deforestation, fragmentation and forest fires in Telangana state, India: conservation perspective’, *Environmental Monitoring and Assessment*, 187(7), p. 455. Available at: https://doi.org/10.1007/s10661-015-4673-5.

Sutomo and van Etten, E.J.B. (2023) ‘Fire Impacts and Dynamics of Seasonally Dry Tropical Forest of East Java, Indonesia’, *Forests*, 14(1). Available at: https://doi.org/10.3390/f14010106.

Szpakowski, D.M. and Jensen, J.L.R. (2019) ‘A Review of the Applications of Remote Sensing in Fire Ecology’, *Remote Sensing*, 11(22). Available at: https://doi.org/10.3390/rs11222638.

Tabarej, M.S. and Minz, S. (2022) ‘Spatio-temporal changes pattern in the hotspot’s footprint: a case study of confirmed, recovered and deceased cases of Covid-19 in India’, *Spatial Information Research*, 30(4), pp. 527–538. Available at: https://doi.org/10.1007/s41324-022-00443-8.

Tran, B.N. *et al.* (2020) ‘High-severity wildfires in temperate Australian forests have increased in extent and aggregation in recent decades’, *PLoS ONE*, 15(11 November). Available at: https://doi.org/10.1371/journal.pone.0242484.

Tselka, I. *et al.* (2021) ‘Assessing Post-Fire Effects on Soil Loss Combining Burn Severity and Advanced Erosion Modeling in Malesina, Central Greece’, *Remote Sensing*, 13(24). Available at: https://doi.org/10.3390/rs13245160.

Vadrevu, K. and Lasko, K. (2018) ‘Intercomparison of MODIS AQUA and VIIRS I-Band Fires and Emissions in an Agricultural Landscape—Implications for Air Pollution Research’, *Remote Sensing*, 10(7). Available at: https://doi.org/10.3390/rs10070978.

Vadrevu, K.P. *et al.* (2012) ‘Hotspot analysis of vegetation fires and intensity in the Indian region’, *IEEE Journal of selected topics in applied Earth Observations and Remote Sensing*, 6(1), pp. 224–238.

Venter, O. *et al.* (2016) ‘Global terrestrial Human Footprint maps for 1993 and 2009’, *Scientific Data*, 3(1), p. 160067. Available at: https://doi.org/10.1038/sdata.2016.67.

Vigna, I. *et al.* (2021) 'Application of the Socio-Ecological System Framework to Forest Fire Risk Management: A Systematic Literature Review', *Sustainability*, 13(4). Available at: https://doi.org/10.3390/su13042121.

Visner, M., Shirowzhan, S. and Pettit, C. (2021) 'Spatial analysis, interactive visualisation and gis-based dashboard for monitoring spatio-temporal changes of hotspots of bushfires over 100 years in New South Wales, Australia', *Buildings*, 11(2), pp. 1–27. Available at: https://doi.org/10.3390/buildings11020037.

Wall, S.A., Roering, J.J. and Rengers, F.K. (2020) 'Runoff-initiated post-fire debris flow Western Cascades, Oregon', *Landslides*, 17(7), pp. 1649–1661. Available at: https://doi.org/10.1007/s10346-020-01376-9.

Waltman, L., van Eck, N.J. and Noyons, E.C.M. (2010) 'A unified approach to mapping and clustering of bibliometric networks', *Journal of Informetrics*, 4(4), pp. 629–635. Available at: https://doi.org/10.1016/j.joi.2010.07.002.

Wang, W. *et al.* (2023) 'Seasonal differences in the spatial patterns of wildfire drivers and susceptibility in the southwest mountains of China', *Science of the Total Environment*, 869. Available at: https://doi.org/10.1016/j.scitotenv.2023.161782.

Wasserman, T.N. and Mueller, S.E. (2023) 'Climate influences on future fire severity: a synthesis of climate-fire interactions and impacts on fire regimes, high-severity fire, and forests in the western United States', *Fire Ecology*, 19(1). Available at: https://doi.org/10.1186/s42408-023-00200-8.

Wei, M. *et al.* (2021) 'Monitoring Landsat Based Burned Area as an Indicator of Sustainable Development Goals', *Earth's Future*, 9(6), p. e2020EF001960. Available at: https://doi.org/10.1029/2020EF001960.

Wei, Y. *et al.* (2019) 'Designing operationally relevant daily large fire containment strategies using risk assessment results', *Forests*, 10(4). Available at: https://doi.org/10.3390/f10040311.

Wooster, M.J. *et al.* (2021) 'Satellite remote sensing of active fires: History and current status, applications and future requirements', *Remote Sensing of Environment*, 267, p. 112694.

Wu, C. (2022) 'Certainty Factor Analyses and Spatiotemporal Characteristics of Landslide Evolution: Case Studies in the Chishan River Watershed in Taiwan', *ISPRS International Journal of Geo-Information*, 11(7). Available at: https://doi.org/10.3390/ijgi11070382.

Wubuli, A. *et al.* (2015) 'Socio-demographic predictors and distribution of pulmonary tuberculosis (TB) in Xinjiang, China: a spatial analysis', *PloS one*, 10(12), p. e0144010.

Ying, L. *et al.* (2019) 'Wildfire Detection Probability of MODIS Fire Products under the Constraint of Environmental Factors: A Study Based on Confirmed Ground Wildfire Records', *Remote Sensing*, 11(24). Available at: https://doi.org/10.3390/rs11243031.

Younas, M. *et al.* (2022) 'Assessing Impacts of Land Subsidence in Victoria County, Texas, Using Geospatial Analysis', *Land*, 11(12). Available at: https://doi.org/10.3390/land11122211.

Zhang, X. and Kondragunta, S. (2008) 'Temporal and spatial variability in biomass burned areas across the USA derived from the GOES fire product', *Remote Sensing of Environment*, 112(6), pp. 2886–2897. Available at: https://doi.org/10.1016/j.rse.2008.02.006.

Zhang, Y., He, H.S. and Yang, J. (2008) ‘The wildland-urban interface dynamics in the southeastern U.S. from 1990 to 2000’, *Landscape and Urban Planning*, 85(3–4), pp. 155–162. Available at: https://doi.org/10.1016/j.landurbplan.2007.11.007.

Zhang, Y., Lim, S. and Sharples, J.J. (2017) ‘Wildfire occurrence patterns in ecoregions of New South Wales and Australian Capital Territory, Australia’, *Natural Hazards*, 87(1), pp. 415–435. Available at: https://doi.org/10.1007/s11069-017-2770-1.

Zimbabwe Climate, Weather By Month, Average Temperature - Weather Spark (no date). Available at: https://weatherspark.com/countries/ZW (Accessed: 21 October 2022).

Zinyowera, N., Ndagurwa, Hilton G. T, and Muvengwi, Justice (2021) ‘Changes in miombo woody assemblage along a disturbance gradient in a smallholder tobacco production communal land, northeast Zimbabwe’, *Forest Ecology and Management*, 502. Available at: https://doi.org/10.1016/j.foreco.2021.119718.

Zúñiga-Vásquez, J.M. *et al.* (2017) ‘Spatial modeling of forest fires in Mexico: An integration of two data sources’, *Bosque*, 38(3), pp. 563–574. Available at: https://doi.org/10.4067/S0717-92002017000300014.