BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE AND ENGINEERING

DISASTER RISK REDUCTION DEPARTMENT

Application Of Machine Learning To Map Underground Fires In Hwange Colliery Using Earth Observation Data

BY

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DISSERTATION SUBMITED TO BINDURA UNIVERSITY OF SCIENCE EDUCATION IN PARTIAL FULLFILLMENT OF THE REQUIREMENTS OF THE BACHELOR OF SCIENCE HONOURS DEGREE IN DISASTER MANAGEMENT SCIENCES

MAY 2024

RELEASE FORM

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DISSERTATION TOPIC:	**APPLICATION OF MACHINE LEARNING TO MAP UNDERGROUND COAL FIRES IN HWANGE COLLIERY USING EARTH OBSERVATION DATA**
DEGREE:	**BACHELOR OF SCIENCE HONOURS DEGREE IN DISASTER MANAGEMENT SCIENCE**
YEAR DEGREE GRANTED:	**2024**

PERMANENT ADDRESS:	**UVE 2540** **VENGERE, RUSAPE** **ZIMBABWE**
DATE:	**MAY 2024**

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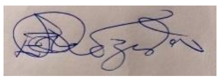

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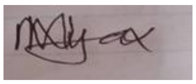
DECLARATION FORM

I, Nyakonda Mitchell K, registration number B202104B, declare that this dissertation is the product of my own work and has not been previously submitted to any University other than Bindura University of Science Education. All sources used or quoted have been indicated and acknowledged as complete references.



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DEDICATION

This project if dedicated to my dearly beloved father and brother, Farai L. Nyakonda, Shawn Nyakonda K and Trevor A. Nyakonda respectively for reinforcing the spirit of perseverance, love and support they gave me during the study. I also dedicate this project to the vulnerable community of Hwange who have fallen victim to the underground coal infernos.

ACKNOWLEDGEMENTS

First and foremost, I am grateful to God for guiding me through my years of university education. The Almighty has been the greater wind beneath my wings. His grace and mercy have been a force that has brought me this far, my heart overflows with gratitude. Much credit goes to Mr. E. Pedzisai, my supervisor who diligently assisted me during this study until the completion of my project. I would also like to extend my gratitude to Mr. M. Gomo, Mr T. Musodza and Dr. T. Manyangadze for the technical assistance during my research.

ABSTRACT

Underground coal fires (UCFs) present a significant challenge with far reaching environmental and safety implications globally, depicting complex spatio-temporal dynamics. This study employed a roust machine learning approach using Random Forest Algorithm to model Underground Coal Fires (UCF's) at Hwange Colliery Mines. The methodology utilized a Semi-automatic Classification Plugin within QGIS, integrating Landsat 8's optical and thermal bands. Analysis of historical UCF events Through Normalized Burn Ratio (NBR) and the Normalized Difference Vegetation Index (NDVI) was relevant to develop a robust predictive model capable of identifying potential UCFs and estimating extent of underground fire propagation. Furthermore, the research explored the probability of implementing monitoring systems to provide timely warning and mitigate the detrimental impacts of underground coal fires on the environment and local communities. Random Forest model detected UCFs in most parts of Hwange mining area such Wankie mine, the road linking Kamandama mine disaster memorial site and the rest Hwange town and Hwange Colliery. Spatial temporal analysis of the propagation of the UCF for the period 2020 - 2023, revealed that the year 2020 had the most UCF affected areas with 6.06% later decreasing to 3.35% by 2023. The NDVI analysis showed minimum plant growth and a majority of bare ground and fire affected areas illuminating the harsh ecological effects of underground coal fires in the region of interest. These findings inform sustainable resource management practices and enhance disaster risk reduction strategies in coal mining regions. Therefore, prevalence of UCFs in Hwange Colliery Mines underscore the urgent need for immediate action to address the environmental menace. Through the synergistic application of advanced machine learning techniques and Earth Observation data, disaster management practitioners can improve their ability to detect, monitor and respond to UCF incidents, thereby safeguarding natural resources and human well-being.

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LIST OF ACRONYMS

CNRG	**Centre for Natural Resource Governance**
GIS	**Geographic Information Systems**
HCCL	**Hwange Colliery Company Limited**
LST	**Land Surface Temperature**
ML	**Machine Learning**
NBR	**Normal Burn Ratio**
NDVI	**Normalized Difference Vegetation Index**
RF	**Random Forest**
ROI	**Region of Interest**
UCF	**Underground Coal Fire**

CHAPTER 1: INTRODUCTION

1.1 Introduction

This chapter introduces the research by outlining the following sections namely, background of the study, statement of the problem, research objectives and research questions, justification of the study, delimitation of the study, definition of key terms, and organization of the study.

1.2 Background of the study

Underground coal fires (UCFs) are a challenge globally. The Global Forest Watch (2021) noted that hundreds of fire events burn low and slow on dirty fuel beneath the earth with some smoldering for decades. The UCFs are a slow creeping hazard that is constantly over looked and underestimated considering the amount of damage it can cause to the environment and people. According to Lui (2021), UCFs refer to the interaction of coal seams with oxygen which can be under the interference of a natural environment or human factor normally occurring in hot and dry environments where oxidation of coal generates heat if not dissipated the temperature of coal rises to the point of ignition which leads to spontaneous combustion. These fires bring a serious wastage of resources and causes serious harm to the environment. The nature and character of underground coal fires make them complex. According to UNEP (2023), UCFs are a significant environmental and economic hazard, endangering human health, ecosystems, and resource management. Hwange Colliery in Zimbabwe is an extreme example of the catastrophic impacts of UCFs, requiring immediate attention and inventive solutions (Manika, 2022). As a result, making accurate mapping and monitoring crucial for mitigation efforts. Yu et al. (2022) posit that Earth Observation data combined with machine learning (ML) provide a way to achieve this goal. Ultimately, this study aimed to develop and apply a ML model to map UCFs in Hwange Colliery using satellite imagery Earth Observation data.

The UCFs are seamless that occur below the surface when a layer in the Earth's crust is ignited (Du et al., 2021). The overarching challenge is due to their out-of-sight occurrence hence hard to detect at first and even harder to extinguish (Blaike, 2013). The Global Forest Watch (2021) further noted that there are thousands burning around the world in coal mining countries, estimated to cause 40 tons of mercury to enter into the atmosphere each year representing 3% of the world annual carbon dioxide emissions. The problem of UCFs is not confined to Hwange Colliery; it is a global concern that has been reported in several other countries, including the United States, China, India, and Australia (Nichols and Finkelman, 2023). UCFs are a global environmental and economic threat, silently burning beneath the surface in coal-rich regions around the world (Finkelman et al., 2021). Assan (2024) posits that these invisible infernos contribute significantly to greenhouse gas emissions, estimated to be 3% of global CO_2 emissions every year. According to Giridhar and Neeraja (2021), coal fires are responsible for the emission of an estimated 40 million tons of CO_2 per year, which is equivalent to the annual emissions of 7 million cars, while emitting hazardous pollutants that threaten air quality and human health. The economic implications are substantial, with the World Bank projecting $20 billion in annual losses globally, with afflicted populations bearing major health-care expenditures. (World Bank, 2020). As a result, there is a crucial need to address the global crisis of UCFs. Coal can heat up on its own and eventually combust if there is continuous oxygen supply; the heat is not dissipated and under the right combination of sunlight and oxygen triggers spontaneous combustion (UNEP, 2023). Some of the fires are triggered by human ignition and mining. According to Onifade (2022), they can be compacted by pressure and land can collapse into sinkholes, sucking in buildings and more oxygen to fuel the flames leading to rugged and uneven landscape.

UCFs burn away the important nonrenewable energy resource causing financial losses, hindering economic exploitation of coal, they pose a danger to man and machines raise the temperature of the area and engulf surface features such as buildings, transportation network and land subsidence (World Bank, 2020). Therefore, UCFs pose serious challenges to human security and the environment. In addition to that, the situation is particularly concerning in Africa, where several countries, like Zimbabwe, South Africa, and Botswana, are grappling with UCFs (Xiao et al., 2023). UCFs have been reported in various coal mines in South Africa, notably Witbank and Ermelo (Onifade et al., 2022). According to Lombardo (2021), UCFs have been observed in Botswana's Morupule Coal Mine, the country's sole operational coal mine. Habib and Khan postulate that nearby communities endure health risks from air pollution and ground subsidence while economic activities such as agriculture and tourism are disrupted. Payne and Oliva (2023) posit that respiratory illnesses are common near UCFs, raising concerns about long-term health consequences. Animals fall victims to ground collapses or suffer burns from exposed fires, while UCFs make land unsuitable for grazing, threatening livelihoods dependent on animal husbandry.

In addition, Hwange Colliery in Zimbabwe stands out as a prominent hotspot, with more than 100 documented UCFs (Gushungo et al., 2021). These fires not only add to regional air pollution by exceeding national air quality standards in adjacent Hwange Town (Maponga, 2021), but they also endanger the well-being of the local community. Additionally, the impact of UCFs on Hwange extends far beyond air quality problems. The fires disrupt agricultural productivity, destroy infrastructure, and impose a burden on healthcare systems, all of which have an impact on local people's livelihoods and health (Finkelman et al., 2021). Water resources are also impacted, as UCFs can contaminate groundwater with harmful metals and heat water bodies, endangering aquatic ecosystems and water availability (Johnson et al., 2020). Ultimately, the scale of the UCF problem necessitates immediate attention, and the utilisation of machine learning and earth observation aids in efforts to mitigate the gravity of the problem.

Subsequently, understanding the global, regional, and local contexts of UCFs, particularly the grave situation at Hwange Colliery, emphasizes the need and urgency of tackling this environmental issue. This study employed ML and Earth observation data to map and monitor UCFs at Hwange Colliery. However, the findings and methodology can be adapted and applied to other UCF-affected regions, so adding to wider efforts to address this global environmental issue. By illuminating the UCFs and empowering stakeholders with data-driven insights, we can pave the way towards effective mitigation strategies that protect human health and our planet's invaluable resources.

1.3 Problem Statement

While there exist many research outputs on UCFs and their effects globally, however, there is little attention paid especially on developing countries yet many have coal deposits and mine the fossil fuel for various reasons. Since coal is buried beneath the surface as a fossil mineral, UCFs are prevalent in Hwange, throughout the concession owned by Hwange Colliery Company Limited (HCCL) where there are human settlements for the mine labour. Furthermore, residue dumps especially in Number 2 and 3 areas of HCCL are some of the most hazardous sites with raging underground coal seam fires. Mine refuse dumps and carbonaceous material in the proximity of mining sites is prone to spontaneous combustion and mining activities being practiced in the area are causing these UCFs (Madzivire et al., 2011). Since it is a mining location with many workers, residents are vulnerable to infernos as a serious threat to life and property. Furthermore, these fires can burn underground undetected for decades but can occasionally protrude to the surface with severe effects on flora and fauna (Sauna, 2014). Their surface expression on vegetative mortality and animal discomfort can be valuable to their detection and management hence reduce their impacts on society although their potential remains unexplored. Therefore, a comprehensive study is needed to assess the extent of underground coal fire extents including the rate at which the hazard is spreading.

In addition, UCFs pose a major environmental and economic threat, smoldering silently beneath the surface in coal-rich regions around the world (Li et al., 2022). The situation is extremely serious, and Hwange Colliery in Zimbabwe presents as a vivid example, with over 100 documented UCFs (Maponga, 2021). These fires not only contribute to regional air pollution by exceeding national air quality limitations in surrounding Hwange Town, but they also affect the well-being of surrounding populations through health concerns, land subsidence, and economic disruption (Nichols and Finkelman, 2023). The traditional methods for mapping UCFs, which rely on field surveys and visual interpretation of satellite information, tend to be time-consuming, expensive, and subjective. This results in inaccurate and incomplete fire maps, which impede effective mitigation efforts leaving communities vulnerable and hindering effective resource management. Furthermore, the dynamic nature of UCFs needs continuous monitoring, which is difficult with traditional approaches.

1.4 Significance of the Study

UCFs are a severe problem, providing a multidimensional threat to the environment, communities, and economies of coal-rich regions around the world while additionally restricting the safe exploitation of coal mines (Brodn and Tutak, 2022). The problem is not limited to Hwange Colliery; it is a global concern that has been recorded in many countries, including the United States, China, India and Australia (Sahoo, 2022). Monitoring and mitigation efforts are hampered by a lack of effective methodologies, as addressing this concealed hazard necessitates novel solutions. This study addresses this essential gap by exploring the use of ML with Earth observation data to map UCFs at Hwange Colliery. Coal fires are a major issue over the past years in Hwange occurring in various areas of the mining town. Large scale underground blazes cause the ground temperature to heat up and killing surrounding vegetation, produce greenhouse gases and can even ignite forest fires (Kingsley, 2003). The community expects the colliery to do more to prevent the accidents and help those affected. The utility of geographic information systems (GIS) to manage, monitor and map hazards as well as for decision support is therefore important for effective disaster management that saves life and property in the community.

The rationale for this study stems from the urgent necessity to address multifaceted consequences of ignoring UCFs. For instance, UCFs increase greenhouse gas emissions, pollute the air and water, and disturb ecosystems (Deng et al., 2021). According to Ivanova et al. (2022) air pollution from UCFs exacerbates respiratory illnesses and creates long-term risks to local communities. Liang et al. (2023) posit that UCFs harm infrastructure, impair agriculture, and result in enormous mitigation expenditures. Ground subsidence and fire dangers endanger the safety and livelihood of communities living around UCFs (Onifade, 2022).

The significance of this study stems from its capacity to revolutionize UCF mapping and contribute to better sustainable resource management. The need for an innovative approach is critical for a variety of reasons, including a lack of data and understanding. Existing data on UCFs is often fragmented and insufficient, limiting our understanding of their spatial extent, dynamics, and drivers (Young et al., 2023). This hinders the development of effective mitigation strategies. Early detection of new UCFs and tracking of their activity over time is crucial for early measures to minimize environmental damage and protect communities (Kamran et al., 2023). Traditional approaches often lack the required efficiency and reach. Also, accurate and comprehensive UCF maps are essential for enabling targeted mitigation strategies, resource allocation, and community protection efforts. Current methods often fall short of providing the necessary granularity and objectivity (Upadhyay and Bhattacharya, 2022).

Lastly, by integrating ML and Earth Observation data, the findings of this study offer enhanced accuracy and efficiency. The ML algorithms can swiftly assess vast datasets, resulting in precise fire maps with higher spatial resolution and accuracy than traditional methods (Shao et al., 2022).

Accurate and timely fire maps allow stakeholders to prioritize mitigation efforts, improve resource allocation, and carry out targeted interventions (Emery et al., 2020). Besides, satellite data enables early detection of new UCFs and continuous monitoring, allowing for swift interventions to mitigate environmental damage. Improved UCF monitoring helps guide responsible coal extraction techniques, minimizing environmental damage and strengthening resource sustainability (Yan et al., 2020). Moreover, the study's findings provide a framework for comprehensive fire maps as well as insights into UCF dynamics that influence targeted mitigation strategies, resource allocation, and community safety measures. Data-driven insights can guide policymakers in developing more effective regulations and approaches for UCF management and prevention (Zeng et al., 2024).

Subsequently, addressing the UCF dilemma at Hwange Colliery is not merely an option, but a necessity for safeguarding human health, environmental well-being, and sustainable resource management. This study, by combining the power of ML with Earth Observation data, provides an intriguing approach with far-reaching implications and the capacity to create a brighter future for Hwange and beyond.

1.5 Aim

i. Assess the spatio-temporal occurrence of UCFs in Hwange area.

1.5.1 Objectives

1) Detect active UCF using thermal imagery to analyze heat patterns.
2) Evaluate the spatiotemporal distribution of UCFs in Hwange using Thermal Remote Sensing data.
3) Assess the ecological effects UCFs in Hwange Colliery Mines.

1.6 Research Questions

1) Where are the active UCFs in Hwange?
2) How are the UCFs distributed spatially and temporally?
3) What are the ecological effects of UCFs in Hwange?

1.7 Delimitation of Study

The study concentrated mapping UCFs at Hwange colliery in Hwange district. Given the nature of the UCFs and how hard they are to extinguish, mapping them would provide a starting point to provide response mechanisms that would provide coping strategies to the community and conserve the environment while more permanent solutions are being sought to deal with the problems being faced. The study utilized images from 2020 to 2023 covering the entire year, to ensure fire propagation was accurately identified over a period of five years. This approach helped to avoid misidentifying naturally hot areas as active hotspots.

1.8 Definition of key terms

Copying strategy: UNISDR (2009), define copying strategy as the means by which people or organizations use available resources and abilities to face adverse consequences that could lead to a disaster.

Early warning: The provision of timely and effective information, through identified institutions, that allows individuals exposed to a hazard to take action to avoid or reduce their risk and prepare for effective response (UNISDR, 2009).

Underground coal fire (UCF): An underground coal fire is defined as the combustion of coal below the Earth's surface accompanied by heat-energy transfer and the emission of gas, but not necessarily flames and consequently, the emission of light (Stracher, 2013).

Vulnerability: According to UNDRR (2023) vulnerability is the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards.

1.9.1 Organization of the Study

The study is organized into five chapters. The chapters are as follows. Chapter 2 reviews the conceptions and previous researches on UCFs how earth observation data and ML where applied in other studies and the techniques that were used. The gap in literature reviewed is exposed at the end of this chapter. Chapter 3 describes the study area, outlines the sampling methods, data collection instruments and methods, data analysis, limitations of the study and ethical considerations in form of validity and reliability. Chapter 4 presentation of results, and discussion of the findings of the research. Finally, Chapter 5 concludes the research by proffering a summary of the findings, conclusion and recommendations of the study.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The susceptibility of coal fires is directly connected to environmental consequences. Systematic monitoring is critical for determining the effects of habitats living in close proximity to coal fire-affected areas. Blake (2013), cites that major explosions in coal mines are not uncommon events in first world countries. This chapter is a review of underground coal fire detection methods using Earth Observation data and ML also covering the conceptual and theoretical framework link of this study.

2.2 **Conceptual Framework**

Coal mining is associated with increase in disaster risk given the development of UCFs due to spontaneous combustion and human induced (improper mining methods or illegal mining). This study seeks to identify active underground coal fire through hazard identification and risk mapping which is critical formulation of preventive mitigation measures to reduce the vulnerability of communities in underground coal fire affected areas. According to Health Disaster Management (2002), the lack of disasters in many settings leads to lack of identification of hazards. Risk assessment and vulnerability mapping assist in knowing the severity and extent of the active UCFs which are important aspects of disaster risk reduction. This information can be utilized in creating early warning systems (EWS) and dissemination of information to the people close to the affected area which will reduce hazard vulnerability as these seamless UCFs are a slow onset hazard.

2.2.1 **Theoretical Conceptualization**

This study utilized the PAR model (2004), which best explains the progression to vulnerability of many communities. This model identifies the progression of vulnerability which is caused by root such as political system and economic system, dynamic pressures such as lack of ethical standards in public life and unsafe conditions which are societal lacks, settling in dangerous locations and lack of preparedness. The political and economic system of Zimbabwe has left the Hwange community exposed to these seamless fires as the Minerals and Mines Act chapter 21:05 prioritize mineral extraction above any other activity in the country and as the Thermal power station is the main electricity supplier in the country and any disturbances may lead to the fall of the country

GDP as it if affected indirectly through investment and operational costs basing on reports from the Zimbabwe Power Company. The galloping inflation rate in the country has left many with economic vulnerability as they cannot afford the cost of relocation including cost of living in the relocated area. Details pertaining to the PAR model are shown in Figure 2.1 below

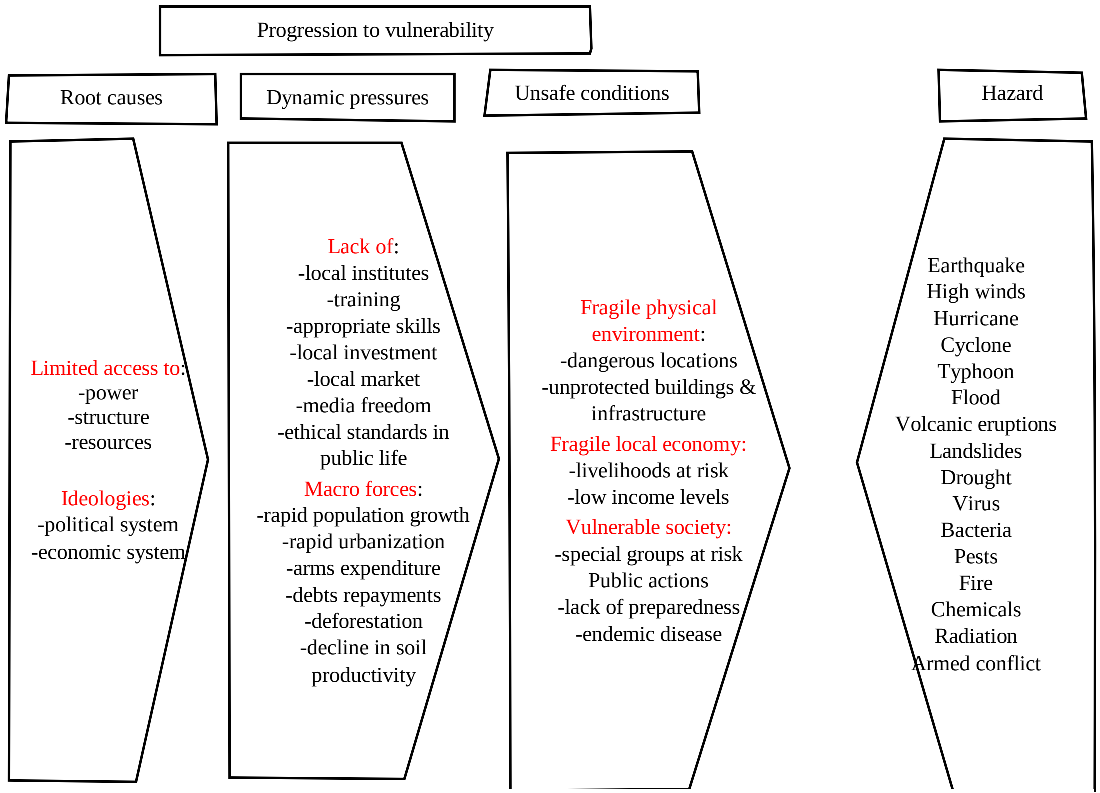

Figure 2.1: The Pressure and Release Model (PAR). [Source: Blaike, 2004]

The PAR model shows that the Hwange community are progressing to vulnerability due to factors such as limited access to power, structures, and resources and ideologies such as the political and economic system. There are also dynamic pressures that are adding on to the progression of vulnerability such as lack of local institutes, training and lack of local investment coupling with unsafe conditions such as dangerous locations, low-income levels, lack of preparedness and vulnerable society and livelihoods at risk. All these factors increase the progression of vulnerability of the Hwange community to UCFs.

2.3 Definition of UCFs

An underground coal fire is a fire that occurs when a coal seam ignites, often due to natural causes like lightning or human activities such as mining operations. These fires can persist for years, even decades and are challenging to extinguish due to their inaccessibility and the depth at which they burn. The fires release significant amounts of pollutants including carbon monoxide, sulfur dioxide, methane and mercury contributing to air pollution and climate change (Kolker et al., 2009; USGS, 2009). In addition to environmental damage, underground coal fires can cause ground subsidence, property destruction and severe health problems for local populations due to the emission of toxic fumes (OSMRE, 2024). Efforts to detect, monitor and extinguish these fires involve advanced technologies such as thermal imaging and inert gas injection, though they are often costly and complex (OSMRE, 2024)

2.4 **Causes of Underground Fire**

Spontaneous combustion is one of the major hazards occurring in coal mines and town globally. Underground coal seam fires with spontaneous combustion rely on factors like the presence of abundant crumbling float coal, an adequate oxygen supply, the heat storage capacity of the surrounding environment and an oxidation reaction that exceeds the coal's spontaneous combustion period (Wanxing, 2011). The absence of one of the above-named factors can prevent spontaneous combustion of coal. Onifade (2022), argues that coal can supply oxygen that is enough to sustain fires for years or decades which makes these fires difficult, hard to extinguish if not impossible even if the mine is flooded with water or inert gas.

Singh (2013) propounds that this suggests that the susceptibility of different coals to spontaneous heating varies greatly, making it crucial to assess their proneness in order to implement preventive measures. These measures are important to prevent fires thereby avoiding the loss of lives or property, the sterilization of coal reserves, environmental pollution, ensuring the safety and economic viability of mining operations. Fire activity increase in the decades has led to a need to develop modelling tools that assist in fire and air quality management in forecasting fire growth and smoke management. These fires have the ability to influence climate which can led to the creation of micro climates as a result of strong heat rising from combustion.

2.5 **Impact of UCFs**

2.5.1 **Environmental Impact of UCFs**

Underground mines inherently present challenging and harsh conditions and when combined with fire scenarios, they can create uncontrolled situations that significantly endanger the lives of miners. Stratcher (2007) highlights that coal fires pose numerous threats to the global environment by emitting greenhouse gases such as carbon dioxide and methane along with mercury, carbon monoxide and other toxic substances that contribute to climate change. These emissions can result in acid rain which depletes soil nutrients, inhibits vegetation growth, makes water bodies uninhabitable for aquatic life and accelerates natural weathering processes. According to the United States Geological Survey (USGS) (2009), mineral condensates formed from gaseous emissions around vents can pose an indirect hazard by leaching metals from mineral-encrusted surfaces into nearby water bodies. Centre for Natural Resource Governance (CNRG) (2017) reports that underground heat from coal deposits is causing the death of trees and plants. Additionally, mining induced subsidence leads to the sudden sinking of the ground surface, which destroys ecosystems, damages roads and results in the deaths of both humans and animals. Areas affected by these fires tend to have high temperature which may affect the growth of vegetation. UCFs causes land subsidence and ground instability leading ground above to collapse (Stratcher, 2013).

2.4.2 **Economic Impacts**

There is hindrance in the economic exploitation of coal since nonrenewable energy is wasted burning away in turn causing financial loses. The nation at large suffers economic losses in firefighting, control system, management and trying to extinguish the fires. Economic losses can be suffered from costs related to human health, dissemination and damaged surface structure. Rehabilitation efforts for displaced populations involve significant costs (Pandey et al., 2016). Mining operations may be halted due to safety concerns also reducing production and revenue (Kuenzer et al., 2015).

2.4.3 **Social Impacts**

People and animals especially children are severely burned by the underground raging fires leading to permanent disability. Children affected by coal seam fires experience various physical and psychological impacts including post-traumatic stress disorder (PTSD) (Mambondiyani, 2022). CNRG (2017), indicates that UCFs in and around Hwange have left some residents with near death experiences and permanent disability. UCFs produce smoke that contains poisonous and obnoxious smelling gases like oxide, carbon dioxide, nitrogen and sulphur and particulate matter that can cause several lung and skin diseases and in worst cases death.

2.5 **Underground Fire Occurrence**

2.5.1 **Global Occurrence of UCFs and Effects**

China is the one of the world largest producers of coal with an annual 2.2 billion tons with 10 – 20 million tons burning uselessly underground with seamless fires being bedspreads in the Xinxiang, Ningxia and Inner Mongolia (Du et al., 2022). Singh (2013) notes that in Germany, coal seam fires in Dudweiler (Saarland) began around 1668 and continue to burn today. Similarly, in Schwalbenthal (Stinksteinwand), on the eastern slope of the Hoher Meibner, the seams ignited centuries ago after lignite coal mining ceased and combustion gases still reach the surface. Many coal fields in the USA are fire leads for example Pennsylvania has 45 known fire zones and in Colorado it is as a result of variations in ground water level which increases the temperature of coal to 30 degrees Celsius which can cause spontaneous combustion (Singh, 2013).

2.5.2 **Regional occurrence of UCFs**

Onifade et al. (2022) indicates that UCFs in South Africa, are attributed to spontaneous combustion, statistics presented in their reports indicate that mine rescue approach for UCFs started in 1981 moving forward with 166 coal mine fatalities that have been dealt with by the Mines Rescue Services. In India, coal fire can be traced back to 1865 in the Jharia coalfield mines due to its coal mining history with the fires being attributed to spontaneous combustions and this area constitutes 12% of the coal reserve (Singh, 2013). This area was studied with a World Bank funded project and the results show that it is an estimated 9 square kilometer from the surface (Singh, 2013).

2.5.3 **Occurrence of UCF in Zimbabwe**

The expansion of the coal industry in Zimbabwe has led to the community of Hwange to experience UCFs and their effects. The poor implementation of Environmental laws in Zimbabwe has left many in death traps especially those in Hwange who are constantly left with injuries due to seamless fire contact. The CNRG (2017), indicates that the lack of investment by mining companies has left many vulnerable to the horrors of these fires. The CNRG (2017) also advised that the government should synchronize its proactive climate change response strategy and policy with tangible reductions in coal operations in Hwange. The leftover mine dumps in area Number 2 and 3 of HCCL represent the most dangerous locations of ongoing underground coal seam fires, which have been notably prevalent in recent years.

2.6 **Assessment of UCFs**

2.6.1 **Global Assessment of UCFs**

Globally, satellite and airborne technology prospects serve to collect data in the optical part of the electromagnetic spectrum (visible, near infrared and shortwave infrared) and microwave length (Lamp, 2013). Du et al. (2022) suggests that earth observation data can be employed to detect the temporal and spatial distribution of UCFs over time by analyzing surface temperature retrieval and thermal anomalies in the Wuda coalfield mining region of Inner Mongolia. Du et al. (2022) examined the spread direction and migration patterns of UCFs by dynamically analyzing the geometric centers of coal fire areas over time. This analysis offers valuable insights for environmental management, fire suppression engineering, ecological resource protection and the sustainable development of the mining area. In these studies, thermal infrared imaging, the surface temperature inversion method and the AET Algorithm were employed to detect UCFs, alongside a method to analyze the propagation tendencies of such UCF’s (L etal., 2016). Vu et al. (2018), indicates the monitoring of spatio temporal changes using Landsat images in Khanh Hoa coal field [2008 – 2016].

2.6.2 **Regional assessment of UCFs**

Gangopadhyay (2007) suggests that remote sensing technology serves as a valuable and convenient tool for detecting and monitoring additional coal fires using both airborne and spaceborne thermal remote sensors. Furthermore, methods such as geomagnetic (Pal et al., 2016), electric (Shao et al., 2016), chemical (Wang et al., 2020) and temperature field analyses (Ahmed and Usama, 2020) can be employed alongside satellite thermal infrared (TIR) remote sensing to identify thermal anomalies associated with UCFs (Saraf et al., 1995). For example, Kuenzer et al. (2008) utilized low-resolution MODIS thermal infrared remote sensing images with a resolution of 1 km, while Pandey et al. (2017) employed medium-resolution Landsat and CBERS-04 satellite thermal infrared images with resolutions ranging from 60 to 120 m. They investigated the lateral variations in surface and subsurface coal fire fields as they spread to new areas. Additionally, Pandey et al. (2017) analyzed daytime Landsat time series thermal anomaly maps of coal fires between 2013 and 2014, using coal fire maps of the Jharia coalfield, India, derived from daytime Landsat thermal infrared imagery spanning from 1988 to 2013.

2.6.3 **Assessment of UCFs in Zimbabwe**

Mambondiyani (2022) indicates that it is a main challenge knowing the extent of the coal seamless fires with residents only being alerted by a disaster. There is lack of documentation that show any methods used to assess the extent of the coal fires in Hwange or other if any in the country.

2.7 **ML Detection of UCFs**

ML embodies an automated rendition of the scientific method as described by Domingos (2015), adhering to a similar framework of formulating, evaluating and either discarding or refining hypotheses. This empirical method operates without preconceived notions about the data at hand. According to Lary et al. (2018), remote sensing involves multiple instruments concurrently observing the Earth, offering data on common parameters like surface vegetation however, there can be inter-instrument bias due to variations in observing geometry and orbit. ML facilitates data fusion of multiple datasets sharing a similar time series which inherently exhibit biases relative to each other. Consequently, merging biased data through fusion methods can lead to significant issues. (Lary et al., 2018). Machine intelligence is employed for onboard analysis of Earth Observation tasks, including hazard analysis such as fire detection, and area monitoring, as highlighted by Manning et al. (2018).

Blake (2013) contends that modeling plays a crucial role in identifying the extent and severity of the impact of fires on different areas of the mine. This understanding aids in assessing the implications for evacuation routes, potential entrapment scenarios and available options for search, rescue and firefighting efforts. Eslami et al. (2020) developed fire susceptibility maps using three different models, namely artificial neural network, logistic regression and random forest to predict the spatial distribution of forest fires in Mazandaran Province, Iran. Although the results showed reasonably accurate predictions overally, the Random Forest Model yielded slightly higher accuracy compared to the other two models.

2.7.1 **Random Forest**

Random Forests consist of a collection of tree predictors, where each individual tree within the forest is influenced by the values of a randomized vector θ. Random Forest (RF) enables the incorporation of data from various scales and sources, making it extensively utilized in mapping applications reliant on satellite imagery. Cutler et al. (2007) highlight that Random Forest (RF) is frequently employed to delineate and map forest areas affected by fires, as well as to assess the structural and spectral characteristics of the burned regions and their impact on classification. RF is praised for its high classification accuracy, innovative approach to determining variable importance, capacity to model intricate interactions among predictor variables, versatility in conducting various types of statistical data analyses (such as regression, classification, survival analysis and unsupervised learning) and provision of an algorithm for imputing missing values.

Ramo and Chuvieco (2017) proposed the creation of two Random Forest Models, one incorporating all Landsat 8 reflective bands and the other using only red (R) and near-infrared (NIR) bands. Both models were trained using a statistically designed sample of 130 reference sites, ensuring representation across various global fire conditions. They found that the shortwave infrared (SWIR) and NIR bands exhibit greater sensitivity to burned areas. Utilizing the random forest presence prediction model proved to be a more accurate method significantly reducing the risk of fire-prone territories. Furthermore, they discussed active fire detection methods based on traditional approaches, which adhere to three fundamental principles such as (1) identifying hot-temperature pixels through thresholding methods, (2) context-based approaches comparing hot-temperature pixels with background information and (3) detecting fire pixels based on the presence of smoke and moving fire plumes. According to Syrris and Loekken (2021), Random Forest achieves the highest overall accuracy at 99.8%, while Partial Least Squares demonstrates the lowest accuracy at 60%. Morphometric indices contribute to achieving 82% producer's accuracy and 85% user's accuracy, and when combined with spectral and texture indices, the results are further improved. However, since morphometric indices may not always be accessible, combining texture and spectral indices with RGB bands enhances producer's accuracy by 12% and user's accuracy by 6%.

2.7.2 **Analysis and Evaluation of UCFs**

ML models require two processes to work simultaneously. There is need to capture a lot of data from Earth Observation Satellites then preprocessing it to get it ready for application. Moreover, the preprocessed data is then entered into datasets called data cubes then training the data into models or algorithms that area required. Depending on the aspect under investigation sometimes it can be a time series instigation for example land use land cover changes which may require working in both space and time. Agarwal (2021), argues that the differences in resolution in satellite imagery may result in the need for a third-party software like Sentinel hub that harmonizes all the Earth Observation data into a single format therefore the processor will not need to keep working with different resolutions and formats.

2.8 **Gap in Literature on UCFs**

Many studies offer insights into the spatial extent and changes in area of UCFs however fail to specify the precise direction of coal fire propagation (Du et al., 2022). As of late, not enough evidence has been produced in relation to Zimbabwe although there has been speculation about the issue in the media. An environmental impact assessment was carried out by the CNRG (2017) where the issue of UCFs was raised in the report. Researchers must depend on incomplete and outdated government reports concerning different aspects of the coal supply chain in the Hwange region. Additionally, they rely on strongly critical assessments from civil society groups and journalists regarding the ongoing expansion and associated projects. In Zimbabwe, remote sensing has been applied in land use land cover changes using Landsat images in combination with socio economic data being used to determine the effects associated with development and land use shifts (Mambondiyani, 2022). Enhancing the delineation of land cover classes through remote sensing indices, ML algorithms like random forest (RF) and support vector machines (SVMs) is known for its advantageous trait of enhancing multispectral classification.

Summary of chapter

In summary, this chapter reviewed the theoretical perspective of the study and how other studies found with regards to UCFs. Many communities are vulnerable to the seamless UCFs due to their nature of occurrence and the fact that they are invisible to the human eye alone make them elusive to detection and monitoring. Therefore, robust computer-based ML algorithms such as Random Forests can be implemented using Earth Observation data can facilitate efficient and accurate detection and monitoring, hence enable effective management of these UCFs through timely mapping for early warning and evacuation actions.

CHAPTER 3: MATERIALS, METHODS AND DATA ANALYSIS

3.1 Introduction

This chapter describes the area of study in the context of its location, climatic conditions, population and economic activities. The chapter also highlights the methods that are used to detect UCFs affected pixels using in Landsat images. It outlines the approach that was taken in gathering relevant data and information for the study.

3.2 Description of Study Area

The Hwange Colliery Company Limited is based in Hwange District in southwestern Zimbabwe, Matabeleland North Province and south western Zimbabwe. The district is situated within Agro-ecological Regions IV and V, stretching from the north to the south. This area is classified as semi-arid, receiving less than 650mm of rainfall annually in region IV and 500mm in region V. Typically, the rainy season occurs from November to April with the remainder of the year being characterized by dry conditions. The district has a total population of 109 598 in the both the rural and urban Hwange. Rural Hwange has 20 wards with a total population of 69 351 and 17 925 total households with an average size of 4. Urban Hwange has 15 wards with a total population of 40 241 and 11 441 total households with an average side of 3, 5 (ZIMSTATS, 2022). The average temperature range in the district is 21 degrees Celsius in June and 32 degrees Celsius in October when high and 8 degrees Celsius in July and 18 degrees Celsius in October when it is low.

Hwange harbors the largest deposits of coal and is the epicenter of coal mining in the country and also a National Park (Hwange National Park). The HCCL currently owns and operates four coal mines namely the Main (Hwange), Number 2, Wankie and Chilota mines being the largest producer in Zimbabwe and one of the largest companies in Africa. The company has coal production capacity of 3.2 million tons per year (Hwange Colliery, 2023) and is a major contributor to the local economy. HCCL practices both surface and underground mining also having total reserves of 90 million tonnes. The Hwange Colliery Company (2019), reported that UCFs are occurring at Wankie and Number 2 mines.

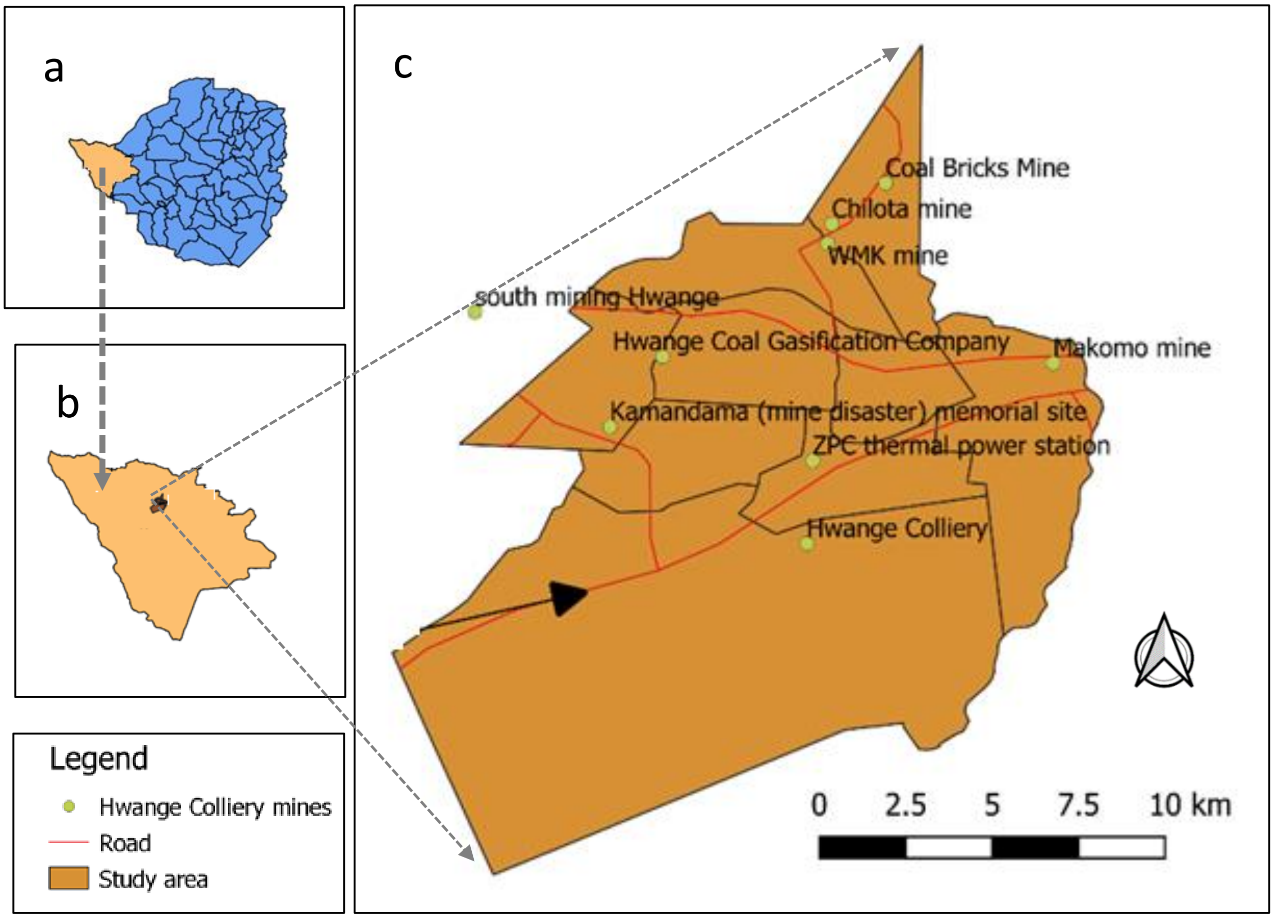

Figure 3.1: Location of Hwange District in Zimbabwe (a), and the study area in the district (b) and the distribution of Hwange Colliery mines in the study area (c).

3.3 Research Design

A case study research design was used for this research in the application of ML to map UCFs in Hwange colliery using earth observation data. A case study is quantitative method where the researcher seeks to understand a problem or a phenomenon in depth (Creswell, 2014). Quantitative research methods were used in the collection of data. This study used satellite images from open sources such as USSGS, and Google Earth.

3.4 Data Collection

This study utilized both primary and secondary to ensure information used was reliable and valid thereby producing an empirical research.

3.4.1 Primary data collection

It is original information that is collected for this research that has never been published before. Information is gathered through experiments, surveys, interviews and observations. It can be tailored to meet the specific needs of the researcher. In this case for primary data the researcher conducted ground truthing.

3.4.1.1 **Ground truthing**

It refers to data that is collected in site, complimenting remote sensed data as it helps by associating the image to ground authenticity. Ground truthing entails gathering data about the study area through field surveys, examination of aerial photographs or high-resolution spatial data and firsthand observations in the field. Ground truthing is accuracy assessment of the site derived from the image data (GISGeography, 2023). In quantitative analysis, ground truthing requires making measurements on the ground. The researcher in this case was mainly concerned with the aesthetic state of the environment for example whether the vegetation was healthy or not as it was the most affected by the UCFs and collecting coordinates for areas that contain or are affected by UCFs. Coordinates of some of the areas affected by UCF's are shown in Table 3.1:

Table 3.1Ccoordinates of Hwange Colliery Mines

Operational status	Name	S	E	Elevation
Fully Operational	Makomo Mine	18°21'03.8"	026°32'18.3"	1167 meters
Not Operational	Wankie Mine	18°19'12.3"	026°28'47.1"	1145 meters
Operational	Chilota Mine	18°18'54.0"	026°28'51.2"	1138 meters
Semi Operational	Coal Bricks Mine	18°18'15.8"	026°29'41.5"	1132 meters
Fully Operational	ZPC Thermal Power Station	18°212'35.1"	026°28'33.1"	1152 meters
Fully Operational	Hwange Colliery	18°23'52.33"	26°28'27.66"	1173 meters
Operational	Kamadama Disaster Memorial site	18°22'3.33"	26°25'23.58"	1157 meters

3.4.2 Secondary data collection

Secondary data can be referred as data that was collected, processed and published by someone else not collected by the researcher first hand. This included journals, government publications and satellite images. This case the researcher utilized satellite images and GIS shape files.

3.4.2.1 **Base Map Acquisition**

The base map and GIS shape files were extracted from DIVA-GIS (www.diva-gis.org). They offer a versatile framework that can be tailored to depict various themes such as population shifts, developmental progress, weather patterns, and even insights into our political environment (Acaddrafting, 2016). The shape files acquired were used to create an outline of the district under study.

3.4.2.2 **Satellite Image Acquisition**

Landsat 8 satellite images were downloaded from United States Geological Survey, which is a scientific agency of the United States Department that researches the earth's systems and provide scientific data to help people understand the earth, prepare for natural disasters, monitors and management of national natural resources (National Geographic Society, 2023). The study used Landsat as it has a free and open data policy which was adopted by USGS in 2008 according to Hansen et al. (2013). Landsat satellite operates using passive sensors. Landsat 8 data has been utilized at local level, continental, national and regional level when projects are being implemented due to its spatial detail (30m- visible, NIR, SWIR and 100 meters thermal) and temporal range (16 days) (Wulder et al., 2019). Landsat 8 thermal infrared band is used to detect burnt area scars.

3.5 **Data Processing**

3.5.1 **Thermal Anomaly Extraction**

Thermal Infrared Remote Sensing technique was firstly applied for coal fire detection by Slavecki RJ as cited by Biswal et al. (2019) to acquire land surface temperature (LST) using thermal infrared data and identifying the coal fire related thermal anomalies by particular criteria. It is a practical and effective detection method that of thermal anomalies. Singh et al. (2020), The thermal anomaly method that can be utilized is the density slicing thermal imagery given there is a fixed threshold for coal fire (Huo et al., 2014, Singh et al., 2020) it can quickly and relatively detect thermal anomalies although the results are relatively rough. Landsat 8 thermal band 10 was used to calculate LST and anomaly extraction was carried out through density slicing. Temperatures projected were grouped into 4 classes with the following intervals $30^{o}C \leq$ average temperature < $25^{o}C$ (moderate), $25^{o}C \leq$ average temperature < $30^{o}C$ (warm), $30^{o}C \leq$ average temperature $\leq 35^{o}C$

(hot) and 35ºC ≥ average temperature ≥ 40°C (very hot) for 2020, 2021, 2022 and 2023 respectively the output produced is as shown in Figure 4.1 in the next chapter.

3.5.2 **Normalized Difference Vegetation Index (NDVI) Inversion**

In order to prevent the growth cycle of different types of vegetation and the time fluctuations of the annual temperature rise Wang et al., (2021) propounds the use of NDVI inversion in identifying areas with UCFs through comparative analysis of different scenes as vegetation might differ significantly in these areas. When vegetation is subject to state of stress NDVI decreases (Piro et al., 2017). NDVI values range between -1 to 1 where -1 could be water (contaminated or not), 0 could be bare ground or rocks and 0, 2 to 1 is vegetation that is healthy. NDVI is calculated as shown below on Equation (1

$$\boldsymbol{NDVI = \frac{(Band\ 5 - Band\ 4)}{(Band\ 5 + Band\ 4)}} \qquad\qquad \boldsymbol{Equation\ (1)}$$

Where Band 4 is the red and band 5 is the near infra-red bands respectively.

3.5.3 **Normalized Burn Ratio (NBR)**

The Normal Burn Ratio is an index that highlights areas that are burnt in large fire zones. Prakash et al., (2003) advocated for this index as it is effective in detecting thermal anomalies associated with UCF's and they release a heat that alters the spectral characteristics of the affected area. It associations the use of both Near Infrared (NIR) and shortwave infrared (SWIR) wavelength. When the NBR is high it indicates healthy vegetation whereas low value indicates bare ground or of late burnt areas. The values range between 1 to -1 where values close to zero are attributed to non-burnt areas. Normalized burnt ratio (NBR) is calculated as shown below on Equation (2);

$$\boldsymbol{NBR = \frac{(Band\ 5 - Band\ 6)}{(Band\ 5 + Band\ 6)}} \qquad\qquad \boldsymbol{Equation\ (2)}$$

Where Band 5 is near infrared and band 6 is short wave infrared respectively.

3.6 **Data Analysis**

Data analysis involved modelling using Random Forests machine learning. The modelling involved Training and testing using partitioned data as outlined

3.6.1 Training and Testing Data Split

The model was manually trained into two distinct micro classes which are fire and non-fire area manually defining each pixel whether its fire or not. The data were split into 70 percent training and 30 percent testing for the RF model.

3.6.2 **Random Forests classification**

After data training, the study went on to predict the fire and non-fire areas on new data sets over a period from 2020 to 2023. A random forest model is constructed on the majority vote of the individual decision tree in a forest (Breiman, 2001). Each tree classifies the new data drawing a final prediction based on the class which receives the most votes across all the trees. Random forest was executed in QGIS using the semi-automatic classification plugin as shown on Appendix 1.

3.6.3 **Accuracy assessment**

Data was tested to facilitate accuracy assessment to determine the correctness and effectiveness of the trained model. It was critical to evaluate the effectiveness of classification of fire and non-fire areas using Random forest algorithm. Accuracy assessment was done using Cohen's Kappa (k) statistic with a score between 0-1 for perfect classification. It is calculated using the formula on Equation (3);

$$\boldsymbol{k = \frac{(p_o - p_e)}{(1 - p_e)}} \qquad \textbf{\textit{Equation}}\ (\mathbf{3})$$

Where $\mathbf{p_o}$ is relative observed agreement among raters and $\mathbf{p_e}$ is hypothetical probability of chance agreement.

3.7 Ethical Considerations

In adherence to ethical principles for quantitative research, clearance was secured from local governance bodies such as local councils and district administrators. Consultations were also conducted with traditional local leadership and the university resulting in formal authorization for the research. Prior to data collection, clear communication was provided through written consent forms and research instruments outlining that the obtained data would strictly serve academic purposes. Assurance of respondent confidentiality was given, with an emphasis on voluntary participation to prevent any form of coercion or undue influence.

3.8 Limitations of the study

A number of challenges were encountered. Firstly, the time consumed in acquisition of Earth Observation data was longer than expected. Acquiring Landsat 8 satellite images over the region of interest was time consuming as it involved downloading multiple scenes since the area was not covered within only one scene. These mages had to be merged and clipped to form one image to represent the area of interest. The study was conducted within a limited timeframe, which may have limited the field observations. Secondly, some of the candidate satellite images were affected by more than 10% cloud-cover hence unusable. The research had to search for images that had a cloud cover of less than 10 percent. Thirdly, access to the study area was limited since some of the areas had active UCFs. Areas such, as Hwange Colliery Company, the road linking the village with the town and mine No. 2 and the road linking Makwika village and the rest of Hwange town were barricaded and off limits to the public due to the dangers associated with the UCFs that has been raging for years in the area. Fourthly, the area is sensitive as it affects the image of HCCL and other stakeholders. Therefore, it was difficult to gather information from the company and the victims of the UCFs. The victims were especially afraid to speak out against the company as it is state run and might get in trouble with people occupying positions of power. Some the victims were families of people who work at the subsidiaries of HCCL and would not risk losing their livelihoods and face economic vulnerability. The study involvement of the local community was limited and hence extensive fieldwork was necessary. During fieldwork, negotiation for data collection and the university's data collection letter proved helpful in this regard. The study was confined to focus only on Hwange Colliery mines which may limit the findings generalizability to the whole district as they may not be an accurate representation of all the UCFs in the area.

3.9 Validity and Reliability of the study

The validity and reliability of a study are crucial for ensuring credible and actionable results. Validity in this context involves confirming that the RF model accurately detect and map the underground coal fires, meaning the algorithms must correctly interpret the thermal anomalies and surface changes indicative of coal fires. External validity pertains to the generalizability of the results to other regions or time periods, implying that the methods used should be applicable to different mining areas and adaptable to future data from Landsat or similar satellites. In the study images with less than 10% cloud cover that were acquired on the 8th month of each year. Image preprocessing was done to remove the atmospheric effect, in the event the images were affected by cloud cover more than 10%, near anniversary images were used to ensure consistency in surface land cover as influenced by seasons. Reliability refers to the consistency of the machine learning model's performance over time and across different datasets. This can be assessed through test-retest reliability, ensuring that the RF model produces stable results when applied to multiple Landsat 8 images from different dates. Ensuring high validity and reliability in this study would provide robust, repeatable and generalizable findings critical for ongoing monitoring and mitigation of underground coal fires at Hwange Colliery. The research utilized three methods with field work as ground truthing, while satellite imagery was downloaded from a credible source (USGS) hence results triangulation corroborates the reality of UCFs in Hwange.

3.9 Chapter Summary

This chapter explores the advantages of procedures in data collection, processing and analysis that were favoured by the researcher. Data collection methods and processing procedures were addressed. Ethical considerations were also highlighted.

CHAPTER 4: RESULTS AND DISCUSION

4.1 **Introduction**

This chapter presents the findings from the research conducted in Hwange District in Hwange Colliery area focusing on the application of ML in mapping UCFs at Hwange Colliery. The information is presented in the form of maps, graphs and tables. The main objective of the study was to assess the spatio-temporal occurrence of UCFs by detecting active fires using thermal images for detecting heat n surfaces, modelling underground fire hotspots areas and predicting the spatial extent of UCF's. The study performed RF using the Semi-automatic Classification Plug in in QGIS. The outputs of the classification were categorized into a binary map with UCF and non-UCF classes. The subsections below outline the key findings starting with thermal anomaly extraction.

4.2 Thermal anomaly extraction

As Hwange is relatively an area that is associated with high temperatures detecting and extracting these thermal anomalies from satellite was crucial for identifying potential underground coal fire occurrences. Land surface temperatures (LST) project abnormal heat signatures which allows quantification of fire intensity and assessment of severity as shown in Figure 4.1:

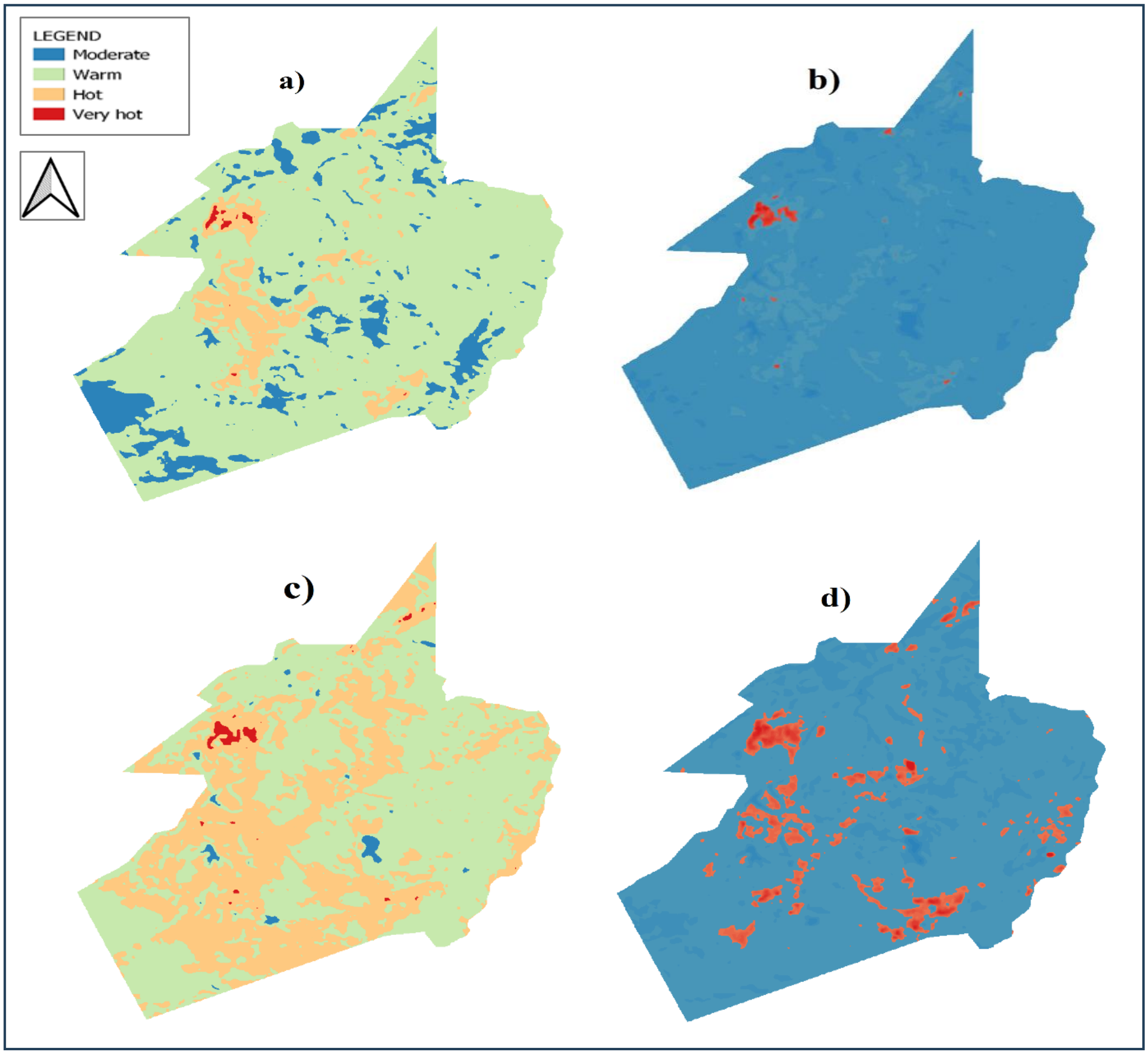

Figure 4.1: Land surface temperature maps for the study area on the dates 2020/08/26 (a), (2021/08/13 (b), 2022/08/16(c) and 2023/09/11 (d) respectively.

Land surface temperatures (LSTs) were critical in detecting thermal anomalies that deviate from significantly from expected thermal patterns and exhibit abnormal temperatures identifying regions of interest (ROIs). Detection of possible UCFs was made possible with the assumption that areas that projected very hot temperatures against areas projecting moderate temperatures.

Figure 4.1 depicts the distribution of LST from 2020 to 2023, which reflect changes in thermal anomalies and show the presence and progression of UCFs. The 2020 map (Figure 4.1a) shows a predominance of green areas, signifying warm temperatures, along with a few yellow patches and very few red spots, indicating the presence of hot to very hot locations, respectively. For the year

2021 (Figure 4.1b), the map is predominantly blue, indicating moderate temperatures, with fewer green patches hardly visible and few red areas although slightly higher than in the year 2020. This indicates that temperatures in the area decreased.

For the year 2022 (Figure 4.1c), there is a mix of green and yellow, signifying warm to moderate temperatures, with considerable amounts of blue and red spots, indicating an increase in hot and very hot temperatures over the previous year. Lastly, in the year 2023 (Figure 4.1d), the map is predominantly blue again, with numerous red areas scattered throughout, indicating the presence of extremely hot temperatures amidst moderate temperatures.

4.3 The Normalized Difference Vegetation Index Analysis

The NDVI analysis of the study area was carried out to assess vegetation health and density, classification was done to determine the distribution of vegetation and different types that are found within the study area. A time series vegetation analysis of the area was done using four different years. The analysis was done to determine the impact of UCF's on the ecosystem and vegetation within region of interest. The NDVI analysis results are shown in Figure 4.2:

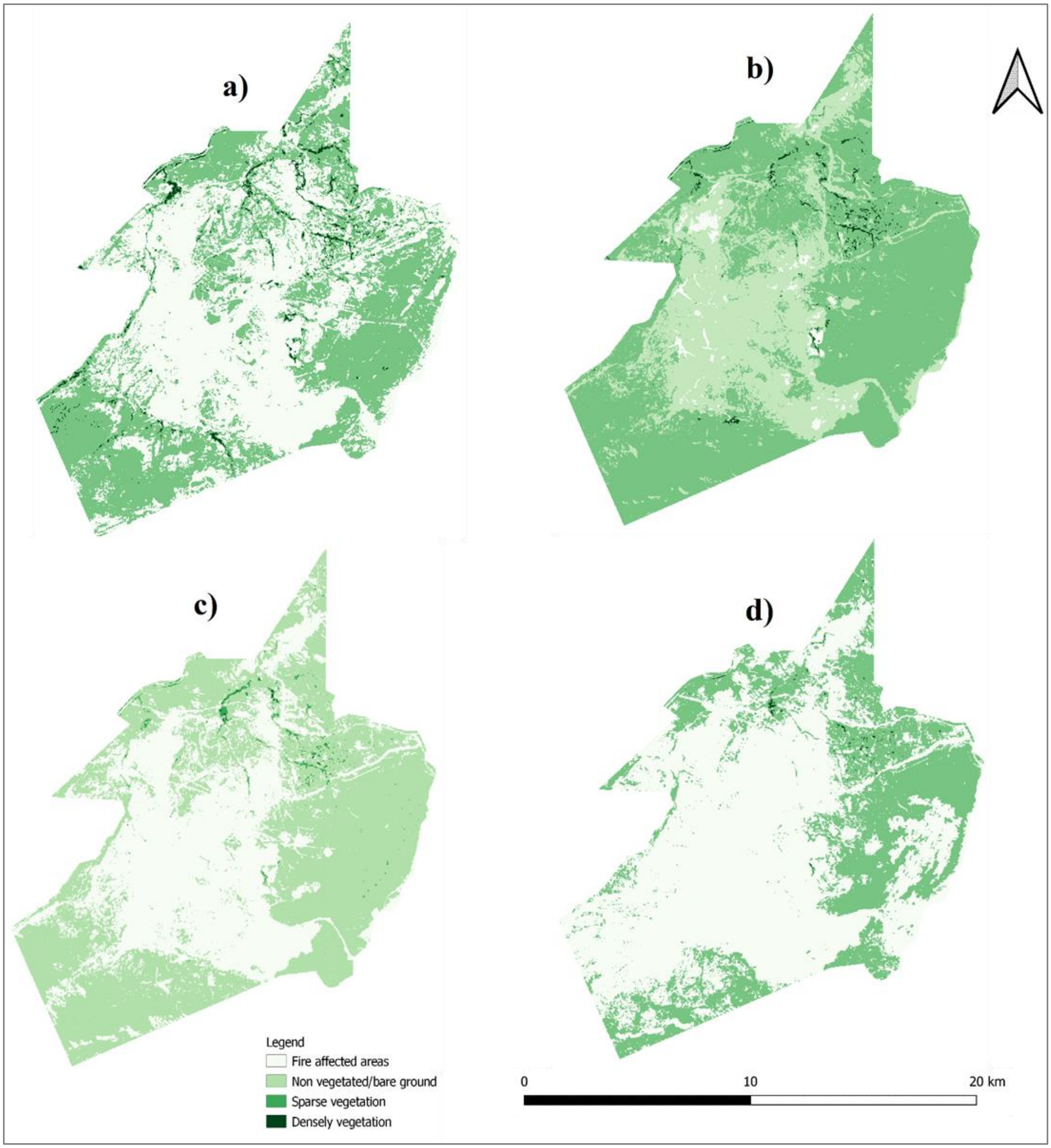

Figure 2.2: The NDVI analysis results for 2020/08/26 (a), 2021/08/13 (b), 2022/08/16 (c) and 2023/09/11 (d) projecting different vegetation distribution and cover respectively

The analysis shows that on Figure 4.2a, areas classified as fire-affected, sparse vegetation were mostly projected and noticeable dense vegetation was shown as UCF's contribute to elevated temperatures leading to dry conditions which led to vegetation damage or removal. In Figure 4.2b, it is observed that there is sparse vegetation persists and bare ground and dense vegetation is noticeable in some parts of the ROIs. A fewer fire affected areas were observed compared to insert (a) although fire might have continued in some areas reducing vegetation cover. Reduced fire-affected areas could indicate mitigation efforts or natural extinguishment of some fires. The observation in Figure 4.2c is that projection of fire-affected areas is highly noticeable along with extensive bare ground. Continued UCFs could have expanded to new areas or intensified in existing ones which led to noticeable projection fire-affected areas. Increased bare ground can be attributed to loss of vegetation due to ongoing fires or the expansion of the affected area. In Figure 4.2d fire-affected areas are still present but less noticeable, along with sparse vegetation. This could have been due to efforts to contain the UCFs might have started to show some success, leading to a decrease in noticeable fire-affected areas. Sparse vegetation persists possibly due to the lingering effects of the fires on the ecosystem or ongoing challenges in vegetation recovery.

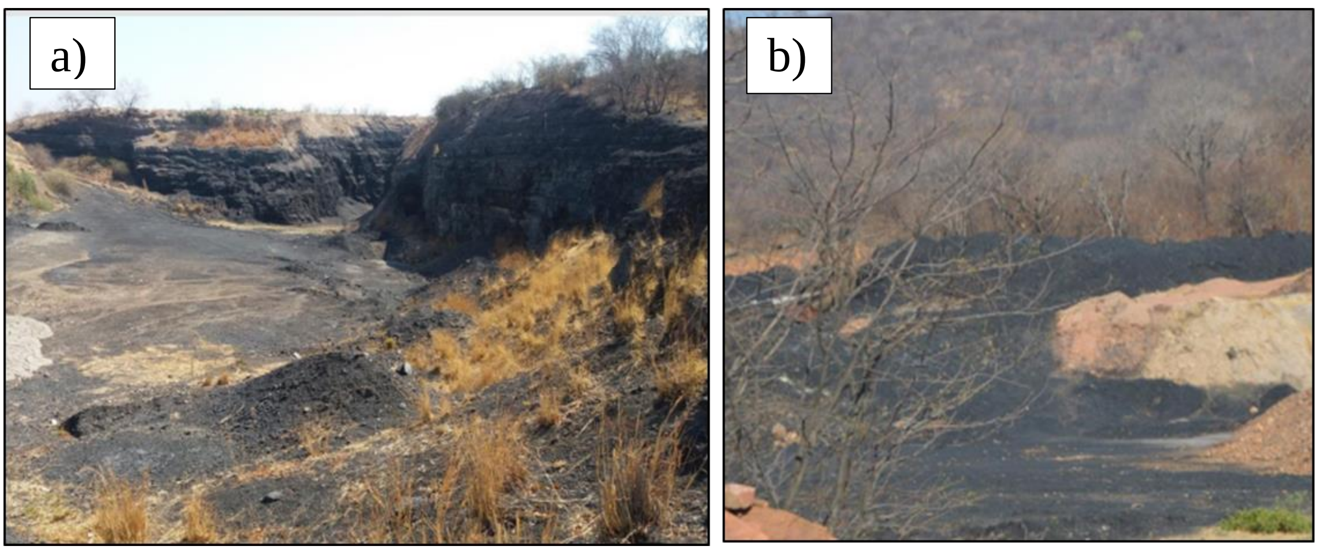

Plate 4.1: Areas showing effects of underground fire at (a) Hwange Colliery b) Chilota mine

Plate 4.1 is a visual representation of the vegetation at Hwange Colliery mines showing 4.1(a) Hwange Colliery where there has been land subsidence due to open cast mining and underground mining disrupting the growth cycle of vegetation. Plate 4.1(b) shows Chilota mine an area with a suspected underground coal fire with the surrounding vegetation mostly burnt. The UCFs do not manifest on the ground but can only be detected when one comes in contact with an object or person. The vegetation in areas of Hwange Colliery Mines affected by UCF's is significantly impacted displaying reduced density and altered species composition due to thermal, chemical and hydrological changes. The intense heat causes soil temperatures to rise, scorching and burning nearby plants, while altering soil chemistry and depleting essential nutrients. Natural vegetation succession is slowed with visible indicators such as sparse cover and dead or dying plants as also shown by the NDVI analysis Figure 4.2. Overall, biodiversity is reduced and the ecosystem suffers from significant disruption and imbalance.

4.3.1 Normal Burn Ratio results

For the study the researcher utilized the NBR index which is commonly used to assess the severity of burnt areas in remote sensing analysis. NBR analysis was done to help detect UCF's indirectly as they can alter surface temperatures and vegetation health, which can be detected through changes in NBR values. Anomalies produced in NBR values for example persistent low values or abrupt changes in spatial patterns might indicate the presence of UCF's. Figure 4.3 represents NBR results projecting different anomalies:

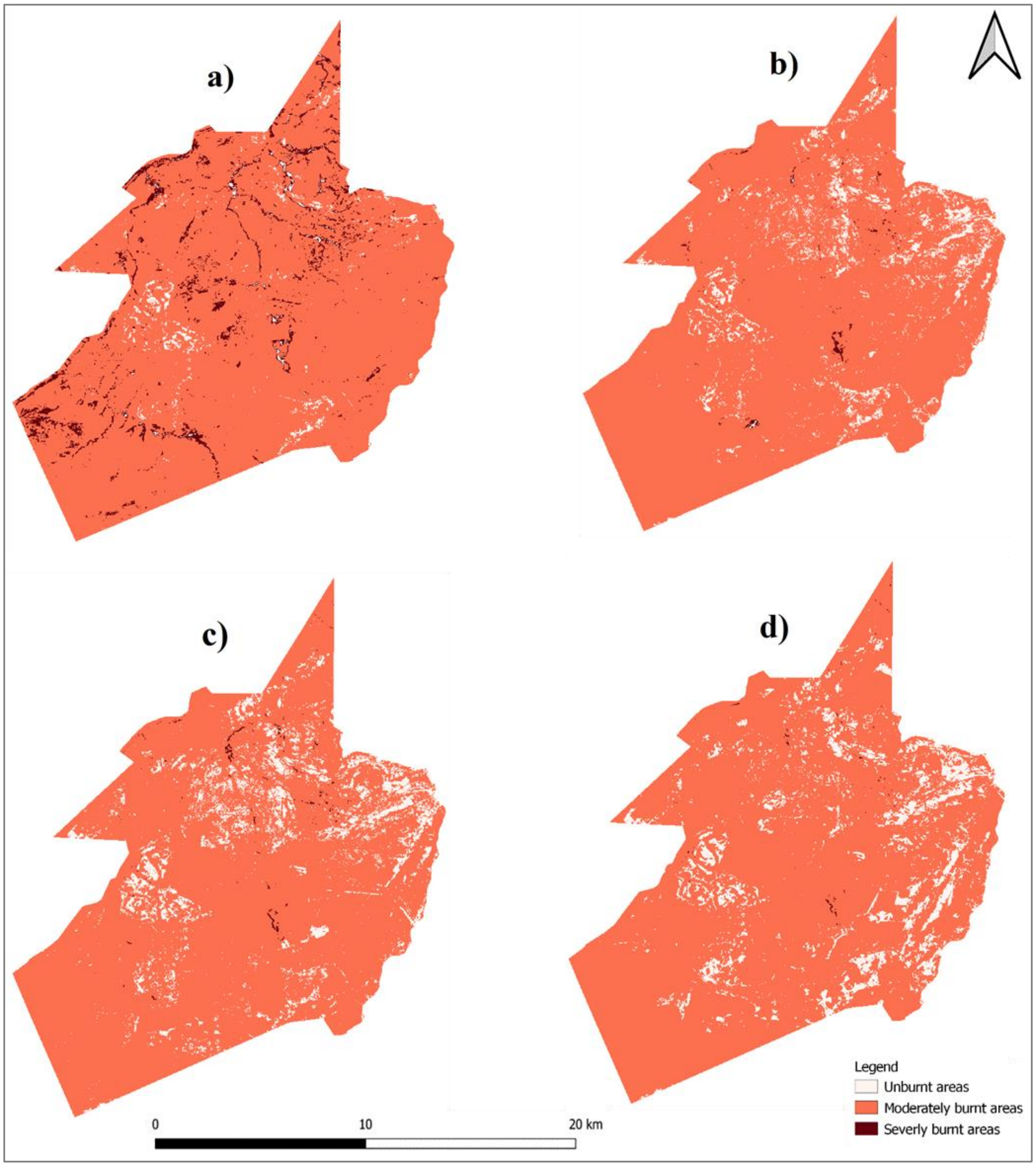

Figure 4.3:The NBR analysis of the study area for the dates 2020/08/26 (a), 2021/08/13 (b), 2022/08/16 (c) and 2023/09/11 respectively.

In the year 2020 (Figure 4.3a), the NBR analysis revealed a significant presence of severely burnt areas and a substantial portion classified under moderately burnt areas. This finding suggests ongoing UCFs and surface fires in the ROI. The prevalence of severely burnt areas indicates intense burning, likely attributed to the UCFs reaching the surface or spreading through underground coal seams. In the year 2021 (Figure 4.3b), noticeable changes were observed in unburnt areas, with a decrease in severely burnt areas while moderately burnt areas remained relatively constant. This could be indicative of mitigation efforts targeting the containment of surface fires or successful interventions to suppress UCFs. The stabilization of moderately burnt areas suggests that while some progress has been made, the overall situation remains challenging. There was an increase in unburnt areas by the year 2022 (Figure 4.3c), potentially reflecting improved fire management practices or successful rehabilitation efforts. The consistent presence of moderately burnt areas indicates sustained fire activity, likely fueled by the persistence of UCFs. The decrease in severely burnt areas could signify effective control measures or natural attenuation processes occurring within the underground coal seams. In the year 2023 (Figure 4.3d), while there were minimal changes overall, there was a noticeable decrease in severely burnt areas. This significant reduction suggests continued progress in mitigating the impacts of UCFs. The persistence of moderately burnt areas may indicate ongoing fire activity, albeit at a reduced intensity. The observed changes underscore the importance of ongoing monitoring and intervention efforts to address the complex interplay between surface fires and UCFs.

As shown by Figure 4.3a, the initial state of the area revealed a large number of severely burnt areas, mainly in the south-west, middle, and northern parts. The number of severely burnt areas had decreased significantly in Figure 4.3b, leaving only a very few. In Figure 4.3c, there was a modest rise in severely burnt areas, but the change was not significant. Finally, in Figure 4.3d, just a very few areas were affected by severe burns.

4.3.2 Landsat 8 colour composite for ROI

Before training the model, images were pre-processed by first clipping images to Hwange Colliery mines layer extent. Satellite images of different band compositions were used to establish a color composite to display areas affected by an underground fire in Landsat imagery. For Landsat 8 images band combinations (7-6-4) was used as the study utilized satellite imagery for Landsat 8. Figures 4.4 illustrates the colour composite used to display areas affected by UCFs across the study period.

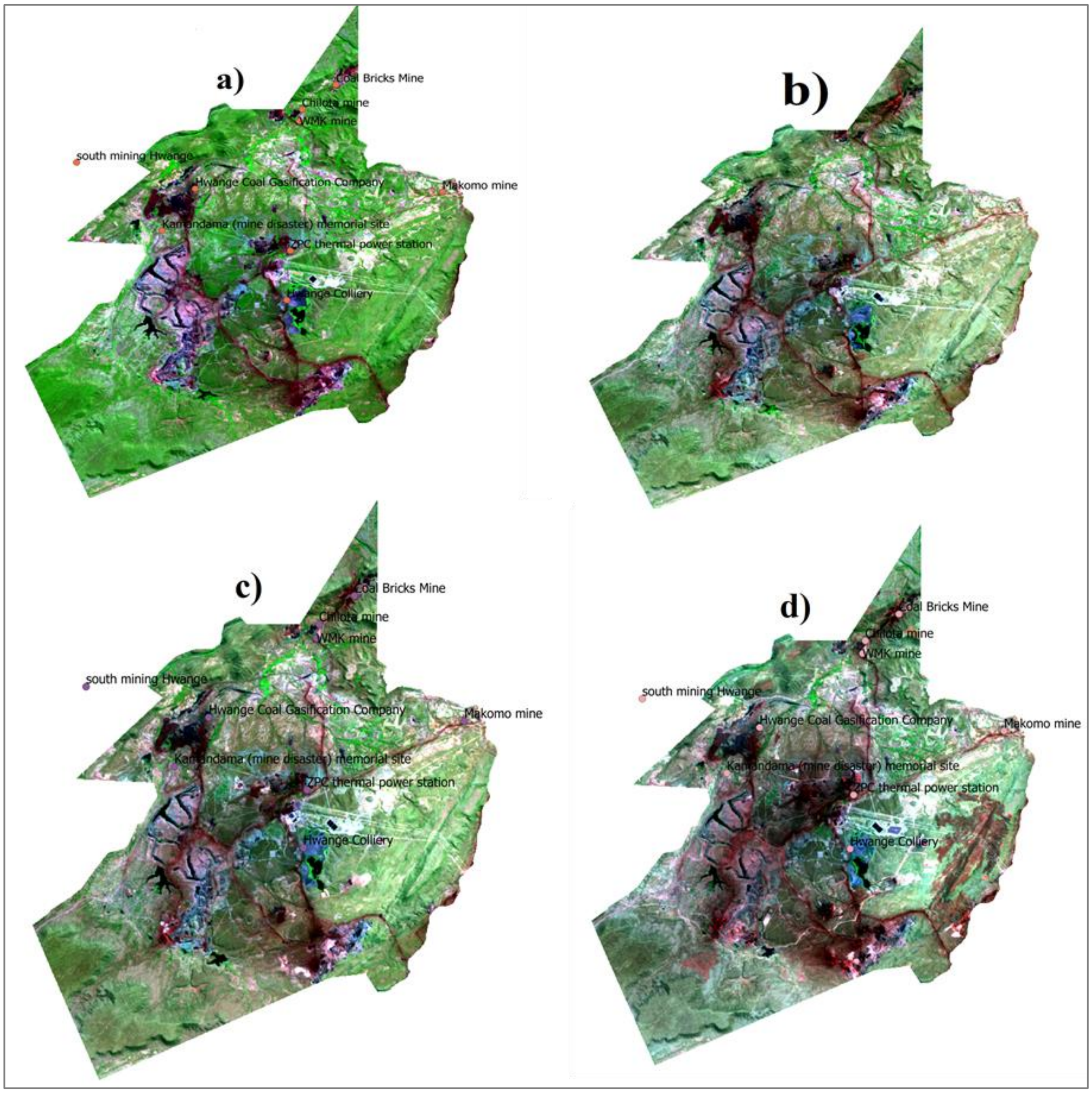

Figure 4.4: Color composite of band 6, (SWIR), 5 (NIR) and band 2 (red) in Landsat 8 that were used for visual image interpretation for fire detection for dates 2020/08/26 (a), 2021/08/13 (b), 2022/08/16 (c) and 2023/09/11 (d) respectively.

Figure 4.4 shows visual representations of Hwange Colliery mines environments and land cover types over the period of four years from the year 2020 to 2023. Band colour combinations were very critical in navigating within the study area and identifying regions of interest (ROIs) which were used for training the RF model. The 7-5-4 colour composite, identification of possible underground fire occurrence areas was easier with the assumption that areas with UCF's could reflect a lot of red.

4.4 The UCF classification using RF through SPC

The major thrust of this study was to map UCF's using ML in this case the study used Random Forest algorithm. RF was therefore applied in SCP to classify fire and non-fire areas as shown in Figure 4.5. The visual representation clearly shows that the environment is susceptible to the impacts of UCFs in the RIOs. These maps offer a period of recession and growth in the UCFs detected in the RIOs.

The four maps from the year 2020 to 2023 depict how UCFs changed over time. This temporal analysis helps in understanding the progression and containment of fires. The year 2020 (Figure 4.5a) map depicts the initial locations of UCFs, especially around the Bricks Mine, Hwange Colliery, and ZPC thermal power station. While some fires appear to be localised, others seem to be a part of a broader, interconnected network of fires.

In (b), there appears to be a minor drop in the areas marked as fire zones, which could imply that some of the UCFs have been extinguished or controlled, resulting in a reduction in the overall affected area. The extent of the fires appears to have decreased further (c), with fewer places illuminating red on the map. This indicates either an improvement in the UCF situation or an advance in detecting and mitigation methods or a natural firefighting efforts. However, there is a modest rise in fire areas (red) in (d) compared to (c), indicating that there may have been new developments or challenges in managing UCFs.

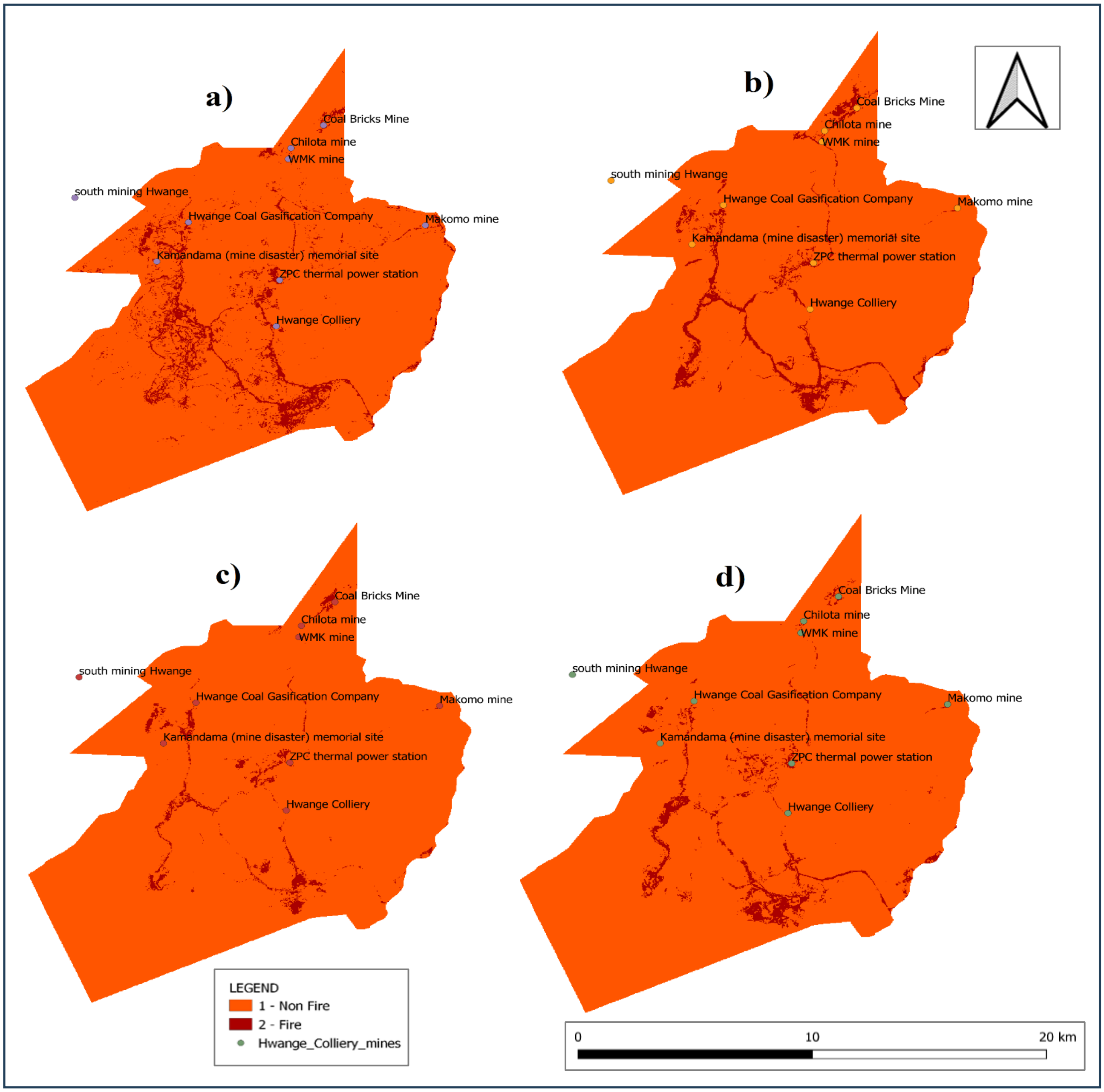

Figure 4.5: Detected UCF and non-UCF areas from the study area of 2020/08/26 (a), 2021/08/13 (b), 2022/08/16 (c) and 2023/09/11 (d) respectively.

4.4.1 Random Forest model performance

An assessment of the accuracy of the model in UCF classification at Hwange Colliery was carried out. This was conducted to establish the reliability of the RF algorithm towards the classification of fire and non-fire areas. This section demonstrates the accuracy assessment, cross validation of the model as shown in Table 4.1:

Table 4.1 Accuracy assessment for 2020/08/26

Year	Parameter	UCF	Non-UCF
	Producer Accuracy	**0.9935**	**0.9908**
2020	**User Accuracy**	**0.9921**	**0.9910**
	Standard Error	**0.0001**	**0.0001**
	Overall Accuracy =99.9912		

The model achieved higher producer accuracy in classifying fire instances (99.3%) compared to non-fire instances (99%). When the model predicted an instance as fire, it was correct approximately 99.2% of the time, and when predicting non-fire, it was correct about 99.1% of the time. The model had a standard error of approximately 0.01% of fire instances and 0.01% of non-fire instances. The model achieved an overall accuracy of 99.99%.

Table 4.2: Accuracy assessment for 2021/08/13

Year	Parameter	UCF	Non-UCF
	Producer Accuracy	0.9925	0.9942
2021	User Accuracy	0.9931	0.9940
	Standard Error	0.0001	0.0001
	Overall Accuracy =99.9934		

The model achieved higher producer accuracy in classifying non-fire instances (99.25%) compared to fire instances (99.42%). When predicting fire instances, the user accuracy was correct approximately 99.31% of the time, and for non-fire instances, it was correct about 99.40% of the time. The model misclassified (standard error) around 0.01% of fire instances and 0.01% of non-fire instances.

Table 4.3: Accuracy assessment for 2022/08/16

Year	Parameter	UCF	Non-UCF
	Producer Accuracy	0.9916	0.9927
2022	User Accuracy	0.9919	0.9921
	Standard Error	0.0001	0.0002
	Overall Accuracy =99.9920		

The model achieved higher producer accuracy in classifying fire instances (99.3%) compared to non-fire instances (99%). The user accuracy was correct approximately 99.19% of the time when predicting fire instances and approximately 99.21% of the time when predicting non-fire instances. The model misclassified around 0.01% of fire instances and 0.02% of non-fire instances. The model had an overall accuracy of 99.9920% in classifying fire and non fire areas.

Table 4.4: Accuracy assessment for 2023/09/11

Year	Parameter	UCF	Non-UCF
	Producer Accuracy	0.9951	0.9945
2023	User Accuracy	0.9943	0.9950
	Standard Error	0.0001	0.0001
	Overall Accuracy =99.9948		

The model achieved higher accuracy in classifying fire instances (99.51%) compared to non-fire instances (99.45%). When predicting fire instances, the model was correct approximately 99.43% of the time, and for non-fire instances, it was correct about 99.50% of the time. The model misclassified approximately 0.01% of fire instances and 0.01% of non-fire instances.

4.5 The UCF and Non-UCF areas by dates

The Figure 4.5 provided below shows a trend in the distribution of areas with and without UCFs at the Hwange Colliery Mines from 2020 to 2023. The data is given as percentages, where Non-UCF represents areas unaffected by UCFs and Fire represents areas affected by these fires.

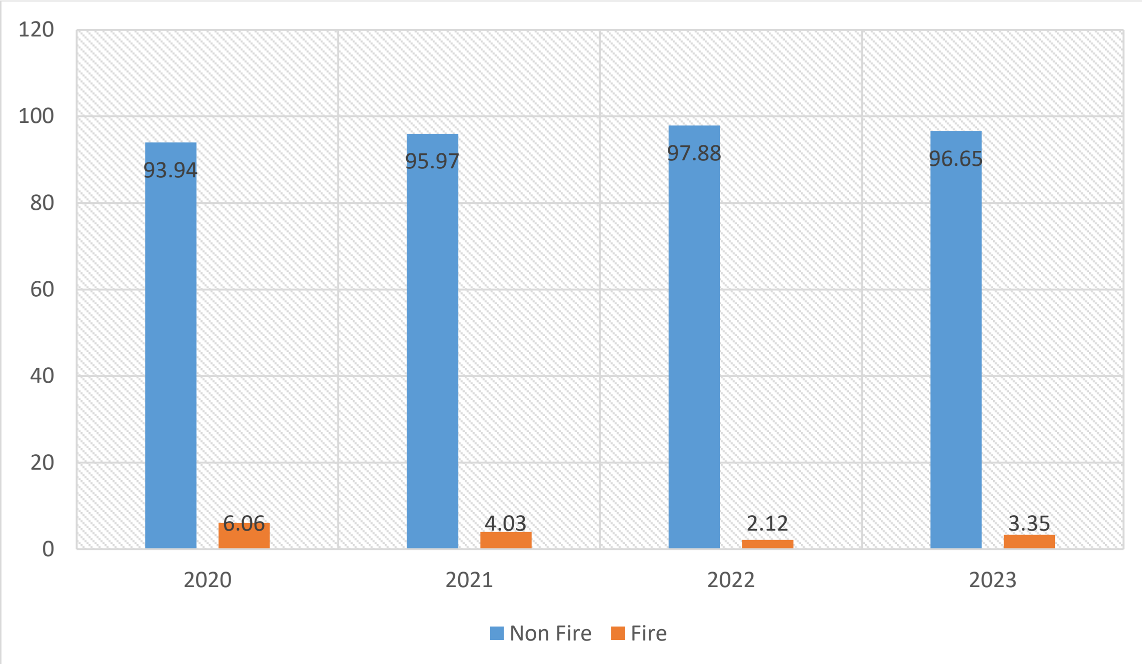

Figure 4.5: Percentage of area affected by UCF (orange) versus those not affected by UCFs (blue) for the study period (2020-2023).

In the year 2020, about 6,06% of the area was affected by UCFs, while the vast majority constituting of 93,94% was not affected. The area affected by fires decreased to 4,03%, while the non-affected area increased to 95,97% by the year 2021. The figures continued in the year 2022, with fire affected areas further decreasing to 2,12%, and non-fire areas increasing to 97,88%. From the year 2020 to 2022, there is a clear and significant decrease in the percentage of areas affected by UCFs at Hwange Colliery Mines. This suggests that there were effective measures implemented to control and reduce the propagation of these fires. In the year 2023, there was a slight increase in the area affected by fires, rising to 3,35%, while the non-affected area decreased slightly to 96,65%. In the year 2023, the data shows a slight increase in the area affected by fires, from 2,12% in 2022 to 3,35%. This could indicate a temporary setback or a challenge in maintaining the previously achieved reduction. Possible reasons for this increase could be a new ignition source, failure in existing control measures or environmental factors that facilitated fire spread.

4.6 Discussion of findings

The research focused on the application of ML to map UCFs using earth observation data. The ML algorithm that was used for this study was Random forest to detect and map the

UCFs for a period of four years from 2020 to 2023. This section of the study focuses on discussion of obtained findings in relation to the objectives.

4.6.1 **UCFs detection using thermal images for detection of heat on surfaces.**

The study illuminated the classification of UCF and non-UCF areas implementing RF algorithm using temporal Landsat image thermal and optical bands for Hwange Colliery with trained micro class regions of interest (RIOs). Classification of UCF and non-UCF areas was key to detecting potentiontially hazardous areas especially active UCFs. Random forest can be utilized to classify UCFs based on thermal anomalies detected from satellite data (Gupta et al., 2019). Their results demonstrated high accuracy in identifying areas prone to coal fires thereby showcasing the effectiveness of Random Forest in this application.

In this study Landsat 8 imagery aided the applicability of Random Forest utilizing its high spatial resolution of 30m was sufficient to model UCF distribution. There are also other studies that utilized Landsat imagery to detect UCF using Random Forest algorithm. For instance, Zhang et al. (2019), used Landsat 8 to detect UCFs in Shanxi Province in China. Their RF model however had high classification accuracy, with overall accuracy at 92%, although lower than that obtained in this study. In the same vein, Kumar et al. (2020), applied Landsat 8 imagery to focus on detecting UCFs in Jharia coalfield, India. RF was employed to the study due to its ability to handle complex, nonlinear relationships between spectral features and the presence of UCF’s. The study intended to provide accurate and timely detection of coal fires in a bid to support mitigation efforts in the heavily affected region. Similarly, Muller et al. (2018), examined the monitoring and detection of UCFs in the Ruhr District, Germany, utilizing Landsat 8 imagery using RF. The Random Forest algorithm was applied due to its ability to handle large scale datasets whilst at the same time providing accurate classification results. The aim of the study was to contribute to the assessment and management of coal fires hazard in the region by leveraging Landsat 8 data and Random Forest classification. The study was able to detect UCF in most parts of Hwange although some of these fires receded annually. The UCFs were detected at Coal Brick mine, Chilota Mine, Wankie Mine, Hwange coal gasification company, Makomo Mine, the road linking

Hwange Town and Kamadama Mine disaster memorial site, Zimbabwe Power Company thermal power station, Hwange Colliery and the road linking Makwika village and the rest of Hwange town. UCFs at Wankie mine in 2020 where not highly noticeable but later increasing and becoming noticeable in 2021 and disappearing again in 2022 and reoccurring in 2023. The same case applies to Hwange Colliery were in 2020 UCF's were predominant and decreasing significantly in 2021 and 2022 and started reoccurring in 2023 as shown on Figure 4.5.

4.6.2 Spatiotemporal occurrence of UCFs in Hwange.

The objective of assessing the spatiotemporal occurrence of UCFs in Hwange using thermal remote sensing data was effectively fulfilled through the analysis of the given data. The results demonstrate changes over time in the areas affected by UCFs at Hwange Colliery Mines from 2020 to 2023. These results are indicative (Figure 4.6) of the dynamic nature of UCFs and the effectiveness of fire management strategies implemented during this period. In 2020, the data shows that 6,06% of the area was affected by UCFs. By 2021, there was a significant decrease in fire-affected areas to 4,03%. This downward trend continued in 2022, with fire-affected areas dropping to 2,12%. However, in 2023, a slight increase to 3,35% was observed in the fire-affected areas. These temporal changes indicate fluctuations in the extent of fire-affected areas over the four years demonstrating the dynamic nature of UCFs and the effectiveness of fire management strategies over time. The summarized data implies that thermal remote sensing data was used to map and quantify the spatial extent of fire and non-fire areas within the Hwange Colliery Mines. This approach allows for a detailed spatial analysis of where the fires were occurring and how they were spreading or being contained over the years.

Voigt et al. (2004) conducted a detailed study on the application of thermal remote sensing to monitor UCFs in North China. The authors emphasized that thermal remote sensing is particularly effective in detecting underground fire dynamics due to its ability to capture temperature variations on the surface that correspond to subsurface combustion (Voigt et al., 2004). The study demonstrated that regular monitoring through remote sensing allows for the timely identification of fire-affected areas enabling more effective fire management and mitigation strategies. The findings of this research underscore the utility of thermal remote sensing in providing a comprehensive and continuous assessment of underground fire propagation which is crucial for managing the environmental and safety impacts of coal fires. Gangopadhyay et al. (2006) conducted a comprehensive study on the application of thermal infrared remote sensing to monitor the dynamics of UCFs in the Jharia coalfield, India. This study is particularly relevant to the Hwange Colliery Mines study as it utilizes similar methodologies to detect and track underground fire progression. The researchers employed thermal infrared sensors to capture heat anomalies, which were then analyzed to determine the spatial and temporal changes in fire intensity and spread. The study demonstrated that thermal infrared remote sensing is an effective tool for identifying fire hotspots and monitoring their development over time. The authors highlighted that the technology allows for continuous monitoring, which is crucial for timely intervention and effective fire management (Gangopadhyay et al., 2006). Recent studies have confirmed the efficacy of thermal remote sensing in monitoring UCFs. For instance, Peng et al., (2021) utilized Landsat-8 and Sentinel-1 data to detect thermal anomalies and subsidence in coal fire regions, demonstrating significant improvements in identification accuracy by integrating multi-source data. This approach reduced false positives and negatives substantially, showcasing remote sensing's capability in providing precise spatiotemporal analysis of UCFs. The study also highlighted the correlation between surface temperature changes and subsidence rates, reinforcing the utility of thermal remote sensing in fire management strategies.

4.6.3 Ecological effects UCFs in Hwange colliery mines.

Several studies have assessed the ecological effects of UCFs using NDVI and other remote sensing techniques providing valuable insights into the environmental impacts. For instance, a study on the Wuda coalfield in Northern China utilized ALOS PALSAR data to monitor land subsidence due to coal fires demonstrating significant environmental degradation and surface displacement caused by UCFs (Huang et al., 2013). Similarly, research on the Rujigou coalfield in NW China used multi-temporal nighttime Landsat data to track coal fire dynamics and found substantial increases in the spatial extent of coal fires, severely affecting the local environment (Gao et al., 2014).

Another study focusing on the cumulative ecological effects of mining in the Pingshuo mining area employed Google Earth Engine to analyze land cover changes and their impacts on ecosystem services over several decades (Zhao et al., 2022). The results highlighted the extensive loss of natural land and the complex trade-offs among ecosystem services due to mining activities (Zhao et al., 2022). These studies align with the NDVI analysis for Hwange Colliery mines, which revealed a continuous decline in vegetation health and increase in fire-affected areas over four years as shown in Figure 4.2 and illuminated by Plate 4.1. The observed NDVI ranges indicate significant ecological degradation, with areas showing decreased vegetation and increased bare ground, corroborating the findings of similar studies that have documented the severe environmental impacts of UCFs. The UCFs in Hwange colliery mines have caused significant ecological effects. Vegetation decline is evident with thermal stress from the fires increasing soil and air temperatures, stressing plant roots and reducing photosynthetic activity leading to lower vegetation density. Soil degradation is also severe as fires alter soil structure reducing fertility and moisture retention and destroying essential soil microorganisms. There is a marked loss of vegetative cover with persistent low NDVI values indicating expanding bare ground and sparse vegetation, making soil erosion more likely. Biodiversity has been impacted through habitat loss, reducing plant and animal species diversity forcing animal migration and potentially leading to local extinctions. There are also hydrological changes which include disrupted water cycles, decreased groundwater recharge and increased runoff, exacerbating soil erosion and causing sedimentation in water bodies, degrading aquatic habitats. Furthermore, the fires release pollutants like carbon monoxide and methane, degrading air quality and impacting both plant health and human populations while soil contamination from ash and combustion by-products introduces toxins that further inhibit plant growth and soil quality.

4.7 Chapter Summary

This chapter focused on the presentation of research findings and discussion of the findings. Major outcomes of the chapter demonstrated that RF algorithms are an effective method of classifying and detecting UCF’s. The study notes the decrease and relapse of UCF’s in the RIO, the area is also poorly vegetated based on the findings of the NDVI analysis. The subsequent chapter outlines the conclusions and recommendations of this study.

CHAPTER 5: SUMMARY, CONCLUSION AND RECCOMMENDATIONS

5.1 **Introduction**

This chapter provides a summary on the findings and concludes there study of the application of ML to map UCFs using earth observation data at Hwange Colliery. The study utilized satellite imagery from Landsat 8 and thermal data and Random forest algorithm to train its model to identify UCF's, spatial temporal occurrence of the fires in a four-year period and the ecological effects that can emanate from the occurrence of these UCFs. The subsequent discussion was aimed at addressing the realizations of the research objectives formulates in the first chapter of this study and ends with a conclusion section. Recommendations are provided basing on the findings of the previous chapter.

5.2 Summary of the study

The study focused on classifying underground coal fires (UCF) and non-UCF areas in Hwange Colliery using a Random Forest (RF) algorithm applied to temporal Landsat thermal and optical band images. The UCFs were detected at several locations including Coal Brick Mine, Chilota Mine, Wankie Mine, Hwange Coal Gasification Company, Makomo Mine, the road linking Hwange Town and Kamadama Mine disaster memorial site, Zimbabwe Power Company thermal power station, Hwange Colliery and the road linking Makwika village and Hwange town. The UCFs at Wankie Mine showed varying visibility, noticeable in 2021 but not in 2020 or 2022 and reappearing in 2023. Similarly, UCFs at Hwange Colliery were predominant in 2020, decreased significantly in 2021 and 2022 and reoccurred in 2023 as shown in Figure 4.5.

The spatiotemporal occurrence of underground coal fires (UCFs) in Hwange using thermal remote sensing data was successfully assessed, revealing dynamic changes in fire-affected areas from 2020 to 2023. The analysis showed that in 2020, 6.06% of the area was affected by UCFs. This decreased significantly to 4.03% in 2021 and further to 2.12% in 2022. However, there was a slight increase to 3.35% in 2023. These fluctuations indicate the effectiveness of fire management strategies and the dynamic nature of UCFs over time. The data underscores the utility of thermal remote sensing in mapping and quantifying fire and non-fire areas, providing detailed spatial analysis of UCF occurrence and containment within Hwange Colliery Mines.

The NDVI analysis for Hwange Colliery Mines from 2020 to 2023 showed a continuous decline in vegetation health and an increase in fire-affected areas highlighting significant ecological degradation due to persistent underground coal fires (UCFs). These fires increase soil and air temperatures, stressing plant roots and reducing photosynthetic activity, leading to lower vegetation density. Soil degradation is severe with fires altering soil structure reducing fertility and moisture retention and destroying microorganisms. Low NDVI values indicate expanding bare ground increasing soil erosion risk. Biodiversity has been affected through habitat loss, reducing species diversity and causing animal migration and potential local extinctions. Hydrological changes include disrupted water cycles, decreased groundwater recharge and increased runoff exacerbating erosion and sedimentation in water bodies. Additionally, fires release pollutants degrading air quality impacting both plant health and human populations while soil contamination from ash and combustion by-products introduces toxins inhibiting plant growth and soil quality. Persistent UCFs pose risks to human safety through ground collapse and encroachment into populated areas, potentially causing displacement and health hazards.

5.3 Conclusions

This section concludes the application of ML to map UCFs at Hwange Colliery using earth observation data. The research provided valuable insights into the spatial distribution of the UCFs through the use of LST, NDVI inversion, NBR and Random Forest model. The detection was achieved thermal imagery which provided an insight into the distribution and progression of UCF's over time. The assessment revealed the significant environmental impact of these UCF's on the surrounding ecosystem. These findings offered a comprehensive understanding of the scope and implications of underground coal fires in the region.

High temperatures, lack of healthy vegetation and bare ground is very prevalent in areas with UCF's. The random forest model analysis revealed that UCFs were mainly dominant in the roads linking the town with mine no.2 and road linking Makwika village and the rest of Hwange town as well as Hwange Colliery. Prevalence of UCFs at Hwange Colliery underscores the urgent need for intensive action to address the environmental menace. Understanding the occurrence and hotspots of UCFs enables the implementation of targeted interventions and effective mitigation strategies. Hwange Colliery can safeguard its coal reserves as well as protect the environmental and the well-being of the community members.

Subsequently, the study illuminates the complex spatial temporal occurrence of UCFs in Hwange Colliery area. It emphasized detection and assessment of the occurrence spatially in a bid to reduce the vulnerability of Hwange community to the dilemma that they are facing molding a resilient future for the community. Addressing the UCFs areas detected in the study can help Hwange Colliery build a sustainable future while attaining a promise of zero harm to the environment and community. To ensure a sustainable future of Hwange Colliery, there is need to tackle the burning dilemma through collaboration between relevant government bodies, mining companies, research institutions and the local community. Government intervention though policy formulation and enforcement are crucial in regulating the mines activities, enforcing environmental standards and providing advice on the best methods that can be used to deal with UCFs without causing further harm to the environment and people. Involving local communities in decision making process encourages inclusion and raises awareness about the risks associated with UCFs, which can also encourage the community to search for alternative livelihoods strategies which support sustainable livelihood strategies nurturing resilience.

5.4 **Recommendations**

Establishing from the research outcomes, the following recommendations can be drawn to enhance the detection of UCFs in Hwange Colliery mines.

1. Investing in advanced technologies. This can be done through allocating funds towards acquiring and implementing advanced technologies for continuous monitoring of know areas with UCFs and early detection of newly occurring UCFs. This can involve establishing a dedicated monitoring system using satellite imagery for example MODIS which has a temporal resolution of three days, drones and ground-based sensors. Ground based sensors can be used to monitor the concentration of pollutants such as particulate matter, sulphur dioxide and nitrogen oxides that can increase due to activity of UCFs

2. Fostering collaboration with research institutions. Collaboration with research institutions and universities to conduct studies on UCF specific to the region. This partnership can lead to innovative solutions and technologies tailored to the local context. This initiative encourages aallocation of funds for ongoing research and development initiatives aimed at improving the performance and reliability of advanced monitoring technologies for underground coal fire detection. Collaborating with research institutions, technology providers and industry experts can leverage cutting edge innovations and address specific challenges relevant to the local context.
3. Conducting public awareness campaigns on UCFs. Launching public awareness campaigns to educate local communities of Hwange about the risks associated with UCFs and the importance of early reporting. Encouraging the community that is surrounding Hwange Colliery mines to desist from trespassing restricted areas and barricaded areas as some of this contain UCFs. It is important to enlighten the community that is any harm shall be fall on an individual after trespassing the HCCL is not liable to any reparations. It also encourages to maintain open and transparent communication with stakeholders including government agencies, non-governmental organizations, industry partners and affected communities which can help resolve complex issues.
4. Encouragement of international collaboration. Engaging in international collaboration and knowledge sharing initiatives with other countries such as China and India facing similar challenges with UCFs can exchange experiences, lessons learned and best practices to improve management strategies. Engagement with such players can help prevent making costly mistakes by applying solutions that might only add fuel to the problem.
5. Developing a comprehensive plan for environmental remediation to restore ecosystems and mitigate long-term environmental impacts caused by the UCFs. This may involve revegetation, soil stabilization and water quality management. This can improve air quality and habitats for animals as Hwange district is known to harbour wildlife and Hwange National Park.

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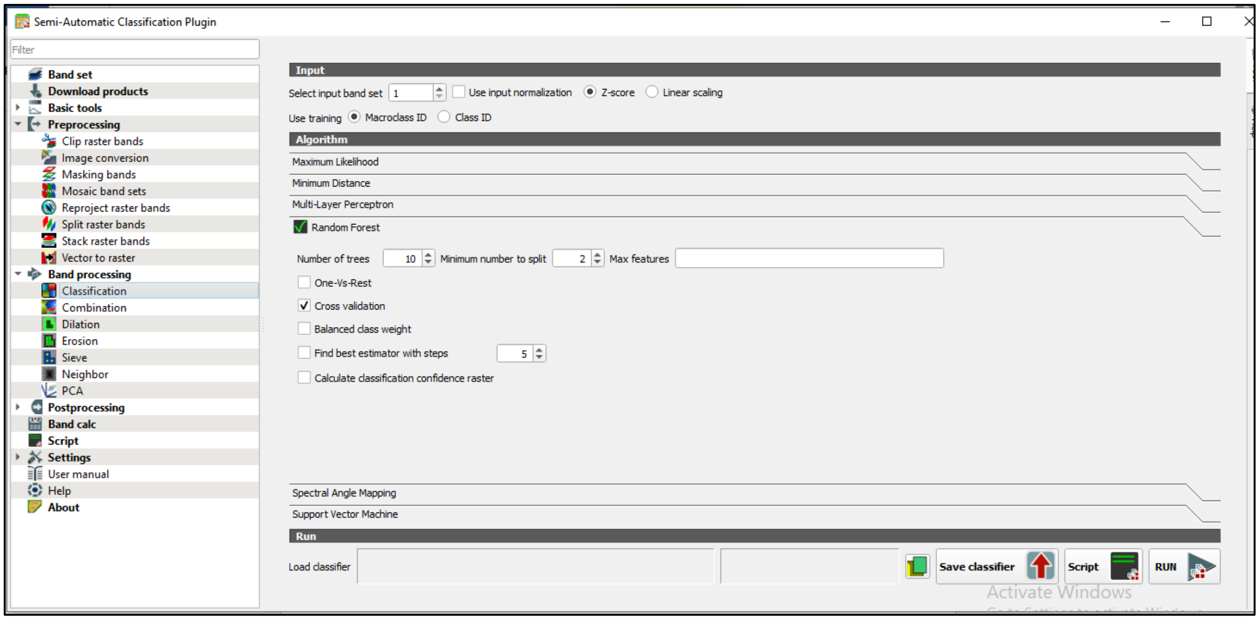
APPENDIX 1: FIELDWORK GUIDE

1. Location :………………………………………
   x coordinates : …………………………………..
   y coordinates :……………………………………
   Elevation: ….…………………………………….
2. Description of area, current vegetation (tick): live ☐ dead ☐ burnt ☐
3. Description of area ecological situation: barren ☐ productive vegetatively ☐ non-productive vegetatively ☐
4. Signs of human influence: Yes ☐ No ☐

APPENDIX 2: RANDOM CLASSIFICATION



APPENDIX 3: 2020 ACCURACY ASSESSMENT

RasterValue	Reference	Classification	PixelSum	Area [metre^2]	
1	1	1	244862	220375800	
2	2	2	15794	14214600	
ERROR MATRIX [pixel count]					
	> Reference				
V_Classified	1	2	Total		
1	244862	0	244862		
2	0	15794	15794		
Total	244862	15794	260656		
AREA BASED ERROR MATRIX					
	> Reference				
V_Classified	1	2	Area	Wi	
1	0.9394	0	220375800	0.9394	
2	0	0.0606	14214600	0.0606	
Total	0.9394	0.0606	234590400	1	
Estimated area	220375800	14214600	234590400		
SE	0.0001	0.0001			
SE area	1204.2	1204.2			
95% CI area	4320.23	5577.01			
PA [%]	0.9935	0.9908			
UA [%]	0.9921	0.991			
Overall accuracy [%] = 99.9912					
Area unit = metre^2					
SE = standard error					
CI = confidence interval					
PA = producer's accuracy					
UA = user's accuracy					

APPENDIX 4: 2021 ACCURACY ASSESSMENT

RasterValu	Reference	Classificat	PixelSum	Area [metre^2]	
1	2	2	10501	9450900	
2	1	1	250155	225139500	
ERROR MATRIX [pixel count]					
	> Reference				
V_Classifie	1	2	Total		
1	250155	0	250155		
2	0	10501	10501		
Total	250155	10501	260656		
AREA BASED ERROR MATRIX					
	> Reference				
V_Classifie	1	2	Area	Wi	
1	0.9597	0	225139500	0.9597	
2	0	0.0403	9450900	0.0403	
Total	0.9597	0.0403	234590400	1	
Estimated a	225139500	9450900	234590400		
SE	0.0001	0.0001			
SE area	900	1837.12			
95% CI area	3600.75	2442.12			
PA [%]	0.9925	0.9942			
UA [%]	0.9931	0.994			
Overall accuracy [%] = 99.9934					
Area unit = metre^2					
SE = standard error					
CI = confidence interval					
PA = producer's accuracy					
UA = user's accuracy					

APPENDIX 5: 2022 ACCURACY ASSESSMENT

RasterValue	Reference	Classificat	PixelSum	Area [metre^2]	
1	1	1	255130	229617000	
2	2	2	5526	4973400	
ERROR MATRIX [pixel count]					
	> Reference				
V_Classified	1	2	Total		
1	255130	0	255130		
2	0	5526	5526		
Total	255130	5526	260656		
AREA BASED ERROR MATRIX					
	> Reference				
V_Classified	1	2	Area	Wi	
1	0.9788	0	229617000	0.9788	
2	0	0.0212	4973400	0.0212	
Total	0.9788	0.0212	234590400	1	
Estimated area	229617000	4973400	234590400		
SE	0.0001	0.0002			
SE area	204.52	817.19			
95% CI area	4320.86	3527.95			
PA [%]	0.9916	0.9927			
UA [%]	0.9919	0.9921			
Overall accuracy [%] = 99.9920					
Area unit = metre^2					
SE = standard error					
CI = confidence interval					
PA = producer's accuracy					
UA = user's accuracy					

APPENDIX 6: 2023 ACCURACY ASSESSMENT

RasterValue	Reference	Classificatior	PixelSum	Area [metre^2]	
1	2	2	8722	7849800	
2	1	1	251934	226740600	
ERROR MATRIX [pixel count]					
	> Reference				
V_Classified	1	2	Total		
1	251934	0	251934		
2	0	8722	8722		
Total	251934	8722	260656		
AREA BASED ERROR MATRIX					
	> Reference				
V_Classified	1	2	Area	Wi	
1	0.9665	0	226740600	0.9665	
2	0	0.0335	7849800	0.0335	
Total	0.9665	0.0335	234590400	1	
Estimated area	226740600	7849800	234590400		
SE	0.0001	0.0001			
SE area	1837.12	1245.02			
95% CI area	1764	3600.75			
PA [%]	0.9951	0.9945			
UA [%]	0.9943	0.995			
Overall accuracy [%] = 99.9948					
Area unit = metre^2					
SE = standard error					
CI = confidence interval					
PA = producer's accuracy					
UA = user's accuracy					

APPENDIX 7: TURN-IT-IN PLAGIARISM REPORT

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