Evaluation of Fire Danger and Fire Potential Indices for South Africa: Case studies in Mpumalanga and the Western Cape

by

Melissa Burgess

Submitted in partial fulfilment of the requirements

for the degree

MSc Geoinformatics

in the

Faculty of Natural and Agricultural Sciences

University of Pretoria

Submitted on 25 November 2016

Declaration

I, Melissa Burgess, declare that the dissertation, which I hereby submit for the degree MSc Geoinformatics at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

MBurgess

Signature

2016/11/24

Date

Evaluation of Fire Danger and Fire Potential Indices for South Africa: Case studies in Mpumalanga and the Western Cape

Melissa Burgess

Supervisor: Professor Serena Coetzee

Co-Supervisors: Mr Philip Frost (CSIR), Mr Graeme McFerren (CSIR)

Department: Geography, Geoinformatics and Meteorology

Faculty: Natural and Agricultural Sciences

Degree: MSc Geoinformatics

University: University of Pretoria

Abstract

Wildfires are a common phenomenon on earth and can have disastrous effects on the environment, infrastructure and surrounding communities. At the same time, many ecosystems are fire prone and require burning at regular intervals, in order to maintain the health of the ecosystems. It is necessary to minimise the negative effects of fires where possible. Information needs to be provided to fire management officials to facilitate efficient planning and mitigation in order to minimise the negative effects. Wildfires are influenced by many variables including vegetation type, fuel load, fuel moisture, proximity to roads, proximity to settlements, elevation, slope, aspect, temperature, precipitation, wind and relative humidity. These variables can be used to build a fire potential index that determines the probability of a fire occurrence and the possibility of the fire to become an out of control fire. Fire potential indices provide information on where fire potential is high so fire management officials can plan resources accordingly and thus minimise negative impacts of wildfires. Many fire potential indices have been developed but their usefulness in South Africa has not been verified. The aim of the research was to implement and evaluate different fire potential indices utilising geographic information, including remote sensing products, to predict fire potential in South Africa. The Mpumalanga and the Western Cape provinces were used as case studies. The time periods included February to December 2015 for Mpumalanga and August 2014 to June 2015 for the Western Cape. A number of candidate fire potential indices were implemented in the Python scripting language. A variety of data sources were used to implement the fire potential indices. The fire potential indices were evaluated along with a few fire danger indices. The performance evaluation compared satellite detected active fire events to the fire potential indices in the study areas based on statistical metrics including Pseudo R^2, C-Index, Eastaugh's Two-Part Parametric, Bhattacharyya Coefficient and Percentile Shift. The evaluation was performed per pixel for the entire date range. A performance ranking was then calculated for all the indices based on the pixel performance and a final ranking was assigned to each index. The Fire Potential Index performed best amongst the implemented candidate fire potential indices. The Canadian Fire Weather Index performed well in Mpumalanga and the Fine Fuel Moisture Code performed well in the Western Cape. The overall performance of the indices was not very high. This is due to the fact that even though fire potential is high in an area, an ignition source might not be present to cause an actual fire event. The performance of fire potential indices and fire danger indices were different in the two provinces. Future work can be done to develop an index based on South African conditions or calibrate the indices implemented in this research for an area.

Acknowledgements

I would like to thank my Heavenly Father for allowing me to have the opportunity to be able to have worked on this project and to be in an environment where I could learn so much from a number of individuals.

I would like to thank my supervisor Professor Serena Coetzee and my co-supervisors Mr Philip Frost and Mr Graeme McFerren for all their input and guidance given during this project. Thank you for your valuable input on the dissertation and for reviewing the dissertation and making recommendations.

The EOSIT team at the CSIR, thank you for all the encouragement you have given me throughout the last two years.

Linda Kleyn, thank you for your valuable input on the dissertation.

The management team at the CSIR, thank you for granting me the opportunity to complete my MSc.

My husband, Anthony, thank you for always being there and for supporting me in completing this project.

I would like to thank my mother, father, sister and grandmother for your support and love. I really appreciate everything you have done for me.

List of Abbreviations and Acronyms

Abbreviation or Acronym	Meaning
3D	3 Dimensional
AFIS	Advanced Fire Information System
AIC	Akaike's Information Criterion
API	Application Programming Interface
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ATSR	Along Track Scanning Radiometers
AVHRR	Advanced Very-High-Resolution Radiometer
AVIRIS	Airborne Visible / Infrared Imaging Spectrometer
BRDF	Bidirectional Reflectance Distribution Function
BUI	Buildup Index
CFFDRS	Canadian Forest Fire Danger Rating System
CSIR	Council for Scientific and Industrial Research
CSR	Cumulative Severity Rating
DC	Drought Code
DEA	Department of Environmental Affairs
DEM	Digital Elevation Model
DMC	Duff Moisture Code
DSR	Daily Severity Rating
DTM	Digital Terrain Model
ECMWF	European Centre for Medium-Range Weather Forecasts
EGM96	Earth Gravitational Model 1991
EMC	Equilibrium Moisture Content
EOSIT	Earth Observation Science and Information Technology
FDI	Fire Danger Index
FDS	Fire Dynamics Simulator
FFDI	McArthur Forest Fire Danger Index
FFMC	Fine Fuel Moisture Code
FFR	Forest Fire Risk Index
FHI	Fire Hazard Index
FIREHARM	Fire Hazard and Risk Model
FlogA	Fire Logic Animation
FMC	Fuel Moisture Content
FPA	Fire Protection Association
FPI	Fire Potential Index
FPO	Fire Protection Officer
FRI	Fire Risk Index
FVS-FFE	Fire and Fuels Extension to the Forest Vegetation Simulator

Abbreviation or Acronym	**Meaning**
FWI	Fire Weather Index
GBS	Global Burned Surfaces
GDAL	Geospatial Data Abstraction Library
gdal_translate	The gdal_translate utility “can be used to convert raster data between different formats.” (GDAL.org, 2017)
gdalwarp	The gdalwarp utility “is an image mosaicking, reprojection and warping utility.” (GDAL.org, 2017)
GeoTIFF	Georeferenced Tagged Image File Format
GFDI	McArthur Grassland Fire Danger Index
GFED	Global Fire Emissions Database
GFS	Global Forecast System
GIS	Geographical Information System
GOES	Geostationary Operational Environmental Satellite system
GPM	Global Precipitation Measurement
GPS	Global Positioning System
GPW	Gridded Population of the World
GRUMP	Global Rural-Urban Mapping Project
GTI	GeoTerraImage
HDF-EOS	Hierarchical Data Format – Earth Observing System
HFI	Hybrid Fire Index
I / O	Input / Output
ISI	Initial Spread Index
KBDI	Keetch-Byram Drought Index
LFDI	Lowveld Fire Danger Index
LiDAR	Light Detection and Ranging
MODIS	Moderate Resolution Imaging Spectroradiometer
MSG	Meteosat Second Generation
NASA	National Aeronautics and Space Administration
NDMI	Normalised Difference Moisture Index
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NGA	United States of America National Geospatial-Intelligence Agency
NOAA	National Oceanic and Atmospheric Administration
NPP	Suomi National Polar-Orbiting Partnership
pgsql2shp	A utility that is included as part of shp2pgsql
RAWS	Remote Automatic Weather Stations
RG	Relative Greenness
SAVR	Surface-area-to-volume Ratio
SFI	Structural Fire Index

Abbreviation or Acronym	Meaning
shp2pgsql	shp2pgsql is a data loader utility that "converts ESRI Shape files into SQL suitable for insertion into a PostGIS/PostgreSQL database." (###)
SPOT	Satellite Pour l'Observation de la Terre
SRTM	Shuttle Radar Topography Mission
SSR	Seasonal Severity Rating
TRMM	Tropical Rainfall Measuring Mission
UNEP	United Nations Environment Programme
URL	Uniform Resource Locator
VC	Vegetation Content
VIIRS	Visible Infrared Imaging Radiometer Suite
WFDS	Wildland-urban interface Fire Dynamics Simulator
WoF	Working on Fire
X-SAR	X-band Synthetic Aperture Radar

Table of Contents

Table of Figures

Table of Tables

1. Chapter One: Introduction

1.1. Chapter Overview

This chapter provides a high-level overview of the problem addressed in this research. Many fire potential indices have been developed, but their suitability for South Africa has not been verified. Context is given to the problem by providing some background information on topics encountered during the research such as wildfires, factors influencing wildfires, wildfire potential indices and the role of wildfire potential indices. The research problem statement, research questions, aims and objectives are provided to supply more detail on the problem that was investigated in the research. The significance of this research is included to explain why it is needed and the limitations of the research are included to give insight into the challenges encountered during the research. An overview of the outline of the rest of the chapters is also given.

1.2. Background

Wildfire is a common feature of the earth (Flannigan et al. 2013:54) and fires are a part of the landscape of South Africa (Working on Fire, 2013). Figure 1 shows a wildfire burning trees in a forest in the Western Cape, South Africa. These wildfires can hold disastrous consequences for the environment, infrastructure and surrounding communities. At the same time, many ecosystems are fire prone and require burning at regular intervals, in order to maintain the health of the ecosystems (van Wilgen et al. 2012:1).

Figure 1: Wildfire burning in Tokai Forest in the Western Cape, South Africa (The Telegraph 2015).

Fire management is essential to ensure that the damage caused by fires is controlled and minimised. In South Africa the Veld & Forest Fire Act of 1998 regulates fire management to ensure that the necessary precautions are taken to reduce damage from wildfires. The Act takes both the need to maintain the health of ecosystems and the need to reduce risk of fires into account (van Wilgen et al. 2012:6).

In this research, focus is placed on fire potential. According to the Oxford Dictionary (2016) ‘potential’ is defined as “having the capacity to develop into something in the future”. Therefore, fire potential, in context of this research is the probability of a fire to occur and become an out of control wildfire (a problem fire).

Fire potential is based on a number of influencing variables. These variables can either cause the ignition of a wildfire, or they can increase or decrease the intensity of a burning fire. The amount of fuel, type of fuel, continuity of fuel, structure of fuel and the moisture content of fuel has an influence on wildfire potential and spread. Moisture content of vegetation or vegetation greenness is influenced by temperature, precipitation, relative humidity, solar radiation and wind (Caetano et al. 2004:320). According to Aricak et al. (2014:102) closeness to settlements, slope, aspect, elevation, vegetation moisture and proximity to roads can also influence fire potential and spread. By making use of some or all of these variables, a fire potential index can be developed to attempt to quantify the likelihood or probability of a fire igniting in an area (Caetano et al. 2004:320). The variables used can be split into two categories, namely, structural variables and dynamic variables.

Structural variables, in the context of wildfires, are long term variables. They are derived from variables that do not change over a short period of time. An example of a structural variable is land cover (Caetano et al. 2004:320). A structural fire potential index can be developed by making use of variables such as vegetation cover, elevation, slope, aspect, climate, roads, soils, population density and topography (Caetano et al. 2004:320).

Dynamic variables, in the context of wildfires, are short term variables. These variables change over a short period of time. An example of a dynamic variable is weather (Caetano et al. 2004:320). Dynamic variables can still be measured despite short term changes. The purpose of a dynamic fire potential index is to reveal changes in the ability of forest fuels to ignite (Caetano et al. 2004:320).

Fire management officials can use these fire potential indices to plan resource readiness in case of high fire potential in an area. By conducting thorough planning the effects of wildfires can be minimised and officials can maximise control of a fire in case a fire occurs.

The fire potential indices can feed into related fields such as fire behaviour modelling and fire spread modelling. As an example, fire spread simulations can be performed on areas with high fire potential. Better understanding of wildfires can be gained from combining different fields of research. Fire potential is an important base for fire behaviour and fire spread modelling because it deals directly with the fuel characteristics that drive fire activity.

Currently, there is no operational fire potential index in South Africa to assist organisations such as Working on Fire (WoF) and Fire Protection Associations (FPA's). An operational fire potential index is required that will aid not only fire managers, but also other stakeholders such as the South African system: the Advanced Fire Information System (AFIS).

AFIS was developed by the Meraka Institute of the Council for Scientific and Industrial Research (CSIR) to provide information on wildfires detected by earth observation satellites, weather and fire danger forecasts. AFIS is a web-based system that provides prediction, detection, monitoring and alerting capabilities to users. It is hoped that this research will aid in determining the best fire potential index for possible use within AFIS. Figure 2 shows a screenshot of the AFIS viewer displaying the active fire hotspots detected via satellite for South Africa on 20 June 2016.

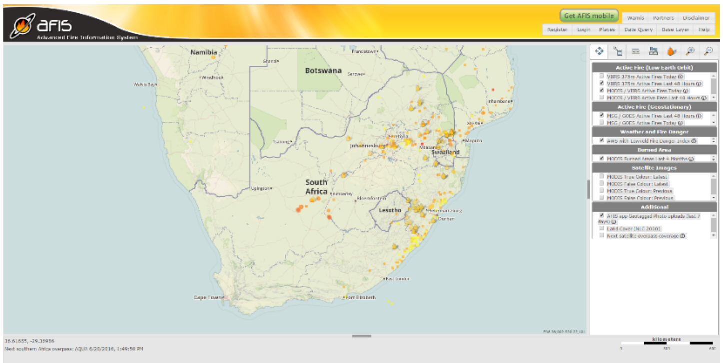

Figure 2: AFIS Viewer (AFIS 2016).

This research investigates fire potential indices and variables that affect fire potential. Existing fire potential indices were studied and compared to ascertain suitability for application in South Africa. A number of these indices were implemented in a data rich environment to map the necessary data to the fire potential index variables.

1.3. Research Problem Statement

Many fire potential indices have been developed, but their suitability for South Africa has not been verified.

1.4. Research Questions

The following research questions will be answered during this research process:

- Which variables influence fire potential, i.e. the likelihood of a fire to occur in the future?
- How is fire potential described and estimated in different existing fire potential indices?

- Can any of the existing fire potential indices be used to predict fire potential in South Africa?

1.5. Research Aims and Objectives

The aim of the research is to implement and evaluate different fire potential indices utilising geographic information, including remote sensing products, to predict fire potential in South Africa.

The objectives of this research are listed as follows:

- To conduct a literature review to provide basic information in order to study and compare fire potential indices.
- To specify requirements for a fire potential index that can be used in the South African context.
- To select candidate indices and implement the candidate fire potential indices.
- To evaluate the implemented fire potential indices for use in the Mpumalanga and Western Cape provinces in South Africa.

1.6. Significance of Research

This research contributes to the prediction of the probability of a wildfire in the Western Cape and Mpumalanga provinces in South Africa. Fire potential indices can be used to provide fire management officials with the necessary information to be able to conduct efficient planning and resource allocation and deployment in order to limit the negative consequences of wildfires.

This research specifically investigates the use of fire potential indices in the Western Cape and Mpumalanga provinces of South Africa, but it is possible to apply the research process followed and implement the indices in the remainder of the South African provinces. The Western Cape and Mpumalanga were selected because they represent two fire seasons in South Africa. The Western Cape fire season is from December to April and the Mpumalanga fire season is from June to October.

No operational fire potential index exists for South Africa and this research may make it possible to implement a fire potential index in other provinces of South Africa.

The index implementation will allow the index to be executed as new data becomes available therefore making it data driven (evidence based) and dynamic to provide the latest information to fire management officials.

The research will potentially feed into an operational system such as AFIS to provide the information in a practical way to fire management officials. The research could contribute to other fire related topics, such as fire spread and fire danger to provide additional information that may be useful in the fire spread and fire danger fields.

1.7. Overview of Remaining Chapters

The remaining chapters will unpack the problem and research introduced in chapter one. Chapter two provides necessary background information on topics related to fire potential indices and provides the basis for the rest of the dissertation. Related research is also presented in chapter two. Chapter three provides the details on the research methods used and the experiment that was designed to evaluate the effectiveness of the fire potential indices. The requirements for the evaluation of the fire potential indices are also described. Chapter four provides details on the implementation of the fire potential indices for use in the evaluation of the indices. The results of the experiment and a discussion of the results are provided in chapter five. Chapter six describes the conclusions of the research and presents a few ideas for future research that follows on this research. The references used in the research are listed after the chapters. Finally, appendices are provided with a URL where the source code, developed for the research, can be found and the ethics approval document.

1.8. Chapter Summary

This chapter provided an overview of the problem addressed in this dissertation by providing some background information, the problem statement, research questions, research objectives, the significance and limitations of the research and an overview of the remaining chapters of the dissertation. Fire potential indices can potentially be used to prevent large scale disasters in terms of wildfires. Implementation of a useful fire potential index for operational use should be considered. It is important to consider the most important variables influencing wildfire potential. A number of fire potential indices, influenced by many different variables, will be implemented and evaluated to determine which of them could potentially be used in an operational system that will provide useful fire potential information to fire management officials and other stakeholders. The following chapter provides more background information on the topics covered in the research.

2. Chapter Two: Literature Review

2.1. Chapter Overview

This chapter provides background information on some of the topics encountered during this research. The first section lays down the groundwork for research context. Topics discussed in the first section include: wildfires, fire management, factors influencing fires, fire behaviour, fire spread, fire potential indices and fire potential index analysis. The second section provides information on related work and background information on the indices implemented in this research as they were implemented in other areas around the world. Finally, a chapter summary will be provided.

2.2. Wildfires

Wildfires are a common feature of the earth (Flannigan et al. 2013:54) and fires are a part of the landscape of South Africa (Working on Fire, 2013). Many ecosystems are dependent on fires at regular intervals and these fires are necessary to maintain the health of the ecosystems (van Wilgen et al. 2012:1). Around 70% of ecosystems in South Africa are fire-adapted (Working on Fire, 2013) and this means that these ecosystems require occasional fire to maintain ecosystem health. In South Africa, wildfires take place in grasslands, fynbos, woodlands and indigenous forests (Working on Fire, 2013) which covers a large proportion of the country.

Fires occur in areas around a specific time of year and this time period is known as a fire season (Gregoire et al. 2013:107). The fire seasons in South Africa occur around two separate time periods based on the rainfall pattern. The fire seasons are defined as follows: the Western Cape experiences its fire season during Summer (December to April) and the rest of the country during Winter (June to October) (Working on Fire, 2013).

The occurrence of fires in a specific area is influenced by the type of vegetation and the load of vegetation fuel that is present. Vegetation fuel is the amount of vegetation available to sustain a fire. This is in turn influenced by the prevailing weather conditions in the area. For example, the fuel load will be higher if high rainfall occurred during the rainy season in an area and fuel load will be low if low rainfall occurred. Southern Africa's long dry seasons and fast fuel build-up creates the perfect conditions for frequent vegetation fires (Archibald et al. 2008:1). This is because large amount of fuel is available to burn every fire season because of the fast regrowth rate of grass in grasslands. Three conditions influence fire return intervals, including sufficient fuel to burn, dry weather and an ignition point (van Wilgen et al. 2010:636). This means that fire can return to a previously burned area if these three conditions are met.

A fire is started at a specific point known as the ignition point. The fuel present at the ignition point is triggered by some influencing factor to cause it to catch fire. Fires can start naturally, e.g. by lightning or falling rocks particularly in mountainous regions. Fires can also be started by humans (anthropogenic) and this can either be by accident, due to carelessness, or intentionally (Working on Fire, 2013). Gregoire et al. (2013:107) reports that the causes of fires in Africa can be attributed to lightning strikes or anthropogenic causes such as agricultural waste burning or land clearance.

Grassland and savanna fires contribute over 80% of total area burned in South Africa. Most of the fires that occur in southern Africa are surface fires that are fuelled by litter and grass (Archibald et al. 2008:2). Africa and Australia are the most fire prone continents, but fires also occur in Europe, Asia and the Americas. The only areas worldwide, that are not very prone to fire, are areas near the north and south pole and deserts (Flannigan et al. 2013:54).

Annually about half a million hectares of forest is destroyed in the Mediterranean regions of Portugal, Spain, Italy, France and Greece (Kalabokidis et al. 2014:541). According to Kanga et al. (2014:30) around six million square kilometres of forest have been lost due to forest fires in the last 200 years.

Climate change and anthropogenic causes have sparked an increase in wildfires over the past ten years (Kalabokidis et al. 2014:541). According to Gregoire et al. (2013:107) fire frequency is likely to increase in future, because fire is used to clear land for agricultural use (deforestation).

Wildfires are needed to maintain the health of many ecosystems, but fires can hold many negative consequences in some areas. Fire can have a negative influence on resources and lives, especially during intense fire seasons (Zhang et al. 2014:1). Areas where development has taken place near fire-prone ecosystems pose the biggest threat to livestock, infrastructure and human life (van Wilgen et al. 2012:1). Figure 3 shows a fire burning near wildlife in a forest in the United States of America. If fires get out of control in these areas lives can be lost and vegetation destroyed to a point where the vegetation structure of the area is permanently altered. Forest fauna and flora, resources, biodiversity, property and the atmosphere are affected negatively by fire on an annual basis (Kanga et al. 2014:30). Kalabokidis et al. (2014:541) also mentions that fires can have major environmental and socio-economic effects. The negative effects of wildfires have to be reduced to ensure a safe living environment for people, animals and vegetation.

Figure 3: Wildfire burning in Bitterroot National Forest (Wikipedia.org 2000).

Other aspects of a community can also be negatively influenced. Ager et al. (2011:1) and Aricak et al. (2014:101) both report that water, and recreational and aesthetic opportunities can be negatively influenced by wildfires. According to Aricak et al. (2014:101) forest fires have a negative influence on water management, protection, science, climate regulation, social well-being and soil reclamation. Ager et al. (2011:1) reports that wildfires threaten services such as critical habitat for protected species, wood products and carbon storage. Forest fires cause deforestation and desertification (Pourtaghi et al. 2014:2). A combined effect of economic loss and damage can be caused by the above-mentioned issues.

Nutrient cycles and vegetation succession patterns are influenced by fires (Jurdao et al. 2013:59). A large amount of the above ground biomass is removed by fires and reproduction and coexistence conditions are created in plant communities (van Wilgen et al. 2010:632). Ecosystems have their own fire regime and the fire regime is characterised by the fire season, fire frequency and size and intensity of fires (van Wilgen et al. 2010:632). The ecosystems are dependent on fire to remain healthy.

Atmospheric aerosols and greenhouse gasses are negatively influenced by fires (Jurdao et al. 2013:59) and fires act as a source of greenhouse gasses (Archibald et al. 2008:1). The troposphere and air quality is influenced by the burning of biomass (Gregoire et al. 2013:107). The air quality is therefore influenced and this can be dangerous to people and animals that have to live in the burned area. If fires are not managed, the negative effects on the resources mentioned above can become disastrous.

Fires can have numerous negative influences on the environment, infrastructure and lives in a community. Figure 4 shows chaos on highway 63 near Fort McMurray where a wildfire destroyed vegetation and buildings in May 2016. It is imperative to identify areas where the potential of fire occurrence is high.

Figure 4: Residents of Fort McMurray evacuating because of a wildfire (Wikipedia.org 2016).

2.2.1. Factors Influencing Wildfires

Fires are influenced by a number of factors that can either increase or decrease the intensity of a burning fire. According to Flannigan et al. (2013:54) fires are influenced by fuels and ignition mediums. Therefore, an ignition medium has to be present at the location of a fuel to cause a fire. Archibald et al. (2008:1) reports that land use change can influence fire patterns. As an example, areas that were prone to fires in the past may not be prone to fires after the open grassland field has been developed into a residential complex. Flannigan et al. (2013:54) and Archibald et al. (2008:1) both state that population and climate also has an influence on fires. According to Aricak et al. (2014:102) distance to settlements, slope, aspect, elevation, vegetation moisture and closeness to roads has an impact on forest fire ignition and spread.

Fire events and fire spread is further influenced by the amount of fuel, type of fuel, continuity of fuel, structure of fuel and moisture content of fuel. The amount of live and dead fuel and its moisture content influence the flammability of vegetation. Vegetation is more likely to burn if it is dry. Meteorological factors such as temperature, precipitation, relative humidity, solar radiation and wind have an influence on the moisture content of vegetation and relates to vegetation 'greenness' (Caetano et al. 2004:320). Vegetation moisture seems to play an important role in the ignition and spread of wildfires.

In a study conducted by Archibald et al. (2008:6) grazing, land management, land transformation, accumulated rainfall, length of dry season, topography and lightning frequency were considered as factors that can have an influence on wildfires (Archibald et al. 2008:6). Tree cover, rainfall and dry season length were identified as the most significant predictors of burned area (Archibald et al. 2008:6). Grazing, population density and road density were identified as moderately significant and sand percentage and lightning were the least significant predictors of burned area (Archibald et al. 2008:10). Archibald et al. (2008:10) found that an area with a dry season of less than six months had a low amount of burned area. Population densities of more than ten people per square kilometre resulted in less fires than an area with less than ten people per square kilometre (Archibald et al. 2008:13). This contradicts statements by Ertena et al. (1994:2), Jaiswal et al. (2002:3) and Adab et al. (2012:1730), that areas near roads and settlements can be viewed as areas that are more prone to fires. These areas are viewed as being more prone to accidental fires due to human activities such as cooking, using fire for heating purposes and throwing lit cigarettes on the ground.

Fuel material can be defined as any material that can easily ignite. All organic material that can cause a fire and sustain burning is classified as fuels (Keane & Reeves 2011:212). A large number of fuel types exist and the fuel can be located within or above soil. When determining a course of action in fire prevention it is important to determine the amount of material present (Aricak et al. 2014:101). More detailed knowledge about the fuel types and load in an area can lead to more informed decisions in terms of potential fire occurrence and the spread thereof. Chuvieco & Congalton (1989:150) report that the ideal situation is to be able to identify different stand densities, height-area ratios and stress conditions. Having more information on the structural condition of fuel in an area can lead to better comprehension of the behaviour of a fire in an area with single or multiple fuel types. If the amount and structure of material present in an area is known, a better understanding can be gained of how dangerous a fire can be if an ignition source is available, as a fire is more likely to grow if a lot of fuel is present to burn. A small fuel load will cause a small fire with low intensity which will spread slowly. A large fuel load will cause a large fire with high intensity which will spread quickly. It may prove useful to map some of the above-mentioned fuel characteristics in order to be able to use the data in case of a fire.

Fuel has been mapped in many different ways. Fuel characteristics, like fuel bed depth and canopy bulk density, have been mapped as a function of vegetation types, ecosystems and topography (Keane & Reeves 2011:213). Researchers have made use of digital photographs, Landsat data, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data, Airborne Visible / Infrared Imaging Spectrometer (AVIRIS) data, Advanced Very-High-Resolution Radiometer (AVHRR) data and Light Detection and Ranging (LiDAR) data to map fuel characteristics (Keane & Reeves 2011:213). Others have made use of field data in statistical models to map fuel characteristics. Some have combined approaches to create a fuel map with higher accuracy. According to Chuvieco & Congalton (1989:149) overstory and understory are extremely important as it amounts to the complete amount of fuel available to burn. Overstory is the layer of foliage in a forest canopy and understory is the vegetation layer under the forest canopy. Garcia et al. (2011:1378) report that the combined use of multispectral data and LiDAR data presents a way for more detailed fuel mapping. Therefore, a combination of spectral data and 3-dimensional (3D) data provides more distinct fuels types. The mapped fuel characteristics can be used to identify areas that can potentially burn if an ignition source is present and the weather conditions are favourable for a fire to burn.

In the structure of fuel on the ground, a number of different types of fuel can be found. Fuel can be alive or dead and it can be aerial or it can be found on the surface of the earth. Live and dead surface and canopy biomass can aid the spread of wildfires (Keane & Reeves 2011:212). According to Chuvieco et al. (2004:322) dead fuels on the forest floor are the most dangerous because they are very dry and are affected by fast atmospheric changes. The dead fuels on the forest floor are known as surface fuels. Surface fuel can be classified as duff and litter, downed and dead woody biomass, as well as live and dead standing vegetation (Keane & Reeves 2011:212). Canopy fuel is aerial biomass about 2 meters above the surface of the earth. Canopy fuels include branches, lichens, dead ladder fuels as well as other dead material such as needles and branches (Keane & Reeves 2011:212). The amount of biomass per unit area is known as the fuel load. Biomass builds up when there is no fire (Keane & Reeves 2011:212). Therefore, if a fire has not occurred for a long period of time, enough for the biomass to build up in large amounts, a fire can be very dangerous and difficult to control if an ignition source is present to start a fire. When biomass is present in an area, it is important to look at the characteristics of the fuel to determine if it is possible for the fuel to burn and how easily it will burn if a fire ignites.

Fuel properties are very diverse and they differ at different scales (Keane & Reeves 2011:213). Surface fuels are difficult to map with the use of remote sensing data because the fuel on the surface is concealed by the fuel canopy. It is difficult to map fine fuels because the sensors do not really capture data at a desired resolution (Keane & Reeves 2011:213). These challenges are important to note in fire modelling. It may prove difficult to understand surface fires if it is not possible to acquire remote sensing data on the state of surface fuels because of obstruction by canopy fuels.

Moisture content is extremely important in fire spread modelling (Chuvieco et al. 2004:322). If the moisture content of a fuel is high, it is unlikely that it will burn easily. Fires spread easily if the moisture content of the fuel is low. Fuel moisture is influenced by a number of factors. Fuel moisture is influenced by the length of the dry season and how dry the fuel is. If it has not rained for a long period of time, the fuel can be very dry. It is also influenced by the amount of fuel available to burn and the current day's weather conditions (Archibald et al. 2008:2). If the weather conditions are windy and hot, and the relative humidity is low, a fire can easily spread and become difficult to manage or suppress. According to Dimitrakopoulos et al. (2011:84) moisture content of fuel is the most noteworthy cause for the ignition of the fuels. Fuel moisture is an important part of the research project.

Data concerning fuel types has to be updated frequently because it is dynamic. The fuels are dynamic because of some activities such as land use change, agricultural activities and wildfires. These activities alter the condition and possibly the availability of the fuel in an area. Fuel type maps provide information such as where and how much, as well as fuel ratios and fuel varieties (Aricak et al. 2014:102). Fuel type datasets or maps are developed around the world in different ways. Aricak et al. (2014:102) aimed to identify types of flammable materials in forests in order to create a fuel type dataset. Ten fire risk groups were created by Aricak et al. (2014:103), by categorising tree species, crown closure and stand age. Fuel material properties, such as crown diameter, crown length and height, play an important role in biomass estimation. These properties can be acquired from terrestrial measurements and satellite images (Aricak et al. 2014:102). The Landfire project was created to map fuels, vegetation and regime properties in the USA (Keane & Reeves 2011:219). According to Keane & Reeves (2011:214) fuel classification can be divided into two groups. The first is to simulate the effects of fires and the second is to forecast fire behaviour (Keane & Reeves 2011:214).

Many types of fuel exist all over the world. In South Africa, a fire ecology type classification was derived and is presented in the National Veldfire Risk Report (Forsyth et al. 2010). Thirteen classes have been defined and include: Sour Grassland, Coastal Grassland, Sweet Grassland, Moist Woodland, Arid Woodland, Sparse Arid Woodland, Thicket, Grassy Nama Karoo, Nama Karoo, Succulent Karoo, Fynbos, Renosterveld and Forest. The classification was made based on the properties of the different types of fuel and how the fuels would behave in case of a fire.

Fuel models have been developed in the United States of America as part of the BehavePlus program. Initially thirteen classes were designed by Anderson (1982), but later the model was expanded with another forty classes by Scott and Burgan (2005) to create the fifty-three standard fire behaviour fuel models that are currently available in BehavePlus (Andrews 2014:24). A quantitative account of the physical and chemical properties of a range of vegetation types can be provided by fuel models (Caetano et al. 2004:320). Some of the fuel characteristics taken into account by the fuel models created by Andrews (2014) and Scott and Burgan (2005) include: fuel load, surface-area-to-volume ratio, heat content, fuel bed depth and dead fuel moisture of extinction (Scott & Burgan 2005:4). These properties can be used in fire potential indices to determine how vegetation types will burn in a range of conditions (Caetano et al. 2004:320). It is therefore important to ensure a mapping of vegetation types to fuel models that is as accurate as possible for use in fire potential modelling.

The existence of vegetation in an area is based on the climate present in the area. It is important to identify the fire frequency of different fuel types to ensure successful fire management (Curt et al. 2013:151). If the fire frequency of a fuel type is known, sufficient fuel treatment can be applied and damage caused by fires can be mitigated.

The topography of an area is an important factor in the behaviour of a fire. Topography is the arrangement of the physical features of an area (Oxford Dictionary 2016). Topography is related to wind behaviour and it affects how fire prone an area is (Ertena et al. 1994:2). Elevation is the height above some level, such as sea level (Oxford Dictionary 2016). Rainfall increases with elevation (van Wilgen et al. 2010:632). Elevation also affects wind behaviour, vegetation structure, fuel moisture and air humidity (Zhang et al. 2014:2). Slope is defined as a surface where one side is higher than the other side (Oxford Dictionary 2016). Slope is associated with how quickly a fire spreads. Fires spread more quickly when it moves up a slope and less quickly when it moves down a slope. Figure 5 shows a wildfire burning up-slope. The steepness of the slope also has an influence on fire spread. The steeper the slope, the faster the fire spreads (Zhang et al. 2014:2). Aspect is defined as the positioning of a structure in a particular direction (Oxford Dictionary 2016). Aspect is associated with sun exposure, temperature, wind direction and air humidity (Zhang et al. 2014:2). Slope, aspect and elevation can be calculated from Digital Elevation Models (DEMs) (Chuvieco & Congalton 1989:150). The above mentioned physical properties of the environment have to be taken into account to determine if a fire can potentially ignite in an area.

Figure 5: Wildfire burning up-slope (Wikipedia.org 2011).

Human activities have to be taken into account as some fires are likely to be caused by humans. Proximity to roads and human activities deals with the distance of vegetation to roads and areas where humans live and perform activities. According to Zhang et al. (2014:3) a forest fire is more likely to start in a region where it is close to roads and human settlements. Human, animal and vehicle movement and activities can cause fires. Fires can be ignited by accident (Ertena et al. 1994:2).

Narayanaraj & Wimberly (2012:887) report that more manmade fires occur near roads than further away from roads. These fires burn a small area. Fires that occur further away from roads or in areas where no road is present, burn a larger area than the fires close to roads. A road can also act as a fire break and aid in fire suppression (Chuvieco & Congalton 1989:152). The influence of roads in wildfires can therefore be negative or positive.

Human settlements and activities can also influence fires in both positive and negative ways. An increase in population density has been linked to an increase in number of fires. Increased population densities, however, mean that fuel loads are reduced, land use is changed and the landscapes are fragmented which is associated with a decrease in fire activity (Archibald et al. 2008:2).

Climate change is defined as a change in climate patterns (Oxford Dictionary 2016). The global climate is increasing (warming) and this may have a big influence on fire activity (Flannigan et al. 2013:54). The frequency, intensity, duration and timing of fires may be affected by climate change (Thompson & Calkin 2011:1902). With drier climates, the dry seasons can become longer and the warm seasons can become hotter, which can increase the amount of fire occurrences. Fires are largely influenced by temperature, precipitation, wind and atmospheric moisture. It is suggested that fire activity has already changed because of climate change (Flannigan et al. 2013:54). An increase in fire activity in Canada is likely attributed to a change in temperatures because of human activity. Fire seasons will become longer and the percentage of area burned will increase as the climate gets warmer. All of the above-mentioned factors play a role in the ignition and spread of wildfires. Wildfire management can become more effective if sufficient data can be collected and interpreted in order to minimise the effects of wildfires.

Numerous factors can have an influence on fire occurrence. Fuel type, fuel moisture, proximity to roads, proximity to human settlements, rainfall, relative humidity, temperature, slope, aspect and elevation are used as input to indices in this research.

Table 1 contains a summary of the factors influencing fire potential and the sources in the literature that describe them.

Factors	**Sources**
Fuels (Amount, Type, Continuity, Structure)	Flannigan et al. (2013:54), (Caetano et al. 2004:320), (Aricak et al. 2014:101), Chuvieco & Congalton (1989:150), (Keane & Reeves 2011:212), (Curt et al. 2013:151)
Ignition Mediums	Flannigan et al. (2013:54)
Land Use Change	Archibald et al. (2008:1)
Population	Flannigan et al. (2013:54), Archibald et al. (2008:1)
Climate & Climate Change	Flannigan et al. (2013:54), Archibald et al. (2008:1), (Thompson & Calkin 2011:1902)
Distance to Settlements	Aricak et al. (2014:102), Ertena et al. (1994:2), Jaiswal et al. (2002:3), Adab et al. (2012:1730), Zhang et al. (2014:3)
Slope	Aricak et al. (2014:102), (Zhang et al. 2014:2)
Aspect	Aricak et al. (2014:102), (Zhang et al. 2014:2)
Elevation	Aricak et al. (2014:102), (Zhang et al. 2014:2)
Fuel/Vegetation Moisture	Aricak et al. (2014:102), (Caetano et al. 2004:320), (Keane & Reeves 2011:212), Chuvieco et al. (2004:322), Dimitrakopoulos et al. (2011:84)
Closeness to Roads	Aricak et al. (2014:102), Ertena et al. (1994:2), Jaiswal et al. (2002:3), Adab et al. (2012:1730), Zhang et al. (2014:3), (Chuvieco & Congalton 1989:152)
Grazing	Archibald et al. (2008:6)
Land Management	Archibald et al. (2008:6)
Land Transformation	Archibald et al. (2008:6)
Accumulated Rainfall	Archibald et al. (2008:6)
Length of Dry Season	Archibald et al. (2008:6)
Topography	Archibald et al. (2008:6), (Ertena et al. 1994:2)

Factors	Sources
Lightning Frequency	Archibald et al. (2008:6)

Table 1: Factors Influencing Fire Potential

2.2.2. Wildfire Management

Wildfire management is required to reduce damage and loss caused by wildfires. Fire management in South Africa is regulated by the Veld & Forest Fire Act of 1998. The act takes into account the need to maintain healthy ecosystems and the need to reduce risk of fires (van Wilgen et al. 2012:6). The establishment of Fire Protection Associations (FPAs) is addressed in the act. The functions of an FPA include, amongst others, the development of wildfire management strategies, training of members to fight fires and to appoint a Fire Protection Officer (FPO). Working on Fire was established to expand capacity to give assistance to fire prevention, firefighting and prescribed burning (van Wilgen et al. 2012:7). Working on Fire provides support in the form of helicopters and fixed-wing aircraft to help fight fires and assist with prescribed burning. When a wildfire occurs in South Africa, some of the fire fighters trained by Working on Fire are deployed to the field to suppress the fire and protect the environment, lives and infrastructure in the area.

Fire management consists of four types of activities including prevention, pre-suppression, suppression and planned use of fire (Schöning et al. 1997:20). For pre-suppression and suppression purposes it is very important to know how a fire will move across an area (Thompson & Calkin, 2011:1898). By looking at the weather conditions, physical features of the area and the fuel available to burn it is possible to plan the suppression of a fire to ensure that the fire is suppressed before it can get out of control or move into an area where significant loss and damage can be caused. Fire can be used to manage fuel loads before the fuel load becomes too high and dangerous in terms of fire potential. These fires are planned and are not permitted on days when fire danger is high in the area. A large amount of money is spent on fire management and suppression annually.

Fire managers try to maintain a fire regime by burning sections of an area at specific times during a particular season (van Wilgen et al. 2010:632). Management intervention on fire regimes has not been reported on.

Human population growth and invasive alien plants complicate fire management (van Wilgen et al. 2010:632, van Wilgen et al. 2010:633). Invasive alien plants change the structure of vegetation and provide more fuel to burn. South Africa has areas that have dry and warm summers with vegetation that is fire prone. An example of a fire adapted and fire prone ecosystem in South Africa is the fynbos shrublands in the Western Cape and it is managed by prescribed burning to ensure the conservation of the ecosystem (van Wilgen et al. 2010:632).

Fire management is subject to a margin of uncertainty. The uncertainty may be caused by inaccurate data, missing data, or a lack of scientific understanding of fires (Thompson & Calkin 2011:1895). Expert knowledge is important in the field of fire and fuel management because of the high temporal and spatial variability, and diversity of fuels (Keane & Reeves 2011:212).

Fuel maps and information are very important in fire management because it enables managers to visualise an aspect that they can control. Fire managers can make use of coarse resolution fuel maps to plan, allocate and deploy suppression resources (Keane & Reeves 2011:211). At a regional scale, fuel maps can be used to describe fire hazards that can inform decisions about fire-fighting resource deployment and simulate carbon dynamics (Keane & Reeves 2011:212). Intermediate and fine resolution fuel maps can be used to assist in fire danger forecasting (Keane & Reeves 2011:212).

Risk assessments inform fire management on how to take action in future concerning active and preventative fire management, therefore a lack of risk assessment will cause management to be less effective (Thompson & Calkin 2011:1896). Dimitrakopoulos et al. (2011:83) reports that fire potential assessment is important because fire management officials can gain an upper hand from knowing when and where a fire is likely to occur.

Artificial intelligence, geographic information systems (GIS) and remote sensing play a vital role in forest fire management. GIS and remote sensing data can be used to develop fuel type maps, fire activity maps, burned area maps and fire intensity maps that can be useful in fire management (Aricak et al. 2014:102). Mapping the factors that can have an influence on fire ignition and spread is useful in observing trends and potential problems.

Fire management is crucial in minimising the effects of harmful fires and to protect life and the environment. Future fire management demands combining climate and wildfire dynamics with how we understand the influence of fire management on fire activity (Thompson & Calkin 2011:1903). Risk-based decision support has assisted in managing active fires, specifically to control fires before they can spread and cause major damage (Thompson & Clark 2011:1902). Risk-based decision support includes looking at the effectiveness of fuel treatment planning (Thompson & Clark 2011:1901).

Fuel treatment aims to alter the amount of surface and canopy fuel load, and species structure in order to manage fire behaviour. Fuel treatment can have an effect on fire behaviour because of the altered fuel structure (Ager et al. 2011:6). Prescribed burning forms part of fuel treatment.

Prescribed burning is used to decrease the amount of fuel available to burn (van Wilgen et al. 2010:633). In a study conducted by Ager et al. (2010:1562) using fire simulations, wildfire size decreased when the fuel treatment area was increased. Fuel load will need to be changed drastically to ensure that wildfire potential is reduced (Ager et al. 2011:1).

Fuel treatment on agricultural land is important in order to protect crops. Land cover change in sub-Saharan Africa has mostly been a change to agricultural land over the past 50 years (Gregoire et al. 2013:107). More land is used for agriculture and this land has to be managed to protect it from potential fire if conditions become favourable for fires. The fuel load in agricultural land is less than that of natural vegetation (Gregoire et al. 2013:108). A fire on agricultural land will not be as dangerous as a fire on natural land with a higher fuel load. Fire is controlled on agricultural land to protect crops, therefore fire suppression is practiced and fire is only used to burn stubble and crop residue if necessary (Gregoire et al. 2013:108).

Fire management is important to minimise the effects of wildfires. Fire management officials can make use of prescribed burning to reduce the amount of fuel that is available to burn during a wildfire. Identifying areas where fuel load is high or fire potential is high, can have an impact on fuel treatment and fire management to reduce the negative effects of wildfires.

2.3. Wildfire Modelling

2.3.1. Terminology

A number of terms associated with wildfires exist and some confusion is created with different definitions of these terms in the wildfire context. Some of the definitions of the terms are provided in this section. Fire severity is defined as “the magnitude of significant negative fire impacts on wildland systems” (Hardy, 2005:77). According to Hardy (2005:77) fire severity is not directly related to the fire. This means that it is not directly linked to the behaviour of the fire.

Fire risk connected to the National Fire Danger Rating System (NFDRS), is defined as the occurrence of a fire according to Hardy (2005:76). Fire risk within the fire community, according to Hardy (2005:76), is defined as “the chance that a fire might start, as affected by the nature and incidence of causative agents”. In the engineering field, risk is defined as a combination of two aspects, the probability that a fire can occur and the expected damages caused by the fire. Fire hazard is linked to the condition of wildfire fuels. Wildfire hazard only includes the fuel itself and it is not dependent on weather or environmental conditions (Hardy 2005:75). The National Research Council has defined ‘hazard’ as something with the potential to do harm. From these two definitions fire hazard is the potential harm posed by wildfire fuels. According to Chuvieco and Congalton (1989:156) fire hazard is focussed on fuel sources, while fire risk is focussed on fuel sources and ignition sources. Both Chuvieco & Congalton (1989:156) and Hardy (2005:75) define fire hazard as being associated with the fuel present in the area. Based on the definitions of fire risk provided in Hardy (2005:76) and Chuvieco & Congalton (1989:156) it is associated with the ignition of a fire or the possibility that a fire can be ignited in an area.

Fire risk has also been defined in terms of hazard. According to Schöning et al. (1997:3) fire risk measures the hazard posed by fire. It takes both the probability of damage to be caused and the degree of the damage into account (Schöning et al. 1997:3). In assessing wildfire risk, the probability that a fire will occur in an area and the impact it may have on objects in the area must be calculated (Schöning et al. 1997:3). According to Forsyth et al. (2010:8), for a given fire hazard, risk is defined as "a function of the likelihood and the consequence to a vulnerable asset" where likelihood is the probability of a fire occurrence. This risk is defined in terms of social, economic and environmental aspects (Forsyth et al. 2010:8). Forsyth et al. (2010:8) also associates fire risk with the occurrence of a fire ignition event, while Schöning et al. (1997:3) defines risk in terms of the probability of the occurrence of damage being caused. The fact that a fire occurs can be linked to damage being caused, in some cases however, the fire may have been ignited as part of a prescribed burn in which case the fire does not cause any damage.

In this research, focus is put on fire potential. According to the Oxford Dictionary (2016) 'potential' is defined as "having the capacity to develop into something in the future". Therefore, fire potential, in context of this research is the potential for a fire to occur and become an out of control fire in an area, based on a number of influencing factors.

2.3.2. Fire Modelling

Exposure to wildfires has been researched in probabilistic and non-probabilistic ways. Poisson processes, simulation and logistic regression are probabilistic approaches. A probabilistic model that makes use of historical data is different from a model that simulates burn probability, if provided with locations of ignition and weather (Thompson & Calkin 2011:1897).

Non-probabilistic approaches include fuzzy logic, neural networks and knowledge bases. The above mentioned non-probabilistic approaches are classified as artificial intelligence. Expert judgement is used in non-probabilistic approaches. The use of fuzzy set theory is the most common approach. A neural network has been used to predict the occurrence of wildfires in Canada. Jurdao et al. (2012:77) made use of logistic regression to calculate ignition probability of fuel based on live fuel moisture content data that was produced from National Oceanic and Atmospheric Administration Advanced

Very-High-Resolution Radiometer (NOAA-AVHRR) data. A fuzzy logic model has been used to determine fire behaviour (Thompson & Calkin, 2011:1898). Quasi-empirical and empirical models have been used to forecast fire spread rate when provided with wind speed, wind direction and soil moisture (Thompson & Calkin, 2011:1898). Mathematical analogue methods to model spread include spatial Markov Chains, fuzzy logic, neural networks and cellular automata (Thompson & Calkin, 2011:1898). Archibald et al. (2008:8) made use of decision trees to investigate drivers of burned area in southern Africa.

Spatial data from various sources can be used for various applications in fire modelling. The most useful validation dataset in fire modelling is fire occurrence data. Pourtaghi et al. (2014:6) utilised Moderate Resolution Imaging Spectroradiometer (MODIS) imagery to obtain fire occurrences. MODIS is the first satellite that has sensors designed for monitoring fires (Pourtaghi et al. 2014:6). According to Hantson et al. (2013:152) MODIS is the most popular satellite for active fire detection. Bastarrika et al. (2011:3401) reported that MODIS provides a good balance for mapping burned areas at regional or global scale when it comes to spatial resolution, spectral resolution, temporal resolution, thermal infrared band and short-wave infrared band. Fire hotspots have been obtained by making use of data from AVHRR, Along Track Scanning Radiometers (ATSR), Tropical Rainfall Measuring Mission VIRS (TRMM), MODIS, Geostationary Operational Environmental Satellite system (GOES) and Meteosat Second Generation (MSG) (Hantson et al. 2013:152). Fire occurrence can therefore be sourced from various earth observation satellites with the appropriate algorithm to make the detections.

Burned area data can also be used to inspect fire behaviour or fire spread models. According to Bastarrika et al. (2011:1003) coarse spatial resolution images from AVHRR, VEGETATION and MODIS have been used to map burned areas at a global scale, but these sensors do not have high enough spatial resolution to be used for studies on a local scale. Mid resolution sensors have been used for studies on a local scale. Some of the burned area products that are available include the Global Fire Emissions Database (GFED), MCD45A1 (a MODIS burned area product), L3JRC (produced from SPOT VEGETATION data), Globcarbon, Global Burned Surfaces (GBS - produced from NOAA-AVHRR data), GLOBSCAR (produced from ATSR-2 data) and GBA2000 (produced from SPOT VEGETATION data) (Mouillot et al. 2014:67). Burned area can be mapped with the use of many earth observation satellites, however, some satellites with higher spatial resolutions are better suited to local scale burned area mapping.

Vegetation moisture is an important factor influencing fire occurrence and spread. Chuvieco et al. (2004:323) made use of NOAA AVHRR images to estimate Fuel Moisture Content (FMC) of vegetation. FMC is defined as the amount of water over the amount of dry mass (Yebra et al. 2008:524). Dead fuel moisture content is less variable, in space and time, than live fuel moisture content. It is less variable because live fuel is influenced by soil moisture (Danson & Bowyer 2004:309). Chuvieco et al. (2004:323) took the day of the year into account when calculating the FMC, to incorporate the seasonal trends of fuel moisture. Few studies on FMC have made use of in situ data because it is time consuming and expensive to collect (Chuvieco et al. 2004:324). In situ data is more precise than remote sensing data as it is collected directly from the field. According to Aricak et al. (2014:107) the use of satellite imagery to determine fire potential is cost and time efficient, and provides the most updated information. Because of the dynamic nature of vegetation moisture, the use of remote sensing data is more feasible than field measurements.

Along with vegetation moisture, it is important to map vegetation types for use in fire modelling. Chuvieco & Congalton (1989:150) made use of supervised image classification and Landsat Thematic Mapper (TM) images to perform vegetation mapping. Image classification can be defined as a process through which multispectral images are processed or classified in order to create topical maps (Aricak et al. 2014:102). Training areas, for the purpose of supervised classification, were identified on aerial photographs by Chuvieco & Congalton (1989:150). A vegetation map is used to assign fuel models in this research. Several data sources exist and there are also numerous ways to represent data. Some data may be more accurate than others. It is important to determine which data will serve the purpose of a study the best.

Vegetation types and vegetation moisture are important factors in wildfire occurrence. Both of these variables form part of the indices implemented in this research.

2.3.2.1. Fire Behaviour Modelling

The behaviour of a fire is influenced by a number of factors. These factors have been discussed in limited detail in section 2.2.1. According to Andrews (2014:21) fire behaviour modelling systems are important in fire management. Fire behaviour models can be used to determine how a fire may behave if an ignition source is present in an area. Fire behaviour modelling can also be used to investigate potential effects of fuel treatment programs on the fuel available in an area (Ager et al. 2011:2). This section discusses some of the developments in fire behaviour modelling.

Fire behaviour models characterise fire behaviour based on a number of factors. These factors include fuel and weather conditions. The fuel conditions include the type of fuel and as mentioned previously, fire behaviour is largely influenced by fuel moisture (Flannigan et al. 2013:54). Weather conditions influencing fire behaviour include temperature, relative humidity, wind speed and wind direction.

According to Rothermel (1983:6) fire behaviour prediction includes three primary components. The first component involves a method to evaluate the inputs that describe the fuels, fuel moisture, wind speed and terrain slope. The second component is a method to calculate rate of fire spread and fire intensity. The third component involves the interpretation of the rate of fire spread and fire intensity to derive spread distance, perimeter, area, flame length and identifying the conditions that may cause crowning and spotting (Rothermel, 1983:6). In 1972, Rothermel designed a mathematical model to predict wildfire spread. The model has been implemented in software to make it easy for end-users to model fire behaviour and spread. Landscape fire spread models approximate the change of burn probability as a result of fuel treatment plans and patterns (Ager et al. 2011:2). A number of fire behaviour models have been developed to deal with surface fire spread, crown fire initiation, crown fire spread, post-frontal combustion and dead fuel moisture (Kalabokidis et al. 2014:542).

Fire behaviour models have been used in simulation tools such as BehavePlus, FARSITE, FlamMap and HFire (Kalabokidis et al. 2014:542). FARSITE, Fire Area Simulator, is a system that was developed to report on spatial and temporal differences of fire behaviour and spread (growth) (Kanga et al. 2014:31). NEXUS, Fire and Fuels Extension to the Forest Vegetation Simulator (FVS-FFE), FlamMap, BehavePlus, FSIM and FARSITE model fire behaviour. Other software and models approximate fuel moisture and other variables that serve as input to the above-mentioned models (Ager et al. 2011:2). Ager et al. (2011:2) aimed to create an integrated system that makes use of a number of fire spread models. Their system makes use of GIS, databases, landscape fire behaviour models, vegetation growth models and a component that develops fuel treatment plans and tests them (Ager et al. 2011:2).

FlamMap was developed to produce landscape fire behaviour by making use of fuel load, fuel moisture, wind speed and wind direction data. Fuel canopy characteristics are included in the model. Canopy closure, height to live crown, crown bulk density, and average height are used to describe canopy fuel (Ager et al. 2011:3). Live fuel load and dead fuel load, surface-area-to-volume ratio (SAVR) of live and dead fuels, fuel bed depth, moisture of extinction and heat content are used to describe surface fuel (Ager et al. 2011:3).

FVS-FFE provides modelling of fuel dynamics, forest and fuel management, fire behaviour, effects of fire on tree mortality and fuel consumption (Ager et al. 2011:6). The output of FVS-FFE includes predicted fuel load, fire hazard and possible tree mortality (Ager et al. 2011:7). Semi-empirically derived models do not take fire-atmospheric interaction into account (Ager et al. 2011:7). This is considered a limitation of systems like FlamMap and FVS-FFE because they do not take fire and fuel interactions such as combustion and heat transfer into account (Ager et al. 2011:7). The Wildland-urban interface Fire Dynamics Simulator (WFDS) is an extension of the Fire Dynamics Simulator (FDS). FDS was developed to simulate structural fires. WFDS is applicable to wildland fuels and other fire situations (Alexander & Cruz 2013:67).

The fire behaviour modelling software discussed in this section has been used widely in fire management throughout the world. Fire behaviour modelling software has increased because of the complex nature of fire risk modelling. Major advancements have been made possible in wildfire behaviour modelling due to algorithmic development and an increase in computational capacity. Fire behaviour can be predicted with the use of real-time weather information (Thompson & Calkin 2011:1898). Simulation based models are used to model specific events, to predict likelihood of a fire and to predict the intensity of fires (Thompson & Calkin 2011:1898).

According to Rothermel (1983:6) fire spread may be described as a range of fire ignitions where the temperature of fuel is raised to ignition temperature by other parts of fuel that is on fire. Fire behaviour models predict fire spread. A fire behaviour model predicts the energy that is created by a fire and the heat that can be transferred to other fuels by the fire. The energy that is absorbed by the close-by fuels is also predicted (Rothermel 1983:6).

According to Chuvieco and Congalton (1989:149) the type and characteristics of vegetation are the main factors influencing forest fire spread. Fire spread is also influenced by the topography of the area and meteorological conditions according to Aricak et al. (2014:102). Continuity in fuels can support the spread of fires. At least 30% of the area has to be covered by fuels for a fire to spread (Flannigan et al. 2013:54). If the topography of the area, the continuity of the fuel, and the weather is favourable a fire can spread easily.

Fire spread modelling systems have been developed across the world. Fire Logic Animation (FlogA) is a web based system designed to model fire spread and present it in the form of a geo-animation (Bogdos et al. 2013:182). Users can define a ‘forest’ anywhere in Europe where they would like to monitor fire ignition and fire spread (Bogdos et al. 2013:182). Bogdos et al. (2013:183) make use of an open-source library, based on the Rothermel model, called fireLib to create fire spread simulations. Fire hotspot data used by the system is from MODIS and they make use of Weather Underground’s Application Programming Interface (API) to get the necessary weather data (relative humidity, wind speed and direction and temperature) for the simulation (Bogdos et al. 2013:184). The fuel models used in the system are based on the BehavePlus fuel models created by Anderson in 1982. A mapping is created between CORINE land cover classes and the BehavePlus fuel models in order to define all of the necessary parameters for the fire spread modelling (Bogdos et al. 2013:184). FlogA creates a fire spread simulation around a fire hotspot and provides the animation of the fire's spread on Google Earth Bogdos et al. 2013:190). FlogA is a useful application in the sense that it is much easier to use than some of the other fire behaviour software mentioned earlier. Most of the data is retrieved by the application itself, while with the other systems such as FlamMap the user has to provide all of the data in the correct format. The FlogA system can be used quickly and easily to model the spread of a fire. Fire spread models can be used to alert fire management officials in real time if a fire is likely to reach an area in the near future based on current wind conditions in the area.

2.3.2.2. Fire Danger Indices

A fire danger index (FDI) is used to describe conditions that have an influence on the rate of fire spread, damage a fire can cause, and the ease of fire ignition. These indices are used in fire-fighting planning and resource planning (Steenkamp et al. 2012:3375). Figure 6 shows an example of a fire danger rating sign put up with the purpose of informing the public of fire weather conditions in an area.

Figure 6: Fire Danger Rating Sign (Wikipedia.org 2013).

It is difficult to determine how effective an FDI is because of the fact that fire risk is an ambiguous notion. It is not possible to determine fire risk directly, but it can be determined by looking at the influencing components of an FDI. Higher FDI values relate to higher likelihood of fire potential and more dangerous fires. Steenkamp et al. (2012:3375) compared a number of FDIs to determine which one performs the best.

The FDIs compared in the study include the Lowveld Fire Danger Index (LFDI) which is used in South Africa, the Canadian Forest Fire Weather Index (FWI), the McArthur Forest Fire Danger Index (FFDI), and the McArthur Grassland Fire Danger Index (GFDI). South African Weather Service data, including temperature, relative humidity, rainfall and wind speed, was used to calculate the FDIs. Historical fire data and MODIS active fire data was used to determine the performance of the FDIs. Fires were calculated by integrating MODIS MCD45A, MCD64A1, MOD14A1 and MYD14A1 data. Logistic regression was used to calculate fire occurrence probability. The FDIs were then ranked according to their performance based on the active fires detected by MODIS. The FWI ranked as the best performing FDI, followed by the LFDI (Steenkamp et al. 2012:3376) for South Africa.

The Canadian Fire Weather Index (FWI) has been developed as a part of the Canadian Forest Fire Danger Rating System (CFFDRS) (Dimitrakopoulos et al. 2011:83). The Fire Weather Index is built up from three moisture indices and three fire behaviour indices (Dimitrakopoulos et al. 2011:83). The moisture codes include the Fine Fuel Moisture Code (FFMC), the Duff Moisture Code (DMC) and the Drought Code (DC) (Dimitrakopoulos et al. 2011:84). The fire behaviour indices include the Initial Spread Index (ISI), the Buildup Index (BUI) and the Fire Weather Index itself (Dimitrakopoulos et al. 2011:84). This fire danger index has been used globally as an indicator of the danger posed by possible fire occurrences.

2.3.2.3. Fire Potential Indices

Fire potential indices are used to predict the probability of a fire event based on a number of influencing factors. Fire potential indices attempt to quantify the likelihood or probability of a fire igniting in an area (Caetano et al. 2004:320). According to Verbesselt et al. (2006:1623) a fire potential index is used to indicate the risk of fire in an area and not the characteristics of a fire. Both Caetano et al. and Verbesselt et al. therefore describe fire potential as an indicator of the likelihood of fire occurrences.

To create an effective fire risk index, it is important to determine a logical combination of variables to include in the index (Caetano et al. 2004:320). The indices have to be developed and then implemented in order to provide valuable output. According to Zhang et al. (2014:1) GIS and remote sensing has been increasingly used in the development of fire potential indices.

Development of fire potential indices and maps can be useful in fire management, fire mitigation and fire prevention as well as insurance. High potential areas can be identified and proper planning can be done (Kalabokidis et al. 2014:542). Countries around the world, facing wildfires, have developed fire potential rating systems to control fires (Kalabokidis et al. 2014:542). Zhang et al. (2014:1) stated that most of the research that has been conducted in fire potential index development has occurred at a local or regional scale. This may be because of the fact that the fire management is only carried out at a local or regional scale or that the conditions in different parts of the world have to be considered in the development and use of fire potential indices.

Fire potential indices can be dynamic or static. The output from static indices is not updated frequently. Dynamic indices can be updated as new dynamic data becomes available. For a dynamic fire potential index to give effective results it should be updated daily. It should make use of a detailed fuel model and it should take the amount of live and dead fuels into account (Caetano et al. 2004:320).

Two types of variables exist namely structural and dynamic variables. Structural variables are long term variables. They are derived from variables that do not change in a short amount of time. An example of a structural variable is land cover (Caetano et al. 2004:320). A structural fire potential index can be developed by making use of variables such as vegetation cover, elevation, slope, aspect, climate, roads, soils, population density and topography (Caetano et al. 2004:320).

Dynamic variables are short term variables. These variables change in a short amount of time. An example of a dynamic variable is weather (Caetano et al. 2004:320). Dynamic variables, however changing in a short amount of time, can still be measured. The purpose of a dynamic fire potential index is to reveal changes in the ability of forest fuels to ignite (Caetano et al. 2004:320).

Structural and dynamic variables can be combined to create integrated or advanced variables (Caetano et al. 2004:320). Therefore, integrated fire potential indices can be developed by making use of both types of variables. These indices can then be updated as new dynamic data becomes available.

Fire potential indices can take many forms and include many different types of data. According to Zhang et al. (2014:1) fire potential indices usually incorporate variables such as topography, fuel and weather. However, more advanced indices also take asset risk, housing density as well as variables that can attribute to reduction in fire spread such as the width, curve and slope angle of roads into account (Zhang et al. 2014:1). Caetano et al. (2004:320) reported that the distribution, amount and continuity of vegetation and wood should be taken into account when calculating fire potential. Pourtaghi et al. (2014:2) reported that vegetation, topography, climatology, fire history, Normalised Difference Vegetation Index (NDVI), soil, slope degree, slope aspect, land use, meteorological factors and distance from settlements are important factors to consider in fire potential ratings. According to Hernandez-Leal et al. (2006:741) land surface temperature and NDVI should be included in improved risk indices. Aricak et al. (2014:106) performed classification on tree species, stand closure and stand age. The data was then converted to vector format and intersected to create a database that can be used to produce fire risk maps. The different perspectives of different researchers show that the components that are considered as important in a fire potential index vary in individual areas.

In creating a fire potential index, Caetano et al. (2004:320), conducted a review of already existing indices. They proceeded to create a forest fire risk index and map for Portugal. A daily risk map was produced making use of satellite data and other ancillary data. The structural part of the index was based on Chuvieco and Congalton's (1989) index, while the dynamic part of the index was based on research done by Burgan and other authors (Burgan et al. 1998, Klaver et al. 1997, Lopéz et al. 1997).

Zhang et al. (2014) adapted their index from the hybrid fire index (HFI, from Adab et al. 2011) and they combined structural and dynamic variables in their index. They however improved upon the original HFI. They derived their topographic variables from NEXTMap USA 5m Digital Terrain Model (DTM) data and a Normalised Difference Moisture Index (NDMI) from MODIS data over a period of three months (Zhang et al. 2014:1). The NDMI is calculated from MODIS bands 2 and 6. NDMI is a dynamic variable. They made use of MODIS's Surface Reflectance 8-Day Level 3 product to get an overall dryness index of the region. Their aim was to produce a map that indicated wildfire potential in a given position (Zhang et al. 2014:2). Zhang et al. (2014:4) reported that more data layers would be incorporated into the index in future. These data layers include fuel, moisture data from MODIS, historical weather data, current weather data and frequently updated multispectral imagery. The use of frequently updated data sets the index apart from some structural indices, because it is focused on the current conditions which make it more useful in fire management.

Kalabokidis et al. (2014:544) calculated fire potential for every hour based on SKIRON forecast weather data every morning at 08:00 for the following 112 hours. The fire potential rating also makes use of real time weather data that is retrieved from Remote Automatic Weather Stations (RAWS) and the fire potential is calculated every hour (Kalabokidis et al. 2014:544). This index provides output more frequently than the index developed by Zhang et al. (2014:2) which is only updated every eight days.

Schöning et al. (1997:3) reported that a framework permits assessing fire potential at high spatial resolutions if it takes fire spread behaviour into account. The index developed by Schöning et al. (1997:3) is based on the use of risk matrices to define risk in terms of some event. This index is different from the other indices reviewed in this research because of the use of risk matrices.

A study conducted by Flannigan et al. (2013:55) made use of parts of the Canadian Forest Fire Weather Index (FWI) System to calculate global wildland fire severity. The fire severity was calculated with the Daily Severity Rating which is a power of the FWI (Flannigan et al. 2013:55). The Daily Severity Rating (DSR) from the CFFDRS is planned to take the difficulty of controlling a fire into account. The average DSR of a region over a fire season reflects the difficulty to control fires over that particular season (Flannigan et al. 2013:55). The average DSR is the Seasonal Severity Rating (SSR). To take lengthening fire seasons into account the Cumulative Severity Rating (CSR) takes only the sum of DSR values of a season into account (Flannigan et al. 2013:55). The FWI is used in many countries to indicate fire danger and fire intensity. The FWI models fuel moisture, by looking at the wetting and drying of fuel materials in the forest (Flannigan et al. 2013:55). The moisture of fine fuels is represented by three codes including: FFMC, DMC and DC (Flannigan et al. 2013:55). The BUI is a combination of the moisture indices. It is an index indicating the amount of fuel that is available for consumption. The ISI is an approximation of the spread rate of a fire and it is a combination of the FFMC and wind data. The FWI is a made up of the BUI and ISI and it is an approximation of the possible intensity of a fire that can spread.

The FIREMAP project was designed to provide a fire potential index at a one square kilometre resolution, by including a number of fire related risk factors. The index incorporates the estimation of fire ignition and the possible damages that can be caused by fire (Nieto et al. 2012:35).

The Fire Hazard and Risk Model (FIREHARM) was created to determine fire behaviour, fire danger and the effects of fires. FIREHARM would then be used to calculate fire potential by making use of fuel moisture values over eighteen years (Keane et al. 2010:2). Using fuel moisture values in relation to the minimum and maximum historical values for an area helps to ensure that fire potential is calculated in relation to the possible fuel moisture values that can be attained in an area.

The Structural Fire Index (SFI), created by Caetano et al. (2004) takes the following variables into account: slope, vegetation, aspect, elevation and closeness to roads and urban regions (Caetano et al. 2004:321). This index incorporates most of the factors that affect fire potential as discussed earlier in this chapter. Caetano et al. (2004:322) did not include water, urban land, agricultural land and other areas that are not vegetated or natural in the vegetation input to the fire potential index, because these factors cannot have an impact on forest fire potential. Caetano et al. (2004:322) wanted to include the human activity factor in their index, because arson is a notable problem in Portugal. Proximity to human activities is one of the factors that influence fire potential as discussed earlier in the chapter. Human behaviour itself, like the behaviour influencing an arson attack, is not easy to model and literature does not support the inclusion of that factor. Proximity to human activities as described earlier does not take arson behaviour into account. Caetano et al. (2004:322) investigated the relationship between land cover types and fuel models and assigned a fuel model and dead fuel extinction moisture value to each one. Fuel models are also used in the Fire Potential Index (FPI). Caetano et al. (2004:322) made use of the NDVI from AVHRR images to assess the greenness of vegetation. Zhang et al. (2014:3) made use of the Normalised Difference Moisture Index (NDMI) to determine fuel moisture. From this data a Maximum Live Ratio Map was derived (Caetano et al. 2004:322). A maximum live ratio map is also used in the FPI. More details on the SFI are provided in section 2.4. of this chapter.

The FPI was developed in the USA (Caetano et al. 2004:322). The FPI uses surface observations and satellite images to develop input to the index. The Integrated or Advanced Forest Fire Risk Index is developed from the FPI. A fuel model map, maximum live ratio map, greenness map and a dead fuel moisture map is provided as input to the FPI (Caetano et al. 2004:322). The spatial resolution of the inputs provided to the FPI was chosen to maintain a balance between the detail of the data and the processing time and constraints involved. Many fire potential indices have been developed around the world. The details of a number of indices are provided in section 2.4 of this chapter.

The factors influencing wildfires, such as those discussed in section 2.2.1, influence both fire danger indices and fire potential indices. For this reason, fire danger indices could serve the same purposes as fire potential indices and they are both included in the evaluation in this research. The fire danger indices are still referred to as "fire danger indices", as this is what they are commonly known as by the fire community.

2.3.2.4. Evaluation of Fire Indices

Validation of a fire potential index is important to assess the accuracy of the index. According to Dowdy et al. (2010:298) care should be taken when interpreting the output of a fire potential index if it is being used outside of the region it was originally developed for. Environmental conditions vary around the world and a fire potential may be highly effective in the region it was developed in, but it may prove ineffective in other regions. According to Chuvieco et al. (2010:54) it is important to do validation on both the input variables to the fire potential index and the output fire potential indices. The input variables have to be checked in order to ensure that the output produced with the input data is accurate.

Satellite images depicting active fires and estimation of burned areas, can be used as a proxy for fire activity in the evaluation of fire potential indices (Steenkamp et al. 2013:9). According to Zhang et al. (2014:3) hot spot data derived from MODIS and historical fire data has been used in index validation. Zhang et al. (2014:3) made use of historical fire data to validate their index. They combined a fire perimeter dataset, updated daily, with fire event data to create a more complete test dataset. For validation purposes Caetano et al. (2004:321) chose a study area where they were able to identify burned area that coincided with the frequency of fire for that fire season. The burned area was digitised for validation purposes (Caetano et al. 2004:323). Statistical analysis was conducted by Caetano et al. (2004:323) on the relationship between the fire potential indices and the burned area, the ignition location and date of ignition. A daily Integrated Forest Fire Risk index was developed from the analysis. Areas were identified where vegetation greenness decreased, including areas that were burned. Areas smaller than five hectares were, however, not considered due to resolution restrictions.

Fire density was calculated for the indices (Caetano et al. 2004:323). The number of fires that occurred was divided by the total number of cells in each class (Caetano et al. 2004:323). In both cases fire occurrence was used for validation of the indices.

Andrews et al. (2003:214) used logistic regression and percentile analysis to analyse the connection between fire danger indices and fire activity. The analysis was done based on the United States National Fire Danger Rating System, but the methods can be applied to any index that is used to represent fire potential (Andrews et al. 2003:214). According to Andrews et al. (2003:215) the analysis methods they used are more objective than other methods used in the past in other research. A fire danger index is meant to indicate the potential for a fire in a fire management area and not the properties of any particular fire (Andrews et al. 2003:215). This is the same for a fire potential index, because it represents the probability that a fire may occur. An index is deemed useful if there is a positive correlation between the index and fire behaviour (Andrews et al. 2003:216). The fire behaviour refers to the occurrence of real fires. A number of other studies have been done to determine the usefulness of indices.

In a study conducted by Haines et al. in 1986 linear regression was used to analyse the performance of indices. A database of 2682 fire occurrence had to be reduced to 940 records of fire occurrence for varied reasons (Andrews et al. 2003:216). This illustrates how difficult it is to make use of fire occurrence data to determine the usefulness of a fire danger index. The resulting R^2 values from the linear regression were low, with no results over 0.25 (Andrews et al. 2003:216). Low R^2 values may be an indication of low correlation between variables. Andrews et al. (2003:217) calculated the Mahalanobis distance based on the process followed by Viegas et al. (1999). They normalised all indices to a range of zero to 100 and categorised the values in intervals of ten (Andrews et al. 2003:217). As mentioned earlier, they also made use of logistic regression and percentile analysis in the research. The results from the Mahalanobis distance, logistic regression and percentile analysis were used to rank the fire danger indices according to their successfulness as an indicator of fire potential (Andrews et al. 2003:217). The indices were ranked based on their performance in the various analysis methods (Andrews et al. 2003:223). An overall ranking was assigned by summing the ranks assigned to the index throughout all of the metrics. By doing this the best overall performing index was chosen. The index that performed best was the Energy Release Component (ERC). Logistic regression was used in the research because the data used was in binary form (Andrews et al. 2003:220). A value of zero was assigned if no fire occurred in the area and a value of one was assigned if a fire occurred. Many different metrics have been used to determine the usefulness of a fire danger index. According to Andrews et al. (2003:217) there is no completely objective way to evaluate a fire danger rating system.

Verbesselt et al. (2006:1622) evaluated the use of climate data-derived indices to determine their usefulness as fire potential indicator in the Kruger National Park in South Africa. According to Verbesselt et al. (2006:1623) an operational fire risk index is only workable if the index and fire activity have been correlated, and fire activity data is a direct link in evaluating the performance of an index that is used to predict fire potential. Verbesselt et al. (2006:1625) evaluated the NDVI, Normalised Difference Water Index (NDWI) and Keetch-Byram Drought Index (KBDI) as possible fire potential indicators. Logistic regression was used in the research, similar to the method used by Andrews et al. (2003). The C-index, index probability ranges and a modified version of Akaike's Information Criterion (AIC) was calculated for the indices (Verbesselt et al. 2006:1628). The indices were ranked in each of the methods and these rankings were then summed to create a final overall ranking. This is, once again, what Andrews et al. did in their study in 2003. The NDWI performed best in the study (Verbesselt et al. 2006:1628).

Dimitrakopoulos et al. (2011:87) made use of logistic regression to examine the correlation between the components of the Canadian FWI and fire activity and burned area. This is the third study identified in this research project that made use of logistic regression for this purpose. The results indicated that the Duff Moisture Code was highly correlated with fire occurrence and only average correlation was observed between the components of the Canadian FWI and burned area (Dimitrakopoulos et al. 2011:87). It was found that the DMC, DC, BUI and the FWI corresponded with fire activity (Dimitrakopoulos et al. 2011:91). Many different types of fire potential indicators have been evaluated in these research projects and they are constructed in different ways, make use of different input data and have different value ranges.

According to Eastaugh et al. (2012:927) it is difficult to directly compare fire danger indices because of differing frequency distributions. The research compared a number of evaluation metrics to determine how robust they are. The aim was to highlight why non-parametric metrics are needed (Eastaugh et al. 2012:929). Eastaugh et al. (2012:928) introduced a non-parametric method to evaluate fire danger indices. Evaluation can therefore be conducted without being affected by a difference in frequency distribution. The method introduced by Eastaugh et al. (2012:929) is a two-part method that calculates the intercept and slope of ranked fire day percentiles. The most successful index will have a slope of one and an intercept of zero (Eastaugh et al. 2012:929). The research was based on four hypothetical indices defined by Eastaugh et al. (2012:932). Three of the hypothetical indices were mathematical transformations of one another and the fourth index was independent

(Eastaugh et al. 2012:930). Index value range, pseudo R^2 and AIC were calculated with the use of logistic regression. Percentile analysis, Mahalanobis distance and the C-index were also calculated. The new non-parametric method proposed in the research was also calculated. The new method showed that the three indices that are simply transformations of one another had the same predictive strength. This shows the need for non-parametric metrics to be included in fire potential index evaluation.

Research done by Steenkamp et al. (2012) also used a number of metrics to rank fire danger indices. Steenkamp et al. (2012:3376) evaluated four fire danger indices in a unique way. The indices were evaluated per 11km cell over the time series of a dataset. This approach was used to evaluate the effectiveness of the indices on a regional scale (Steenkamp et al. 2012:3376). Steenkamp et al. (2013:11) combined burned area data and fire activity data by considering the closeness of pixels to other pixels in a relevant time period. The study made use of logistic regression, percentile shift analysis and the Bhattacharyya coefficient to rank the FDIs according to their performance (Steenkamp et al. 2012:3376). The following FDIs were included in the study: Canadian FWI, LFDI, McArthur FFDI and the McArthur GFDI (Steenkamp et al. 2013:13). The study followed the methods proposed by Andrews et al. (2003) except for the use of the Mahalanobis Distance. Steenkamp et al. (2013) made use of the Bhattacharyya coefficient instead because it shows the degree of overlap between distributions more successfully (Steenkamp et al. 2013:10). The values produced by the pseudo R^2 in logistic regression are much smaller than the similar R^2 in linear models and they should be interpreted with care (Steenkamp et al. 2013:12). For each FDI, the rank sum was calculated based on the outcomes of the metrics that were calculated. A final ranking was done based on the total rank sums (Steenkamp et al. 2013:13). The Canadian FWI performed best, followed by the LFDI, McArthur FFDI and lastly the McArthur GFDI (Steenkamp et al. 2013:13). All cells where a negative correlation between the fire activity and the index value existed were excluded from the results (Steenkamp et al. 2013:14). In the research the number of cells that could be used in the evaluation was reduced significantly from the initial number of pixels available. This was because of the fact that a pixel was only assigned a value of one and not zero if it made a threshold decided on by the authors. When doing a pixel based analysis, it is important to note that many pixels exist where no fire activity is recorded. Therefore, in a study area, a large number of cells can be assigned a value of zero because it is not affected by a fire occurrence, while only a small number of cells will contain a fire occurrence. A balance between zero and one values is not likely to be present in this type of research.

Many metrics have been used by researchers to determine the usefulness of indices used for the purpose of predicting fire occurrences. Logistic regression can be used to determine a relationship between a fire potential index and fire occurrence.

King et al. (2001:137) did research on logistic regression in rare events data. The study was developed around binary dependent variables which contain far more zeros than ones (King et al. 2001:137). According to King et al. (2001:137) logistic regression underestimates the probability of a rare event. The research proposes a way of eliminating the problems encountered with logistic regression in rare events data. A sampling strategy is proposed for selecting on the independent variable: using a random selection of zero values with either all values that are one or a random selection of values that are one (King et al. 2001:142). The prior correction and weighting methods proposed by King et al. (2001:142) require the observations for the independent variable to be random. King et al. (2001:143) propose not to collect more than two to five zeros more than ones. To correct estimates for selection on the independent variable, King et al. (2001:144) proposes two methods: prior correction and weighting. The prior correction method includes the calculation of the logistic regression maximum likelihood estimator and the use of prior information on the fraction of ones in the population and the fraction of ones in the observed sample to correct the estimates. The prior correction method is easy to use and any statistical package that can calculate logit coefficients would work (King et al. 2001:144). The second method, namely weighting, weights the data to make up for the difference in the fraction of ones in the sample compared to the fraction of ones in the population. In this method the weighted log-likelihood is maximised instead of the log-likelihood (King et al. 2001:145). The biggest disadvantage of this method is that specialised software is required to do the estimation (King et al. 2001:145).

Van Den Eeckhaut et al. (2006:392) made use of rare events logistic regression to create a landslide susceptibility map for an area in Belgium. Landslides are considered to be rare events (Van Den Eeckhaut et al. 2006:395). Van Den Eeckhaut et al. (2006:392) made use of the method developed by King et al. (2001) for the rare events logistic regression. The method includes endogenous stratified sampling of the dataset, prior correction of the intercept and correcting the probabilities to include estimation uncertainty (Van Den Eeckhaut et al. 2006:392). Landslide maps were used along with some data containing variables assumed to influence slope stability (Van Den Eeckhaut et al. 2006:396). These variables include terrain height, aspect, slope, profile, plan curvature, distance to rivers, distance to seismic faults, soil drainage and upslope contributing area (Van Den Eeckhaut et al. 2006:397). One map cell of 116 landslides was used along with 580 cells outside of the landslide affected area (Van Den Eeckhaut et al. 2006:400). The Zelig package in R was used to perform the logistic regression (Van Den Eeckhaut et al. 2006:401). It was found that rare events logistic regression is a suitable method for creating landslide susceptibility maps (Van Den Eeckhaut et al. 2006:408).

Guns & Vanacker did research on logistic regression applied to natural hazards (2012:1937). The research focused on landslides which can be seen as rare events. Rare events cause the occurrence frequencies to be low, therefore the number of events is much smaller than the number of non-events (Guns & Vanacker 2012:1937). Van Den Eeckhaut's logistic regression method was used with minor adjustments (Guns & Vanacker 2012:1941). A ratio of one to ten for events to non-events was used for the endogenous stratified sampling. R was used to automate the process and the relogit function from the Zelig R package was used for the rare event logistic regression (Guns & Vanacker 2012:1941).

Rare events logistic regression is done with replications, as it is a combination of the strengths of probabilistic and statistical models (Guns & Vanacker 2012:1941). It makes use of the logistic regression method as used by King et al. (2001) and Van Den Eeckhaut et al. (2006), but also includes a way to estimate the robustness of the regression estimates (Guns & Vanacker 2012:1941). Guns & Vanacker (2012:1941) averaged the results of fifty copies of an ordinary rare event logistic regression with fifty different endogenous stratified samples. Ten non-events were selected randomly from the population for every one of the fifty endogenous stratified samples (Guns & Vanacker 2012:1941). Ordinary rare event logistic regression was then applied and it was repeated fifty times with different samples (Guns & Vanacker 2012:1941). Only the variables with a p-value of 0.05 which are available in more than four replications are retained (Guns & Vanacker 2012:1941).

The logistic regression is therefore based on robust variables and the parameters are calculated as the average of the number of replications for which the variables were significant (Guns & Vanacker 2012:1941). The method adds Monte Carlo simulations to test the robustness of an index (Guns & Vanacker 2012:1946). Guns & Vanacker (2012:1946) found that their method produced similar modelling quality to the ordinary rare event logistic regression. The method can be applied to any analysis of natural hazards (Guns & Vanacker 2012:1946).

Wildfire is a natural hazard (McCaffrey 2010:509). Guns & Vanacker (2012) have stated that rare event logistic regression can be applied to any natural hazards and can therefore be applied to wildfires.

2.4. Related Work

The following section discusses seven indices that were identified for the purpose of the research. These indices are possible candidates for implementation in the research.

2.4.1. Hybrid Fire Index

The Hybrid Fire Index (HFI) was originally created by Adab et al. (2011) to predict fire probability in the Golestan province of Iran (Adab et al. 2011:171).

Adab et al. (2011) calculated the Hybrid Fire Index as:

$$HFI = \frac{100v + 50s + 25a + 10(r + c) + 5e}{10}$$

Where v = vegetation moisture, s = slope, a = aspect, r = distance from roads, c = distance from settlements and e = elevation (Adab et al. 2011:172). The output range is between 20 (low risk) and 100 (high risk).

A fire risk zone map was derived by normalising the output of HFI to a range between 0 (low risk) and 255 (high risk) (Adab et al. 2011:173). The values were then classified as low risk (between 1 and 10), moderate risk (between 10 and 50) and high risk (between 50 and 100). Zhang et al. (2014) also did a study on the Hybrid Fire Index for the United States of America and calculated the Hybrid Fire Index as:

$$HFI = 20v + 10s + 5a + 2r + 2c + e$$

Where v = vegetation moisture, s = slope, a = aspect, r = distance from roads, c = distance from settlements and e = elevation.

Zhang et al. (2014:2) made use of the MODIS Surface Reflectance 8-Day L3 product (MOD09A1) to calculate the Normalised Difference Moisture Index (NDMI). NDMI shows the flammability and spread likelihood of fire and it is dynamic so can change daily.

NDMI is calculated as follows:

$$NDMI = \frac{(Band\ 2 - Band\ 6)}{(Band\ 2 + Band\ 6)}$$

Zhang et al. (2014:2) made use of the NEXTMap USA DTM to derive slope and aspect. Elevation is associated with wind behaviour, vegetation structure, fuel moisture and air humidity. Slope is associated with how quickly a fire spreads. A fire spreads more quickly up a slope than down a slope (Zhang et al. 2014:2). Aspect is associated with sun exposure (which has an influence on fuel moisture), temperature, wind direction and air humidity.

Zhang et al. (2014:3) made use of Intermap's AccuTerra road product to derive a distance from roads dataset. They also made use of Intermap's 5m land cover mask product to derive a distance from dense and sparse urban areas dataset. Forests are more prone to fire if they are located near roads and settlements (Zhang et al. 2014:3).

Table 2 shows the weights that were assigned to the index variables by Adab et al. (2011:172).

Parameters	Classes	Rating of Hazard	Fire Sensitivity
NDMI (MODIS)	> 0.36	1	Very Low
	0.26-0.36	2	Low
	0.16-0.26	3	Medium
	0-0.16	4	High
	0	5	Very High
Elevation (ASTER)	> 2000	1	Very Low
	1000-2000	2	Low
	500-1000	3	Medium
	200-500	4	High
	< 200	5	Very High
Slope	< 5 %	1	Very Low
	5-10 %	2	Low
	10-25 %	3	Medium
	25-35 %	4	High
	>35 %	5	Very High
Aspect	North	2	Low
	East	3	Medium
	West	4	High
	South	5	Very High
Distance from Roads	> 400m	1	Very Low
	300-400 m	2	Low
	200-300 m	3	Medium
	100-200 m	4	High
	< 100 m	5	Very High
Distance from Settlements	> 2000 m	1	Very Low
	1500-2000 m	2	Low
	1000-1500 m	3	Medium
	500-1000 m	4	High
	< 500 m	5	Very High

Table 2: Weights assigned to Hybrid Fire Index variables.

2.4.2. Forest Fire Risk Index

Ertena et al. (1994) made use of a forest type map, vegetation map, elevation, slope, aspect, topographic map, average wind, rainfall and temperature datasets to derive a fire risk index. The index was implemented in the Gallipoli Peninsula Historical – National Park in Ecebat in Çanakkale (Ertena et al. 1994:2).

The numerical index of forest fire risk (FFR) zones denoted by RC in the formula, was calculated as follows:

$$RC = 7 \times V_T + 5 \times (S + A) + 3 \times (D_R + D_S)$$

Where V_T = vegetation type (five classes), S = slope (five classes), A = aspect (four classes), D_R = distance from roads and D_S = distance from settlements. The index was also used by Siachalou et al. (2009). Table 3 shows the classes used for the Forest Fire Risk Index.

Parameters	**Weight**	**Classes**	**Factors**	**Fire Rating Class**
Vegetation	7	Very Dry	5	Very High
		Dry	4	High
		Moist	3	Medium
		Fresh-like	2	Low
		Fresh	1	Very Low
Slope	5	> 35 %	5	Very High
		25-35 %	4	High
		10-25 %	3	Medium
		5-10 %	2	Low
		< 5 %	1	Very Low
Aspect	5	South	5	Very High
		West	4	High
		East	3	Medium
		North	2	Low
Distance from Roads	3	< 100m	5	Very High
		100-200m	4	High
		200-300m	3	Medium
		300m-400m	2	Low
		> 400m	1	Very Low
Distance from Settlements	3	< 1000m	5	Very High
		1000-2000m	4	High
		2000-3000m	3	Medium
		> 3000m	2	Low

Table 3: Weights assigned to Forest Fire Risk Index variables.

2.4.3. Fire Hazard Index

Chuvieco & Congalton (1989:149) considered the basic factors that affect forest fires when designing the Fire Hazard Index (FHI). The factors include: vegetation species (classified according to fuel class, stand conditions and site), elevation, slope, aspect and proximity to roads, trails, campsites and housing.

The Fire Hazard Index (FHI) was calculated as follows:

$$H = 1 + 100v + 30s + 10a + 5r + 2e$$

Where v = vegetation, s = slope, a = aspect, r = proximity to roads and e = elevation (Chuvieco & Congalton 1989:153). Table 4 contains the values used by Chuvieco & Congalton to map values to each class.

Parameters	Original Classes	Fire Hazard Groups	Coefficient
Vegetation (Weight = 100)	Dense pine tree	High	0
	Medium pine tree	High	0
	Sparse pine tree + shrub	Medium	1
	Dense shrub	Medium	1
	Medium shrub	Medium	1
	Sparse shrub	Low	2
	Almond trees	Low	2
	Vineyards	Low	2
	Orange trees	Low	2
Slope (Weight = 30)	0-4 %	Low	2
	5-8 %	Low	2
	9-12 %	Low	2
	13-16 %	Medium	1
	17-20 %	Medium	1
	21-36 %	Medium	1
	27-40 %	Medium	1
	41-44 %	High	0
	> 44 %	High	0
Aspect (Weight = 10)	Southeast	High	0
	Southwest	Medium	1
	North	Low	2
Proximity to Roads (Weight = 5)	Inside buffer area (< 150m from any trail or < 50m from any road)	High	0
	Outside buffered area	Low	1
Elevation (Weight = 2)	0-3 m	Low	1
	3-6 m	Low	1
	398-400 m	High	0
	401-404 m	High	0
	405-407 m	High	0

Table 4: Weights assigned to Fire Hazard Index variables.

According to Chuvieco & Congalton (1989:149) both overstory and understory are important as they both represent the total amount of fuel available to burn. Landsat TM images were used and standard classification techniques were applied to the images. Non-vegetated areas, like water and urban land, were not included and cultivated fields were retrained because of the high spatial diversity. Training fields were selected with aerial photography (Chuvieco & Congalton 1989:150). A number of areas were identified for each of the vegetation species. Unsupervised classification was added to the process in order to obtain a better statistical definition of the vegetation classes (Chuvieco & Congalton 1989:150). Sixteen categories were identified using a maximum-likelihood classifier.

Chuvieco & Congalton (1989:150) created a DEM from 1:50000 topographic maps in order to calculate slope, aspect and elevation. Chuvieco & Congalton (1989:152) digitised roads and trails and created a 50m buffer around main roads. A buffer of 150m was created around trails and fire breaks. The buffered areas served as the areas that would most likely be affected by fires. The index was successfully implemented in the Mediterranean coast area of Spain (Chuvieco & Congalton 1989:149).

2.4.4. Structural Fire Index

Cipriani et al. (2011:78) chose the Serra de Sao Domingos Municipal Park, southern Minas Gerais State, Brazil, as the study area to test a fire risk index. They made use of an index that was adapted from the index developed by Chuvieco & Congalton (1989).

The Structural Fire Index (SFI) was calculated as follows:

$$SFI = 0.35i + 0.30u + 0.15d + 0.10a + 0.10e$$

Where i = influence of roads and buildings, u = land use, d = slope, a = altitude and e = slope orientation. Table 5 shows the classes created by Cipriani et al. for the variables.

Altitude		**Risk**	**Coefficient**
Above 1400 m		Low	1
1400 m and below		Moderate	2
Slope	**Orientation**	**Risk**	**Coefficient**
Until 14.9 °	South	Low	1
15.0-24.9 °	East	Moderate	2
25.0-34.9 °	Plain	High	3
35.0-44.9 °	West	Very High	4
45.0 ° and Above	North	Extreme	5
Influence of Road System and Buildings		**Risk**	**Coefficient**
Beyond Influence		Low	1
Under Influence		Extreme	5
Land Use		**Risk**	**Coefficient**
Water, buildings, rainforest and exposed soil		Low	1
Agriculture and Mines		Moderate	2
Afforestation		Very High	4
Pasture & Grassland		Extreme	5

Table 5: Weights assigned to Structural Fire Index variables.

2.4.5. Fire Risk Index (Jaiswal et al. 2002)

Jaiswal et al. (2002:2) selected Gorna Subwatershed, Madhya Pradesh in India as their study area because it is prone to fires. The following variables were used in the study: vegetation type, slope, proximity to roads and proximity to settlements. Vegetation in the area was classified into eight forest types and three non-forest types. Buffer zones of 1000 m, 2000 m and 3000 m were created around settlements. Buffer zones of 100 m, 200 m, 300 m and 400 m were created around roads. A union was created with all the layers as input. The output result is a fire risk zone map.

The Fire Risk Index (FRI) was calculated as follows:

$$FR = 10F_{i=1-11} + 2H_{j=1-4} + 2R_{k=1-4} + 3S_{l=1-6}$$

Where FR = numerical value for fire risk, F = vegetation (11 classes), H = proximity to human settlements (4 classes), R = proximity to roads (4 classes) and S = slope (6 classes). Table 6 shows the weights that were assigned to the variables by Jaiswal et al.

Variables	**Classes**	**Rating**	**Fire Sensitivity**
Vegetation type (weight=10)	Dry Mix	10	Very High
	Bamboo Mix	9	Very High
	Sal & Bamboo	8	High
	Bamboo Degraded	6	High
	Sal	6	High
	Plantation	4	Moderate
	Moist Mix	3	Moderate
	Blank	1	Low
	Agriculture	2	Low
	Wasteland	1	Low
	Agriculture with Settlement	1	Low
Settlements (weight=2)	Settlement Area	8	Very High
	< 1000m	7	High
	1000-2000 m	5	Moderate
	2000-3000 m	2	Low
Road (weight=2)	< 100 m	8	Very High
	100-200 m	7	High
	200-300 m	5	Moderate
	300-400 m	3	Low
Slope (weight=3)	> 35 %	10	Very High
	15-35 %	6	Very High
	10-15 %	5	High
	5-10 %	4	Moderate
	3-5 %	3	Moderate
	0-3 %	2	Low

Table 6: Weights assigned to Fire Risk Index variables.

2.4.6. Fire Risk Index (Saglam et al. 2008)

Saglam et al. (2008:3975) made use of an index that was based on the index created by Jaiswal et al. (2002). They chose the Korudag Forest District, a forest area along the coast of the Saros Gulf in the north of Eagan Sea, north-western Turkey as their study area. Saglam et al. (2008:3973) made use of Landsat TM and Landsat ETM images to classify fuel types.

The Fire Risk Index (FRI) was calculated as follows:

$$FRI = 10SC_i + 2AL_j + 2SA_k + 3S_l + 2IS_m$$

Where SC = species composition (5 classes), AL = proximity of agricultural lands to forest (4 classes), SA = proximity to human settlements (4 classes), S = slope (4 classes), IS = insolation (9 classes). Table 7 shows the classification of the variables developed by Saglam et al.

Variables	Classes	Value Assigned	Fire Risk
Species Composition (weight=10)	Calabrian Pine	5	Extreme
	Calabrian Pine & Black Pine	5	Extreme
	Shrub	4	High
	Degraded Areas	2	Moderate
	Oak & Coppice	1	Low
Slope (weight=3)	0-5 %	1	Low
	5-15 %	2	Moderate
	15-35 %	3	High
	> 35 %	5	Extreme
Insolation (weight=2)	0-23 (N)	1	Low
	23-68 (NE)	2	Moderate
	68-113 (E)	2	Moderate
	113-158 (SE)	3	High
	158-203 (S)	5	Extreme
	203-248 (SW)	5	Extreme
	248-293 (W)	2	Moderate
	293-338 (NW)	2	Moderate
	338-360 (N)	1	Low
Proximity of Agricultural Lands (weight=2)	0-100 m	5	Extreme
	100-200 m	3	High
	200-300 m	2	Moderate
	> 400 m	1	Low
Proximity to Settlements (weight=2)	0-100 m	5	Extreme
	100-200 m	3	High
	200-300 m	2	Moderate
	> 400 m	1	Low

Table 7: Weights assigned to Fire Risk Index variables.

2.4.7. Fire Potential Index

The Fire Potential Index (FPI) is a dynamic forest fire potential index that is highly specific for fuel type, weather conditions and vegetation status, resulting in values with high spatial variability. This requires the development of pixel-specific indices to account for specific environmental characteristics (Huesca et al. 2014). The FPI can be seen as a dryness fraction multiplied by a "deadness" fraction.

The Fire Potential Index (FPI) is calculated as follows:

$$FPI = 100 \times (1 - FMC) \times (1 - VC)$$

The following serves as inputs to the above-mentioned index: extinction moisture from a fuel type map (moisture content in small dead fuels at which fires will no longer spread), 10-hour time lag dead fuel moisture values and percentage vegetation cover.

Two fire potential indices were defined by Huesca et al. which include: FPI_{NDVI} and FPI_{NDWI}. FPI_{NDVI} is based on the NDVI and the FPI_{NDWI} is based on the NDWI.

The humidity of the fine and dead fuel is calculated as follows (fuel moisture - dryness):

$$FMC10HR = 1.28 \times EMC$$

EMC (equilibrium moisture) is unique for each temperature/relative humidity combination (Huesca et al. 2009:1949). The algorithms used for the calculation were developed by Fosberg & Deeming (1971).

The live vegetation content (VC) is calculated as follows:

$$VC = VC_{MAX} \times RG$$

VC_{MAX} is calculated for each pixel from the vegetation index used as follows (Huesca et al. 2009:1949):

$$VC_{MAX} = 0.25 + 0.50(\frac{NDVI_{MAX}}{NDVI_{||MAX}})$$

$$VC_{MAX} = 0.25 + 0.50(\frac{NDWI_{MAX}}{NDWI_{||MAX}})$$

Relative greenness (RG) is a proxy for moisture and the percentage of the live vegetation cover. RG is calculated as follows for the vegetation index used (Huesca et al. 2009:1949):

$$RGNDVI = (\frac{NDVI - NDVI_{MIN}}{NDVI_{MAX} - NDVI_{MIN}})$$

$$RGNDWI = (\frac{NDWI - NDWI_{MIN}}{NDWI_{MAX} - NDWI_{MIN}})$$

The FPI has been implemented in the United States of America and some European regions.

2.5. Chapter Summary

This chapter provided a more detailed view into the topics covered by this research. Wildfires occur worldwide and are important to maintain the health of ecosystems. It is important to manage these fires to ensure that they do not cause destruction in terms of life and the environment. Several fire potential indices have been developed around the world to assist in fire management by providing information on where a high probability of fire occurrence is present. Several techniques exist to evaluate the usefulness of fire potential indices.

3. Chapter Three: Research Methods and Experiment Design

3.1. Chapter Overview

Chapter two provided background information on topics covered by the research such as wildfires, fire management, fire potential indices and fire potential index analysis. The objective of the chapter was to lay down information needed to get a basic understanding of the research to be able to conduct this research project. Related work was included and it was found that there is a gap. The fire potential indices have not been tested for South African circumstances.

The aim of the research was to implement and evaluate fire potential indices utilising geographic information, some of it remotely sensed, to predict fire potential in the Western Cape and Mpumalanga provinces of South Africa. The time period used for Mpumalanga was February 2015 to December 2015 (winter fire season) and the time period for the Western Cape was August 2014 to June 2015 (summer fire season). A number of fire potential indices were implemented and evaluated through means of statistical analysis to determine if the indices are useful in the Western Cape and Mpumalanga. Additionally, a number of fire danger indices were included in the implementation and evaluation to allow for some comparison between the fire potential indices and the fire danger indices. The research will be used by AFIS by making the fire potential information available to clients. The information may be provided in the form of a GIS layer on the AFIS web viewer or as a value in a table based on a point of interest. This chapter will deal with the research methodology used in the research project. The research design will be discussed. The methodology, including the research instruments, data and analysis methods will be explored. Details on the limitations and ethical considerations of the research will be provided. The chapter will end of with a chapter summary.

3.2. Research Design

This research falls in the positivistic research paradigm. Positivistic research entails obtaining an understanding in an objective setting through the use of scientific research methods (University of West England Research Observatory 2007). This research falls within the positivistic research paradigm because it follows a scientific method to acquire information on the relationship between two variables, through implementation of indices and evaluating them by applying statistical methods. The analysis conducted in this research is quantitative. A correlation-based research design was followed in the research, as the aim was to establish whether there is a relationship between a set of fire potential indices and the occurrence of fires based on satellite detections. This method was chosen because it is a tried and tested method to determine if a relationship exists between two variables and makes it possible to determine if an index can successfully predict the occurrence of an event.

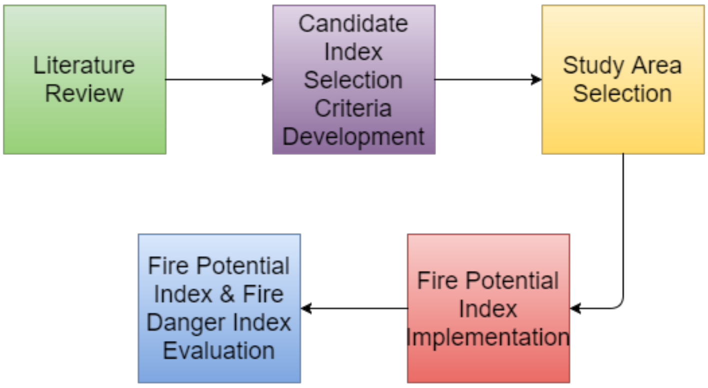

Figure 7: Research Methodology.

The research conducted was done in a number of sub-operations as depicted in Figure 7. The details of the sub-operations will be discussed in subsequent sections of this chapter. Firstly, a literature review was conducted to obtain information on fire potential indices that have been developed around the world. A list of criteria was then developed to decide which of the candidate fire potential indices should be implemented for South Africa (Table 8). The study areas include the Western Cape and Mpumalanga provinces. Implementations of the candidate fire potential indices were then developed and the necessary data was collected for the appropriate time periods. The candidate fire potential index implementations are discussed in chapter four. A description of the datasets used in the index implementations is provided in this chapter, while the data preparation is discussed in detail in chapter four. The indices were then calculated for the necessary time period, with the data collected to create the fire potential index files (output files) that were later used in the evaluation process. The aim of the evaluation process was to find out if a relationship exists between index-based wildfire potential and earth observation satellites active fire or hotspot observations. Fire activity data was used in the evaluation process, to determine the usefulness of the Fire Potential Indices in South Africa. The evaluation process data was then analysed and the results are discussed in chapter 5.

3.3. Selection of Candidate Fire Potential Indices

The indices that were identified through the literature review were evaluated against the following criteria. The selection criteria were based on the presence of factors influencing wildfire ignition and spread, obtained through the literature review. The factors are discussed in section 2.2.1. of chapter two.

Table 8 provides a list of the variables that were found in the literature. The indices selected for implementation in this research had to contain some or all of these variables. All of the variables found in the literature were included.

Variable	**Description**
Vegetation Type	All organic material that can cause a fire and sustain burning are classified as fuels (Keane & Reeves 2011:212). A large number of fuel types exist and the fuel can be located within or above soil.
Fuel Load	Fuel load is defined as the amount of biomass per unit area. Biomass builds up when there is no fire (Keane & Reeves 2011:212).
Fuel Moisture	Fuel moisture content is defined as the amount of water mass in relation to dry mass in vegetation (Yebra et al. 2013:456).
Proximity to Roads	Proximity to roads deals with the distance of vegetation to roads.
Proximity to Human Activities	Proximity to human activities deals with the closeness of vegetation to areas where humans live and perform activities.
Elevation	Elevation is defined as “the distance of a point from a chosen reference surface measured upward along a line perpendicular to that surface” (ISO\TC 211 2017).
Slope	Slope is defined as “the rate of change in elevation with respect to the curve length” (ISO\TC 211 2017).
Aspect	Aspect is defined as “the compass direction that a topographic slope faces, usually measured in degrees from north” (ESRI 2017).
Temperature	Temperature is defined as “a physical quantity characterizing the mean random motion of molecules in a physical body” (World Meteorological Organisation 2017).
Precipitation	Precipitation is defined as “the deposit of atmospheric moisture as rain, hail, sheet, snow, frost and dew or the deposition of minerals in solution due to evaporation” (World Meteorological Organisation 2017).
Wind	Wind is defined as “air motion relative to the Earth's surface” (World Meteorological Organisation 2017).
Relative Humidity	Relative humidity is defined as “the ratio of actual water vapour pressure to that at saturation with respect to liquid water or ice at the same temperature” (World Meteorological Organisation 2017).

Table 8: Fire Potential Index Variables.

The indices were selected based on the fact that they do not contain any complexity that could make them inappropriate for operational use and the indices do not take any economic risk factors into account.

3.4. Study Areas

Two study areas were selected based on the two fire seasons present in South Africa. First is the fire season during the summer months, December to April, and second is the fire season during the winter months, June to October. These fire seasons are rainfall-pattern based. The Western Cape has its fire season in winter and the rest of the country has its fire season in summer. Mpumalanga was selected to represent the summer fire season as it consists predominantly of grassland vegetation which is especially prone to fire (Forsyth et al. 2010:64). Figure 8 highlights the two provinces selected as study areas with black outlines.

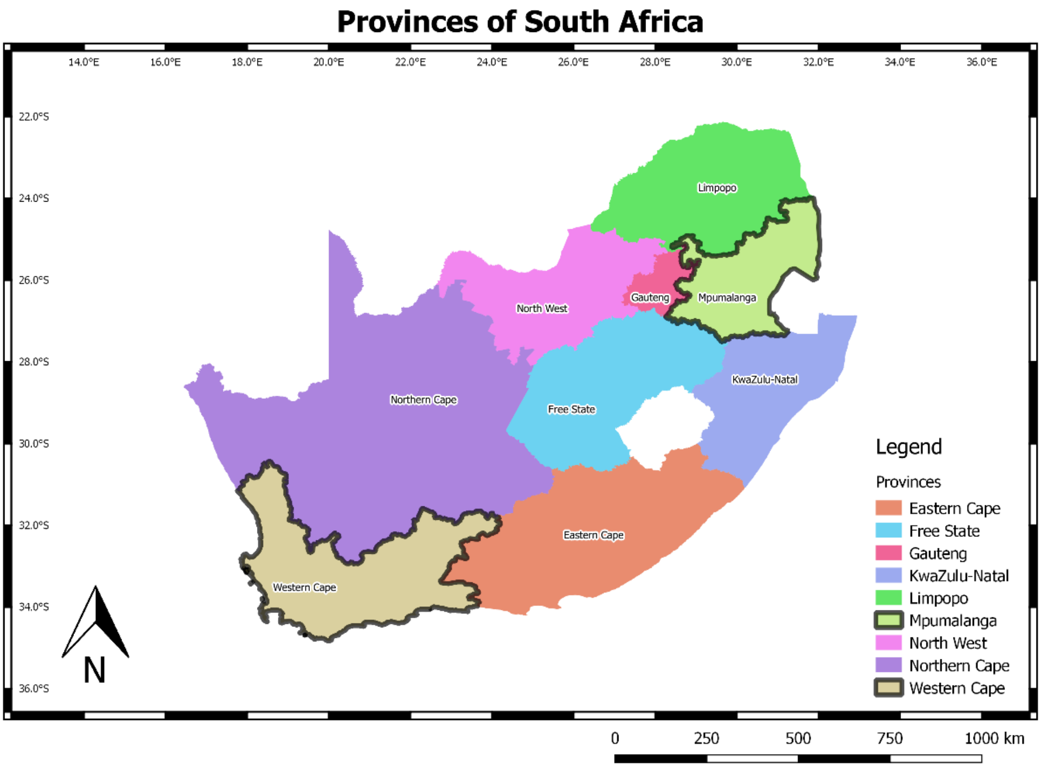

Figure 8: Map of the Provinces of South Africa (Data from the Municipal Demarcation Board 2012).

3.4.1. Mpumalanga

Mpumalanga is situated in the north-eastern part of South Africa. The province covers 76 495 km^2, which is 6.3% of the total area of South Africa (South African Government 2016). Mpumalanga is situated on the high plateau grasslands of the Middleveld. The province rises to mountain peaks and also low land areas called the Lowveld. Mpumalanga is dominated by grasslands, followed by Savanna and Forests (SANBI 2012). A transition area occurs between the Grassland on the escarpment and the Savanna in the Lowveld (South African Government 2016). Mpumalanga receives its rain during summer and becomes dry in winter (Working on Fire 2013). The population of Mpumalanga is 4 283 888, which is 7.79% of the total population of South Africa (StatsSA 2015). Figure 9 provides an overview of the dominant biomes in the province.

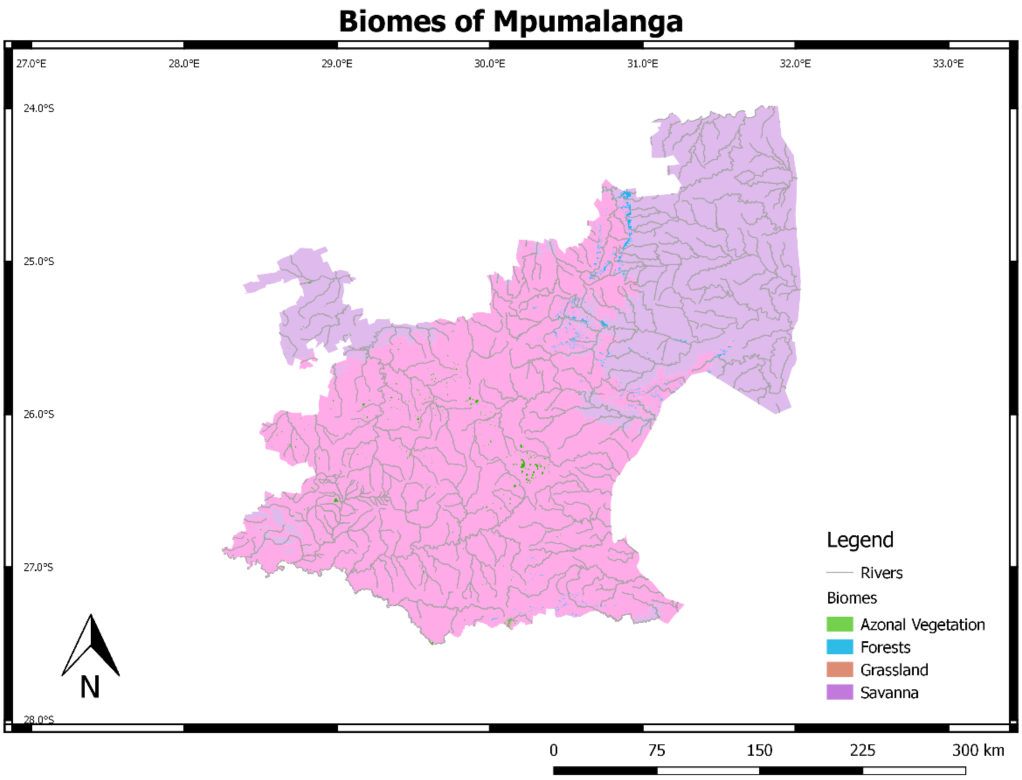

Figure 9: Map of the Biomes of Mpumalanga (Data from South African National Biodiversity Institute 2012).

3.4.2. Western Cape

The Western Cape is situated at the south-western tip of South Africa. The province covers 129 462 km^2, which is 10.6% of the total area of South Africa (South African Government 2016). The largest indigenous forests in South Africa are found in the Knysna-Tsitsikamma area (South African Government 2016). The Western Cape is dominated by Fynbos, Nama-Karoo and Succulent-Karoo (SANBI 2012). The Western Cape receives its rainfall during winter and becomes dry in summer (Working on Fire 2013). The population of the Western Cape is 6 200 098, which is 11.28% of the total population of South Africa (StatsSA 2015). Figure 10 provides an overview of the dominant biomes in the province.

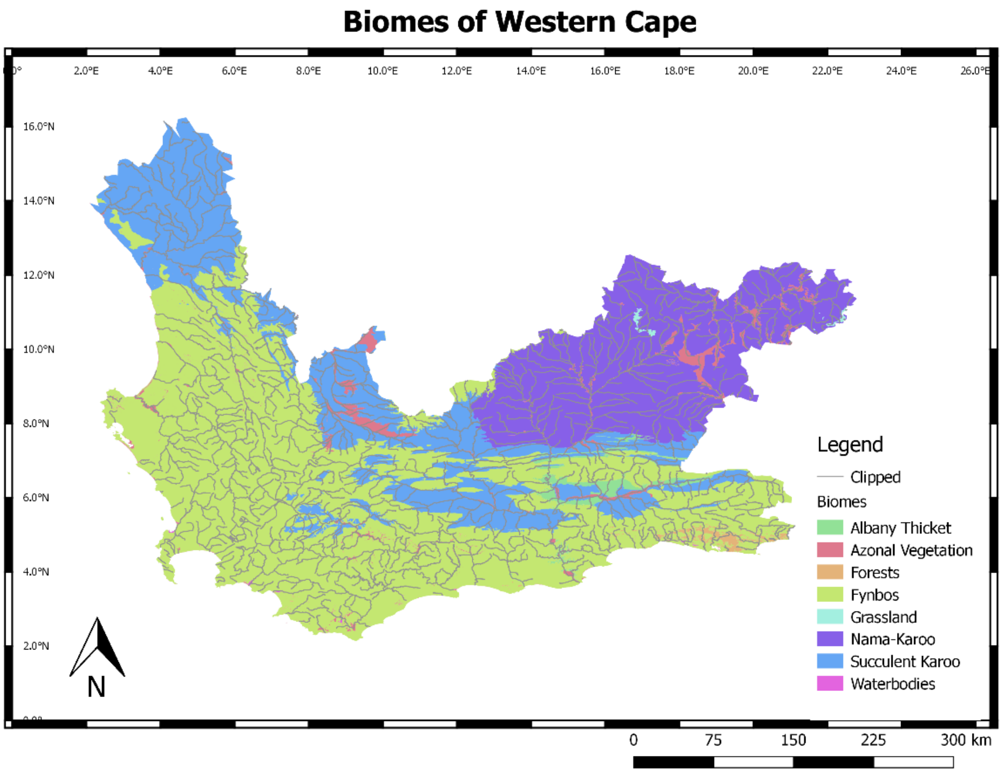

Figure 10: Map of Biomes of Western Cape (Data from South African National Biodiversity Institute 2012).

3.5. Implementation of Fire Potential Indices

This section provides information on the data that is required to run the candidate fire potential indices. Details on the datasets selected for the indices are also given in this section. The preparation of the datasets for use in the fire potential indices is described in chapter four.

3.5.1. Data Required for Candidate Fire Potential Index Implementation

The candidate fire potential indices make use of a number of input variables to determine fire potential in an area. Table 9 provides a list of the datasets that were used in the implementation of the candidate fire potential indices in this research.

Variable	Dataset Used	Description	Indices
Elevation	Shuttle Radar Topography Mission (SRTM) 30m Digital Elevation Model (DEM)	Data describing the height above sea level of the terrain in an area.	Hybrid Fire Index (Adab et al.) Fire Hazard Index (Chuvieco & Congalton) Structural Fire Index (Cipriani et al.)

Variable	Dataset Used	Description	Indices
Slope	Derived from SRTM 30m DEM	Data describing the rising and falling of the terrain in an area.	Hybrid Fire Index (Adab et al.) Forest Fire Risk Index (Ertena et al.) Fire Hazard Index (Chuvieco & Congalton) Structural Fire Index (Cipriani et al.) Fire Risk Index (Jaiswal et al.) Fire Risk Index (Saglam et al.)
Aspect	Derived from SRTM 30m DEM	Data describing the positioning of the terrain in an area in a particular direction.	Hybrid Fire Index (Adab et al.) Forest Fire Risk Index (Ertena et al.) Fire Hazard Index (Chuvieco & Congalton) Fire Risk Index (Saglam et al.)
Proximity to Roads	Derived from OpenStreetMap Roads	Data describing the distance of an area to roads.	Hybrid Fire Index (Adab et al.) Forest Fire Risk Index (Ertena et al.) Fire Hazard Index (Chuvieco & Congalton) Structural Fire Index (Cipriani et al.) Fire Risk Index (Jaiswal et al.)
Proximity to Human Settlements	Derived from Worldpop South Africa Population	Data describing the distance of an area to human settlements.	Hybrid Fire Index (Adab et al.) Forest Fire Risk Index (Ertena et al.) Fire Risk Index (Jaiswal et al.) Fire Risk Index (Saglam et al.)
Proximity to Agricultural Fields	Derived from Department of Environmental Affairs (DEA) 2014 South African National Land cover	Data describing the distance from agricultural fields.	Fire Risk Index (Saglam et al.)
Vegetation Moisture	Normalised Difference Water Index (NDWI) Derived from	Data describing the moisture content of vegetation in an area.	Hybrid Fire Index (Adab et al.) Forest Fire Risk Index (Ertena et al.) Fire Hazard Index (Chuvieco & Congalton)

Variable	Dataset Used	Description	Indices
	Moderate Resolution Imaging Spectroradiometer (MODIS) MCD43A4		Fire Risk Index (Jaiswal et al.) Fire Risk Index (Saglam et al.) Fire Potential Index (Burgan et al.)
Land Cover	DEA 2014 South African National Land Cover	Data describing the land cover type in an area. In this context it provides information on vegetation types and other land cover types that should be excluded from the indices.	Structural Fire Index (Cipriani et al.) Fire Potential Index (Burgan et al.)
Extinction Moisture	Derived from Land Cover (extinction moisture values assigned to vegetation areas, urban areas masked out)	Data describing the extinction moisture of vegetation in an area.	Fire Potential Index (Burgan et al.)
Temperature	European Centre for Medium-Range Weather Forecast (ECMWF) Forecast Model	Data describing the air temperature in an area.	Fire Potential Index (Burgan et al.)
Relative Humidity	ECMWF Forecast Model	Data describing the relative humidity in an area.	Fire Potential Index (Burgan et al.)
Cloud Cover	MODIS Cloud Fraction (MODAL2)	Data describing the cloud cover in an area.	Fire Potential Index (Burgan et al.)

Variable	Dataset Used	Description	Indices
Rainfall	National Aeronautics and Space Administration (NASA) Global Precipitation Measurement (GPM)	Data describing the rainfall in an area.	Fire Potential Index (Burgan et al.)

Table 9: Datasets Used in the Implementation of the Candidate Fire Potential Indices.

More details on the datasets mentioned in Table 9 are provided next. Some information on why the data was collected, how the data was collected, the spatial resolution of the data and some information on the projection and datum used is provided.

SRTM 1 Arc-Second (30 metre) Global DEM

The National Aeronautics and Space Administration (NASA) of the United States of America and the United States of America National Geospatial-Intelligence Agency (NGA) collaborated to acquire radar data in order to create a near-global dataset containing land elevations (USGS 2015). The Shuttle Radar Topography Mission (SRTM) was flown during February 2000 on board the Endeavour space shuttle (USGS 2015). The radar instrument used on SRTM were previously used on other Endeavour missions during 1994. In April and October 1994 the C-band Space-borne Imaging Radar (SIR-C) and the X-Band Synthetic Aperture Radar (X-SAR) were used to collect data on the environment (USGS 2015). Modifications were made to the technology to enable the collection of interferometric radar on SRTM (USGS 2015). Two radar images are taken at a moderately different angle (USGS 2015). Two antennas were used to collect data at the same time in single pass interferometry. One of the antennas was on the space shuttle and the other antenna was on a 60-meter mast that stretched out from the space shuttle (USGS 2015). The surface elevation could then be calculated because of the difference between the two signals (USGS 2015). Data was collected for around 80% of the Earth's surface during an eleven-day mission and 176 orbits (USGS 2015).

The SRTM 1 Arc-Second Global elevation dataset provides void filled elevation data at a 30 meter spatial resolution (USGS 2015). The data is provided in a number of file formats and was downloaded in Georeferenced Tagged Image File Format (GeoTIFF) (USGS 2015). The projection of the dataset is geographic, the horizontal datum is WGS84 and the vertical datum is Earth Gravitational Model 1991 (EGM96) (USGS 2015). The vertical unit of the dataset is meters (USGS 2015). Two datasets were taken into consideration for use in this research. The SRTM DEM and ASTER DEM. Global data coverage is important for operational systems that are used across the world. The Advanced Fire Information System (AFIS) provides services to many countries around the world and it is important to have a DEM dataset that provides global coverage. Both of the DEMs have global coverage, however the SRTM DEM has performed better than the ASTER DEM in comparison studies (Baral et al. 2016; Rokni et al. 2015; Rexer et al. 2014; Nikolakopoulos et al. 2006).

OpenStreetMap

The purpose of OpenStreetMap is to collect data about features like roads, buildings and trails, globally (OpenStreetMap 2016). The data is crowd-sourced by a community of contributors including enthusiast mappers, GIS professionals and engineers maintaining the OpenStreetMap servers (OpenStreetMap 2016).

Global Positioning System (GPS) devices, aerial imagery and low technology field maps are used to verify the data on OpenStreetMap, thereby ensuring that good data accuracy is achieved and that the data is kept up to date with changes (OpenStreetMap 2016).

OpenStreetMap data was used because it is freely available and the data coverage is global. Global coverage is an important factor for this research as an operational system such as AFIS would typically require global data.

AfriPop South Africa Population

The AfriPop South Africa Population dataset was downloaded from Worldpop.org. The data is freely available. The projection of the dataset is geographic and the horizontal datum is WGS84 (Worldpop.org 2016). The unit of measure for the data is estimated persons per square grid tile (Worldpop.org 2016). The data is provided in Georeferenced Tagged Image File Format (GeoTIFF). The 2015 estimation dataset was used in the research. The spatial resolution of the data is 100m (Worldpop.org 2016). The spatial resolution of the dataset is lower than that of the highest spatial resolution datasets used in this research. It would have been even more useful if the dataset were also available at 30 metre spatial resolution. Globcover data and census data was used to create the dataset (Linard et al. 2012:2).

The method used to create the dataset was adapted from research done in East Africa (Linard et al. 2012:2). The dataset was created to overcome sources of doubt in older mapping methods (Linard et al. 2012:3). This is done by accurately mapping settlements where people live, by constructing a database with the latest, comprehensive census data and by making use of semi-automated processes that can make use of other data to easily update the dataset (Linard et al. 2012:3).

Accuracy assessment of the dataset showed that the method produced more accurate results than the methods used to create datasets such as Global Rural-Urban Mapping Project (GRUMP), Gridded Population of the World (GPW), LandScan and United Nations Environment Programme (UNEP) (Linard et al. 2012:3).

The Worldpop dataset was used because the data covers a number of countries around the world. Data is available for some or all countries in Africa, America, Asia and Europe. Other data will have to be acquired to implement the indices in areas not covered by the dataset, if the method has to be repeated for other countries, because the implementation of the indices in these areas are limited by the availability of data.

MODIS MCD43A4

The Moderate-resolution Imaging Spectroradiometer (MODIS) MCD43A4 product supplies reflectance data that is adjusted by using a bidirectional reflectance distribution function (BRDF) to model the data values as if it were captured from nadir view (LP DAAC 2016). The spatial resolution of the dataset is 500 meters (LP DAAC 2016) which is lower than that of the highest spatial resolution datasets used in this research. It would have been even more useful if the dataset were also available at 30 metre spatial resolution. The dataset is produced every eight days with sixteen days of acquisition data (LP DAAC 2016). The projection of the data is Sinusoidal and the data is provided in Hierarchical Data Format – Earth Observing System (HDF-EOS) format (LP DAAC 2016). The validation of MCD43 has reached Validation Stage 3 (MODIS Land Team 2015) which means that uncertainties in the MCD43 product have been identified by comparing the data to other datasets (MODIS Land Team 2009).

The MCD43A4 dataset has been used by the Earth Observation and Information Technology (EOSIT) competence area, Council for Scientific and Industrial Research (CSIR) Meraka Institute to produce NDVI and EVI datasets. The data was used as it was readily available and suited to the purpose of this research.

DEA National Land Cover 2014

The 2013-2014 National Land Cover dataset was developed by GeoTerraImage (GTI). The availability of Landsat 8 data made the creation of an updated, national land cover dataset for South Africa possible (GeoTerraImage 2015). Land cover data is important in a number of fields, for example, environmental resource management, landscape planning and telecommunication planning (GeoTerraImage 2015). The dataset was created by collecting Landsat 8 data for the period from April 2013 to March 2014 (GeoTerraImage 2015). More than 600 Landsat images were used to create the dataset (GeoTerraImage 2015). The overall map accuracy of the dataset was determined as 81.73%

(GeoTerraImage 2015). The dataset has a spatial resolution of 30 meters. The dataset was derived with the use of semi-automated modelling processes that have been operationally proven (GeoTerraImage 2015). The dataset contains 72 land cover classes (GeoTerraImage 2015).

The DEA National Land Cover dataset was used because it is the latest dataset to provide land cover classification in South Africa. Land cover datasets do not have global coverage and are usually provided for countries or continents. Other datasets will have to be acquired for implementation in other countries, for example: the CORINE land cover dataset can be used for Europe.

ECMWF Forecast Model

The European Centre for Medium Range Weather Forecasts (ECMWF) provides forecast data based on a number of basic equations (ECMWF 2015). The forecasts are provided at 00h00 and 12h00 at a spatial resolution of 12.5 kilometres (ECMWF 2015). The spatial resolution of the dataset is lower than that of the highest spatial resolution datasets used in this research. It would have been more useful if the dataset were also available at 30 metre spatial resolution. The following parameters are received from ECMWF: 10 meter V-velocity, 10 meter U-velocity, 2 meter dew point temperature, 2 meter temperature and surface pressure. More accurate calculations can be made on data with higher numerical resolution and a higher spatial resolution permits better modelling of changes caused by topographical variables (ECMWF 2015). The input data to the model is acquired from earth observations instruments such as weather stations, ships, buoys and aircraft (ECMWF 2015).

Global Forecast System (GFS) data is freely available, but ECMWF data is better because the 12.5 kilometre spatial resolution of the ECMWF data is more useful than the 28 kilometre spatial resolution of the GFS data. ECMWF data was acquired by the EOSIT competence area, CSIR Meraka Institute to serve as input to many products. The data was used as it was readily available and other weather data could only be acquired at extra cost. The fire potential index output may have been more accurate if in-situ weather station data was freely available in a gridded format for the time period of the research.

MODIS Cloud Fraction

The MODIS Cloud Fraction dataset provides values for the fraction of the Earth's surface that is covered by cloud (NASA Earth Observations 2016). The data is derived from the cloud mask product (MOD 35) which is a one kilometre resolution, daily, global product (NASA Earth Observations 2016). The dataset is created by counting all cloudy pixels in a 25 kilometre area and dividing the value by 25 (NASA Earth Observations 2016). Therefore, the cloud fraction value provides an estimate of the portion of a number of pixels that are covered by cloud (NASA Earth Observations 2016). The spatial resolution of the dataset is lower than that of the highest spatial resolution datasets used in this research. It would have been more useful if the dataset were also available at 30 metre spatial resolution. MODIS Cloud Fraction data was used because it provides global coverage and it is easy to obtain for operational system use.

NASA GPM

Global Precipitation Measurement (GPM) is an international network of satellites aimed to collect rain and snow data every three hours, globally. The mission is centred around a 'core' satellite with an advanced radar/radiometer system that can measure precipitation in order to serve as a standard by which the data gathered by a constellation of satellites can be combined (Precipitation Measurement Missions 2016). GPM helps to move forward the comprehension of the water cycle of Earth and to improve the forecasting abilities of natural disasters (Precipitation Measurement Missions 2016).

Global precipitation data is beneficial for use in an operational system such as AFIS. The dataset was chosen because it combines many data sources to provide frequent global precipitation measurements.

3.5.2. Software Used for Candidate Fire Potential Index Implementation

The candidate fire potential indices were implemented in Python. The following external Python libraries were used to aid the implementation.

GDAL

The Geospatial Data Abstraction Library version 1.10.1 (GDAL.org 2016) is used for manipulating geospatial raster and vector data (Python Software Foundation 2016). In the index implementation the library is used to write raster files.

Rasterio

Rasterio is used for input/output (I/O) operations and formatting of raster files (Python Software Foundation 2016). In the index implementation the library is used to open raster files.

NumPy

NumPy is used to manipulate multi-dimensional arrays (Python Software Foundation 2016). In the index implementation NumPy is used to manipulate the data arrays and to make the calculation of the index array easy and speed efficient.

3.5.3. Candidate Fire Potential Index Implementation

The candidate fire potential indices were implemented in Python. A number of libraries were used for the implementation. The implementation of each of the candidate fire potential indices is discussed in detail in chapter 4.

The fire potential indices implemented in this research is provided in Table 10. Two of the fire potential indices are dynamic fire potential indices. This means that they take input that is updated over short periods of time. The rest of the fire potential indices are structural fire potential indices. This means that they only take input that does not change over short periods of time. In order to compare all of the indices in this research the structural fire potential indices were changed to be dynamic fire potential indices. The indices were changed by using the vegetation moisture datasets, used in the dynamic fire potential indices, instead of a structural dataset that assigns a potential rating based on the type of vegetation present in a pixel. Therefore, the implementations of all of the fire potential indices in this research is dynamic.

Fire Potential Index	**Literature Source**	**Dynamic/Structural Index**
Hybrid Fire Index	Adab et al. (2011)	Originally dynamic
Forest Fire Risk Index	Ertena et al. (1994)	Originally structural
Fire Hazard Index	Chuvieco & Congalton (1989)	Originally structural
Structural Fire Index	Cipriani et al. (2011)	Originally structural
Fire Risk Index	Jaiswal et al. (2002)	Originally structural
Fire Risk Index	Saglam et al. (2008)	Originally structural
Fire Potential Index	Burgan et al. (1998)	Originally dynamic

Table 10: Implemented Fire Potential Indices.

3.5.4. Implemented Candidate Fire Potential Index Execution

After the model implementation was completed the necessary data was prepared for the execution of the indices, therefore the implementation was carried out for the necessary time period, with the data collected to create the fire potential index files (output files). These fire potential index files or output files were then resampled to match the resolution of the fire potential index evaluation data.

The indices are executed by opening the input files and reading the data into memory. For most of the implemented fire potential indices the input data is transformed by assigning ratings to temporary arrays which are then used in the final index calculation. For the fire potential index the input data is transformed by performing a number of processes to get the required input to the final index calculation. This process is executed for every day in the fire season for the fire potential index because the rainfall, temperature, relative humidity and cloud cover datasets, which are dynamic input variables, are updated daily. The process is only carried out every eight days in the fire season for all of the other fire potential indices because the only dynamic input variable is only updated every eight days. The ratings assigned to the temporary arrays based on the input values are provided in chapter four for every implemented fire potential index.

3.6. Evaluation of Fire Potential Indices

3.6.1. Data Required for Candidate Fire Potential Index Evaluation

Input	**Dataset Used**	**Description**
Fire Potential Indices	Data output from candidate fire potential index implementations; Fire Weather Index (FWI), Fine Fuel Moisture Content (FFMC), Duff Moisture Code (DMC), Drought Code (DC) from database.	Data describing the fire potential of an area.
Active Fires	Suomi National Polar-Orbiting Partnership (NPP) Visible Infrared Imaging Radiometer Suite (VIIRS) 375 meter Active Fire Product	Data describing the occurrence of active fires on the surface of the earth.

Table 11: Datasets Used in the Evaluation of the Candidate Fire Potential Indices.

More detail on the datasets mentioned in Table 11 is provided next. Some information on why the data was collected, how the data was collected and the spatial resolution of the data is provided.

NPP VIIRS 375 Meter Active Fire Dataset (VNP14IMGTDL_NRT)

AFIS provides active fire locations through the AFIS viewer. Some of the datasets made available through the viewer include NPP VIIRS 375 meter active fires and MODIS 1 kilometre active fires. These datasets were considered for use in this research. NPP VIIRS data complements MODIS data (NASA Earth Data 2016). The NPP VIIRS 375 meter fire location dataset was chosen for use in this research. NPP VIIRS data has a higher spatial resolution at 375 meters than the MODIS data which has a spatial resolution of 1 kilometre. The higher spatial resolution means that smaller fires are identified by the sensor which provides a more complete set of active fire locations than that of MODIS. The data is useful for fire management and science applications (NASA Earth Data 2016). NPP VIIRS data does not have Fire Radiative Power (FRP) linked to the fire detections (Nasa Earth Data 2016). The data is received at EOSIT competence area, CSIR Meraka Institute.

The VIIRS 375 meter active fire product is derived from data acquired by the VIIRS sensor aboard the Suomi NPP satellite (NASA 2016). The satellite provides full global coverage every twelve hours (NASA Earth Data 2016). The dataset is available in text (TXT), Shapefile (SHP), Keyhole Markup Language (KML) and Web Map Service (WMS) formats (NASA 2016).

Information attributes provided in the SHP and TXT formats include: latitude, longitude, brightness temperature I-4, scan, track, acquisition date, acquisition time, satellite, confidence, version, brightness temperature I-5 and day/night (NASA 2016).

3.6.2. Software Used for Implemented Candidate Fire Potential Index Evaluation

The candidate fire potential index evaluation was implemented in Python. The following external Python libraries were used to aid the implementation.

GDAL

The Geospatial Data Abstraction Library (GDAL) is used for manipulating geospatial raster and vector data (Python Software Foundation 2016). In the evaluation implementation the library is used to write raster files.

Rasterio

Rasterio is used for I/O operations and formatting of raster files (Python Software Foundation 2016). In the evaluation implementation the library is used to open raster files.

NumPy

NumPy is used to manipulate multi-dimensional arrays (Python Software Foundation 2016). In the index implementation NumPy is used to manipulate the data arrays and to make the evaluation easy and speed efficient.

SciPy

SciPy is dependent on NumPy and it operates on multi-dimensional arrays (Python Software Foundation 2016). SciPy provides a number of user-friendly and efficient numerical tools to users (Python Software Foundation 2016). Statistical functions (scipy.stats) are used to perform statistical operations (SciPy.org 2016).

Matplotlib

Matplotlib provides functionality to create graphics (Python Software Foundation 2016). In the implementation of the evaluation it is used to create data graphs.

Pandas

Pandas provides data structures to simplify working with time series data (Python Software Foundation 2016). In the evaluation implementation it is used to manipulate and perform calculations on the fire potential index time series data and the Active Fire evaluation data.

Statsmodels

Statsmodels provides methods for doing statistical computations (Python Software Foundation 2016). In the evaluation implementation it is used to perform logistic regression and other statistical calculations.

Patsy

Patsy provides ways to describe statistical models and build design matrices (Python Software Foundation 2016). In the evaluation implementation it is used for logistic regression.

Scikit-Learn

Scikit-Learn provides machine learning methods (Python Software Foundation 2016). In the evaluation implementation it is used to for logistic regression, cross validation of logistic regression and providing metrics.

3.6.3. Candidate Fire Potential Index and Fire Danger Index Evaluation

A visual evaluation was done on all of the candidate fire potential indices to see what features and areas may stand out visually in the two study areas for each one of the candidate fire potential indices. The visual evaluation was followed by a statistical evaluation.

All of the candidate fire potential indices were included in the evaluation. Along with the candidate fire potential indices a few other indices were included in the analysis in order to make a comparison between the candidate fire potential indices and official fire danger indices that are used operationally by fire managers across the globe. These fire danger indices include the Lowveld Fire Danger Index (LFDI), the Canadian Fire Weather Index (FWI) and some of its sub-components including Duff Moisture Code (DMC), Drought Code (DC) and Fine Fuel Moisture Code (FFMC). The data used for the fire danger indices was already calculated by an operational system that was set in place at the Meraka Institute at the CSIR to provide fire danger information to fire managers. The fire danger indices were calculated using the same ECMWF data that was used in the fire potential index implementations. The calculation of the fire danger indices was done at the Meraka Institute at the CSIR on a system set in place by a system developer. The fire danger indices data was calculated for the same dates as the implemented candidate fire potential indices and the data was extracted from an operational database and exported to GeoTIFF for use in the evaluation. The spatial resolution of the Fire danger indices data was 12.5 kilometres.

The fire potential index files or output files of all of the candidate fire potential indices were resampled to a 12.5 kilometre spatial resolution, using gdalwarp. The spatial resolution was selected because the lowest resolution dataset used in the fire potential index implementations was 12.5 kilometres. The tool changes the spatial resolution of the input files by creating a grid with the new spatial resolution and assigning a value to a pixel based on the resampling method chosen and the pixel values contributing to the new pixel. The resampling method used was cubic resampling.

The candidate fire potential indices and fire danger indices were then evaluated one by one. All of the files in the time series were opened in a loop and read into a dictionary – i.e. a data structure used to store an unordered set of key-value pairs (Python Software Foundation, 2017). The same process was used for the fire activity data. Therefore, two dictionaries were created, one containing the daily fire potential index values or the fire danger index values for each day of the fire season and one containing the fire activity occurrence for each day of the fire season. The possible fire activity data values were as follows: one, if one or more fires occurred in the pixel, and zero, if no fires occurred in the pixel.

From this point forward the analysis was done on a per pixel basis. All pixels that did not contain any fire activity, therefore having a value of zero, were excluded from the analysis. Figure 11 depicts two grids. The first grid contains the actual fire detections and the second grid shows the ones and zeros assigned to pixels based on whether or not a fire was detected in a pixel. Only the pixels with the value '1' were included in the analysis.

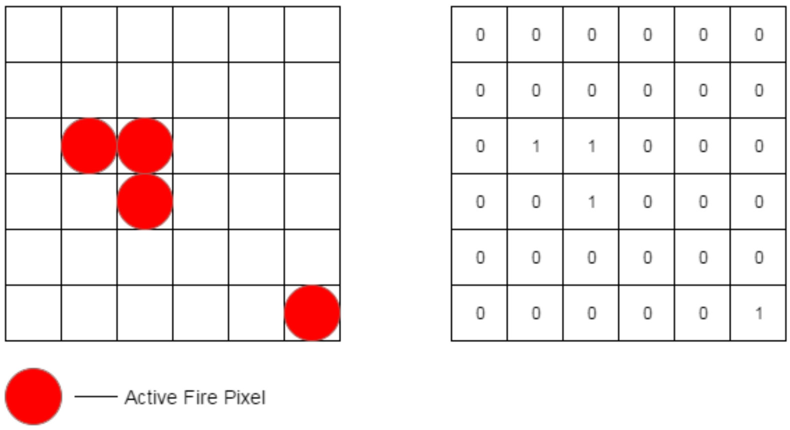

Figure 11: Example of Active Fire Count Raster Used in Index Evaluation.

Only fire potential index pixels within the range of zero to 100 were included in the analysis, as any value above a hundred was a value assigned to a pixel that was not able to burn. Values above a hundred were assigned to non-burnable pixels to make it possible to differentiate between useable and unusable pixels as all of the model ranges were set from zero to a hundred. The sanitised arrays then served as the input to all of the evaluation metric methods. Figure 12 shows, briefly, the fire potential index evaluation process.

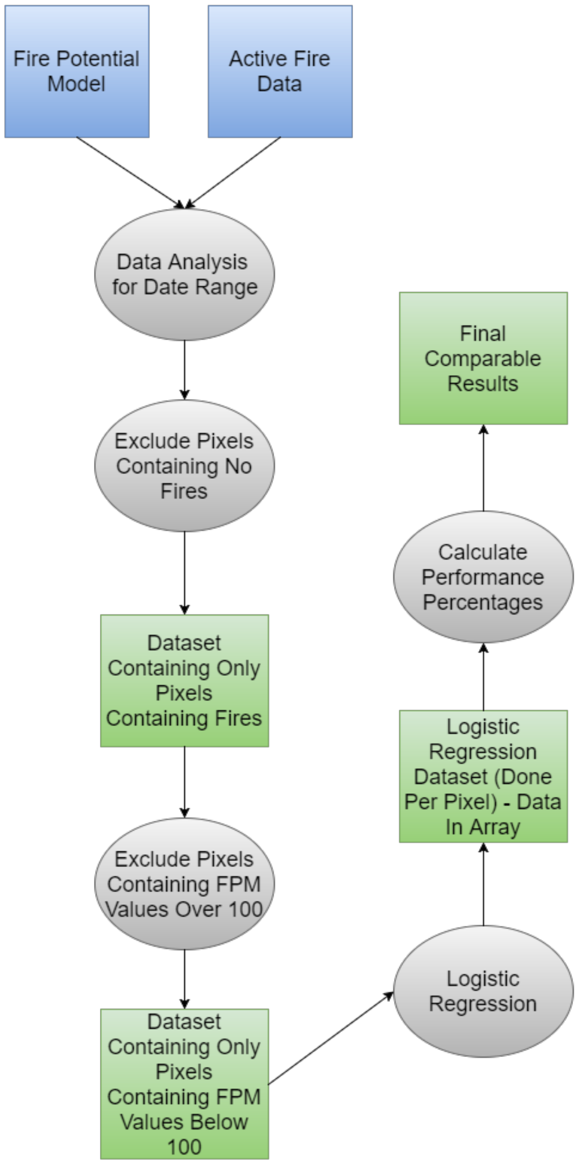

Figure 12: Process Describing Evaluation of Fire Potential Indices.

A logistic regression was run on a per pixel basis. Only pixels containing fire activity for at least one day during the fire season were included in the analysis. Logistic regression was used as the data is in a binary form. The occurrence of fires in the data is far less than the non-occurrence of fires and ordinary logistic regression may cause a problem in this regard. Rare events logistic regression was used in the research as ordinary logistic regression may underestimate the probability of the occurrence of an event (van den Eeckhaut et al. 2006). The independent variable is the fire potential index and the dependent variable is the fire activity. The logistic regression was carried out as done by Andrews et al. (2003), van den Eeckhaut et al. (2006) and King & Zheng (2001). A logistic regression model provides the probability of a fire occurrence based on the fire potential index. The rare events logistic regression made use of three corrections to the logistic regression model. Firstly, a representative sample was selected from the population. For every fire occurrence date five non-occurrence dates were selected per pixel (van den Eeckhaut et al. 2006). The second correction dealt with the correction of the model intercept by taking the fraction of ones in the population and the fraction of ones in the sample into account (van den Eeckhaut et al. 2006). A third correction was needed to ensure that the probabilities were not underestimated by adding a correction factor to the model. The calculation of the correction factor included the probability, values of the independent variable and the variance-covariance matrix (van den Eeckhaut et al. 2006). The model accuracy was calculated to determine if the model fitted to the data was useful. The model intercept and slope was then calculated. The number of ones and zeros as well as the fraction of ones and zeros were calculated.

The following statistics were calculated for use in the evaluation:

- The total sum of squares, sum of squares error and sum of squares residual were calculated.
- The total sum of squares represents the variation in a model that does not have an independent variable (Andrews et al. 2003).
- The sum of squares error is the residual variation for a model (Andrews et al. 2003).
- The sum of squares residual is the explained variation for the logistic regression model (Andrews et al. 2003).
- The sum of squares residual can be used to test if the model was improved by including the independent predictor variable (Andrews et al. 2003).
- The saturated sum of squares error and saturated sum of squares residual was then calculated.
- Using the sum of squares residual and the saturated sum of squares residual the pseudo R^2 was calculated.
- If the pseudo R^2 value is close to one, the logistic model fits the data as represented by the saturated model well (Andrews et al. 2003).
- The saturated model is calculated as the fraction of ‘one’ values at each unique value of the fire potential index.

- The pseudo R^2 can be used to compare indices.

Percentile shift was run on a per pixel basis. The percentile shift was calculated in order to more effectively compare the fire potential indices (Andrews et al. 2003). The 25th, 50th and 90th percentiles were calculated for all fire days. The above mentioned percentiles were calculated based on the research done by Andrews et al. (2003), where the same type of evaluation was conducted. The decision of which percentiles to calculate is subjective. The values were then used to calculate the percentile on fire days of the 25th, 50th and 90th percentile values for all days. The difference in the percentiles on all days (25th, 50th and 90th percentile) and the percentile calculated on fire days was then calculated for all three percentiles. The three difference values were then summed to determine the total percentile shift (differences in distribution). A greater (higher total value) percentile shift for a fire potential index indicates better fire potential index performance (Andrews et al. 2003).

The Bhattacharyya Coefficient was calculated on a per pixel basis. The Bhattacharyya Coefficient is calculated to determine the total overlap between two datasets (Steenkamp et al. 2012). The fire potential index values were placed in ten categories (0-10, 10-20, 20-30, 30-40, 40-50, 50-60, 60-70, 70-80, 80-90, 90-100). This was done for fire days and non-fire days. For each category the square root of the number of fire days multiplied by the number of non-fire days was calculated. The values for each category were summed to calculated the Bhattacharyya Coefficient. A small value indicates a superior relationship between the fire potential index and the active fire data (Steenkamp et al. 2012).

Eastaugh's Two Part metric was calculated on a per pixel basis. The Eastaugh's Two Part metric provides a way to rank fire potential indices by performance (Eastaugh et al. 2012). The percentiles for each value on fire days were calculated. The percentile values were then sorted in ascending order. The slope and intercept of the sorted percentile array were calculated to produce the two metrics. A poor performing index will have a slope of one and an intercept of zero, while a capable index will have a slope close to zero and an intercept close to 100.

The C-Index was calculated on a per pixel basis. The C-Index provides information on the predictive potential of the logistic regression model (Verbesselt et al. 2006). The C-Index is the area under the curve and was calculated based on the logistic regression model fitted to the data. A value lower than 0.5 shows stochastic predictions, while a value of 1 indicates a good index (Eastaugh et al. 2012).

The output from the metrics were used to create a percentage based ranking of the indices. The percentage of pixels where the metric performed well, per fire potential index was used to rank the indices against each other.

3.7. Limitations of Research

3.7.1. Delineations

In this research we looked at indices that can be used for fire potential modelling by looking at literature over several years. The indices were chosen based on the types of inputs they use and how they are calculated. Indices that are calculated based on economic risk and probabilities have not been included in the research because this research does not deal with the impact a fire can have on an area, but the potential of a fire occurring in an area.

3.7.2. Limitations

Some datasets are not easily and readily available and it is crucial to be able to find the necessary data required to build a fire potential index to be able to apply the index in an area such as South Africa. Data availability limited the applicability of the indices on a local or regional scale, globally.

The spatial resolution of some of the data used in this research is not as high as would have been preferred and this can limit other higher resolution datasets and the overall output from the indices.

Datasets with different spatial resolutions make it difficult to determine the best spatial resolution to use in the research. Detail in data can be lost in lowering the spatial resolution and errors can be introduced in resampling data because of the resampling methods used.

The weather data used in this research is based on a forecast model. Active weather station readings will provide actual weather readings which is more reliable than forecasts. The ECMWF forecast data was used in the research because weather data is not freely available and the data was already acquired and paid for by the research group for whom the research was conducted.

The evaluation of the indices is limited because of the fact that only a few fires occur in an area within a fire season and this makes it difficult to work with a set of binary data where most of the pixels are assigned a value of zero. Rare events logistic regression, discussed in the previous section was used to try and overcome the problem.

Data volumes could have an influence on the performance of the fire potential index in an operational system and data has to be processed down to usable sizes based on the study area to ensure fast processing.

3.8. Ethical Considerations

In order to be able to use the external data necessary to complete the research approval was required from the Ethics committee of the Natural and Agricultural Sciences faculty at the University of

Pretoria. Ethical approval is important to protect the university and researchers from probable legal action. Application forms were completed and contained information and permission where necessary on all the external datasets used in the research. Approval from the committee was received on 11 August 2016. The approval form is attached as appendix B.

3.9. Chapter Summary

This chapter provided some information on the method used to conduct the research. Fire potential indices were implemented using data collected and prepared for the implementation of the indices. Some of the datasets used include elevation, slope, aspect, land cover, temperature, rainfall, relative humidity, proximity to human settlements and proximity to roads. The indices were then evaluated to find the index that has the best relationship between fire potential index values and active fire occurrences. Some of the metrics used to do the evaluation include Pseudo R^2, Percentile Shift and Probability Range. The following chapter will discuss the implementation of the individual fire potential indices.

4. Chapter Four: Fire Potential Index Implementation

4.1. Chapter Overview

This chapter provides more detail on the preparation of the datasets used in the implementation of the fire potential indices. The implementation of the candidate fire potential indices chosen based on the criteria set out in chapter three is described in this chapter. The data used and process of implementation will be discussed for each of the fire potential indices.

4.2. Data Preparation

The datasets prepared to serve as input to the fire potential index implementations were in raster format. All of the input datasets contained the same number of pixels and therefore the same number of rows and columns. The number of rows and columns in the files were matching and were spatially aligned in order for a fire potential index value to be assigned to a pixel based on a number of input variable values through the fire potential index implementations. The output from the implementations would therefore also be in raster format and it would contain the same number of pixels as the input files.

All of the data prepared for the implementation of the models was resampled to a 30 meter spatial resolution, unless already in a 30 meter spatial resolution. This spatial resolution was used to ensure that no spatial detail was lost in the implementations and the highest resolution datasets obtained had a 30 meter spatial resolution.

The evaluation of the models was done at a 10 kilometre spatial resolution. This spatial resolution was decided on because it gave a good general estimate of what the fire potential could be in an area. The 'area' resolution of 10 kilometres was chosen to ensure that areas around a pixel containing a fire, which would also seem to have a high fire potential even though an active fire might not have been detected in that cell at the moment of data acquisition, would not be left out of the evaluation and skew the results. For the above mentioned reasons it would not be useful to do the evaluation at a very high spatial resolution.

The datasets obtained for use in the research did not all have the same spatial resolution. The highest spatial resolution was 30 meters and the lowest spatial resolution was 12.5 kilometres. Some of the datasets had to be resampled for use in the fire potential index implementation as all of the datasets had to have the same spatial resolution. Resampling the datasets enabled the fire potential index implementation. Resampling from a higher resolution to a lower resolution or from a lower resolution to a higher resolution decreases dataset accuracy. Cubic resampling was used in the research. Cubic resampling makes use of four points to determine a new value for the output cell. The values in the resampled datasets were therefore aggregated and the accuracy lowered.

The datasets used in the research were clipped to the study areas. Clipping the data ensured that the datasets were smaller and therefore less data had to be processed in the fire potential index implementations. This decreased the fire potential index implementation processing times.

The datasets used in the fire potential index implementation were reprojected if necessary. If the datasets did not make use of the same datum and projection it would not be possible to implement the fire potential indices with those datasets.

4.2.1. Data Preparation and Derived Datasets

4.2.1.1. Elevation

The elevation dataset used in the research as input to the fire potential indices was the 1 Arc-Second (30 meter) SRTM DEM, downloaded from EarthExplorer (http://earthexplorer.usgs.gov). All of the tiles covering South Africa were downloaded in GeoTIFF format. The tiles were merged into a single GeoTIFF file. The projection of the dataset is geographic. The horizontal datum is WGS84 which is the desired projection and datum for the research. The dataset was clipped to the boundaries of the two study areas. Therefore, two elevation datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 13.

Figure 13: Process to Create Elevation Datasets.

4.2.1.2. Slope

The slope dataset used in the research as input to the fire potential indices was derived from the 1 Arc-Second (30 meter) SRTM DEM, downloaded from EarthExplorer. All of the tiles covering South Africa were downloaded in GeoTIFF format. The tiles were merged into a single GeoTIFF file. The projection of the dataset is geographic, the horizontal datum is WGS84 which is the desired projection and datum for the research. The Geospatial Data Abstraction Library (GDAL) was used to calculate the slope for the entire image. The slope was calculated as a percentage. The unit for the elevation (Z) is not the same as the units for X and Y. A scale of 111120 was used to scale the elevation values in terms of the X and Y values with the elevation values being provided in meters (GDAL.org 2016). The dataset's coordinate reference system was WGS84 and therefore the X and Y value unit was degrees. The dataset was clipped to the boundaries of the two study areas.

Therefore, two slope datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 14.

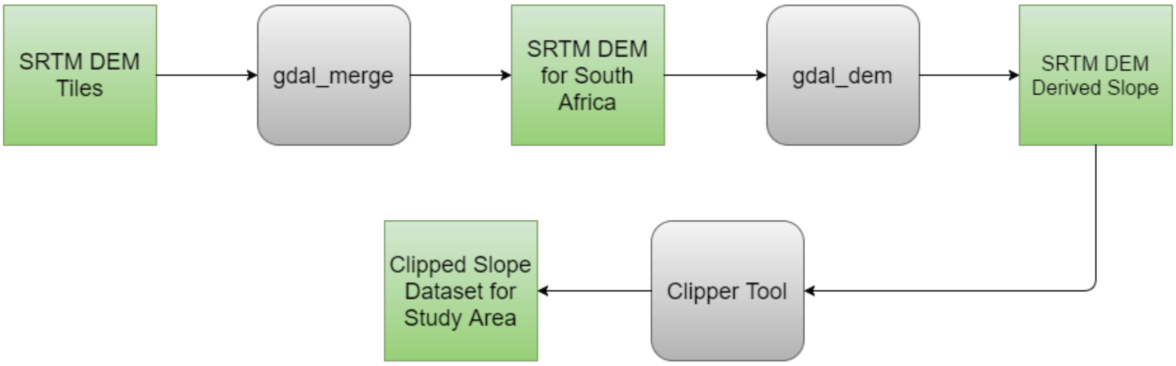

Figure 14: Process to Create Slope Datasets.

4.2.1.3. Aspect

The aspect dataset used in the research as input to the fire potential indices was derived from the 1 Arc-Second (30 meter) SRTM DEM, downloaded from EarthExplorer. All of the tiles covering South Africa were downloaded in GeoTIFF format. The tiles were merged into a single GeoTIFF file. The projection of the dataset is geographic, the horizontal datum is WGS84 which is the desired projection and datum for the research. The Geospatial Data Abstraction Library (GDAL) was used to calculate the aspect for the entire image. The 'trigonometric' flag was used to return the trigonometric angle and not the azimuth. This was done to match the fire potential index implementations where values are assigned based on the angle. The dataset was clipped to the boundaries of the two study areas.

Therefore, two aspect datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 15.

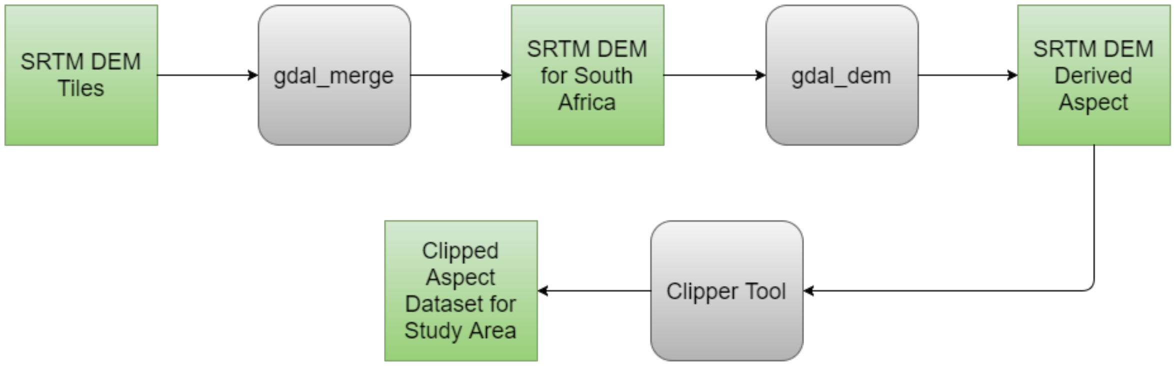

Figure 15: Process to Create Aspect Datasets.

4.2.1.4. Land Cover

The land cover dataset used in the research as input to the fire potential indices was the 2013-2014 National Land Cover dataset for South Africa derived from Landsat. A simplified classification was developed and the dataset was reclassified to make use of the simplified classification with the r.reclass tool from GRASS. The simplified classification simply grouped some land cover classes that would behave the same under fire conditions. The reclassification rules were provided in a text file and served as input to the reclassification tool. The reclassified dataset was reprojected to WGS84 from UTM to match other fire potential index input datasets. The dataset was then resampled to a 30 meter spatial resolution to match other fire potential index input datasets.

The dataset was clipped to the boundaries of the two study areas. Therefore, two land cover datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 16.

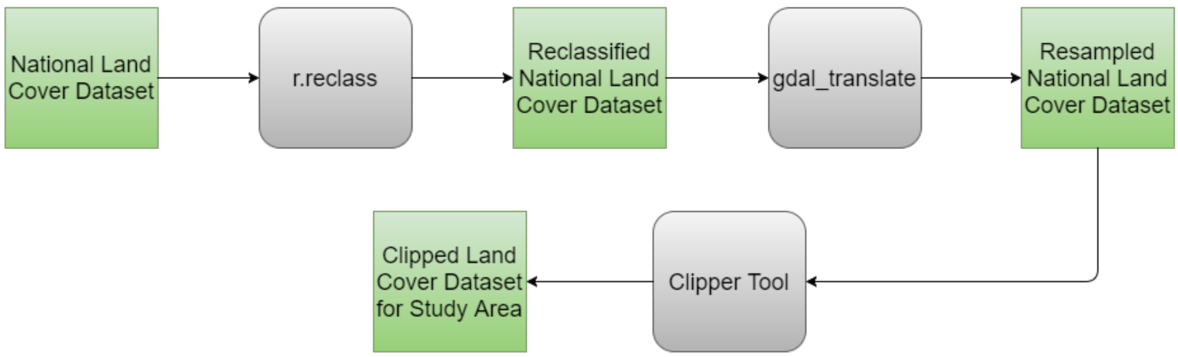

Figure 16: Process to Create Land Cover Datasets.

4.2.1.5. Proximity to Roads

The proximity to roads dataset used in the research as input to the fire potential indices was derived from OpenStreetMaps data for South Africa, downloaded from Geofabrik. The projection of the dataset is geographic, the horizontal datum is WGS84 which is the desired projection and datum for the research. The shapefile was rasterised with the GDAL rasterise tool. A value of 200 was burned into the GeoTIFF image where roads were present in the shapefile and a value of 0 was assigned to all other pixels. This was done in order to keep all of the relevant pixels and have the non-relevant pixels present as 'no-data' pixels. The dataset was created at a 30 meter spatial resolution.

The roads GeoTIFF file was then used to create a proximity to roads dataset with the GDAL proximity tool. The 'distunits' flag was set to pixels so that the proximity can be calculated in terms of distance in pixels and not in degrees. The dataset was created with the WGS84 coordinate reference system and the units are degrees. We know the cell size to be around 0.000277778 degrees

or 30 metres. The output from the proximity tool, with values in terms of number of pixels (distance) from roads, served as input to the QGIS raster calculator. The pixel values (number of pixels from roads) were multiplied with 30 to produce values that serve as the proximity to roads in meters at 30 metre spatial resolution.

The dataset was clipped to the boundaries of the two study areas. Therefore, two proximity to roads datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 17.

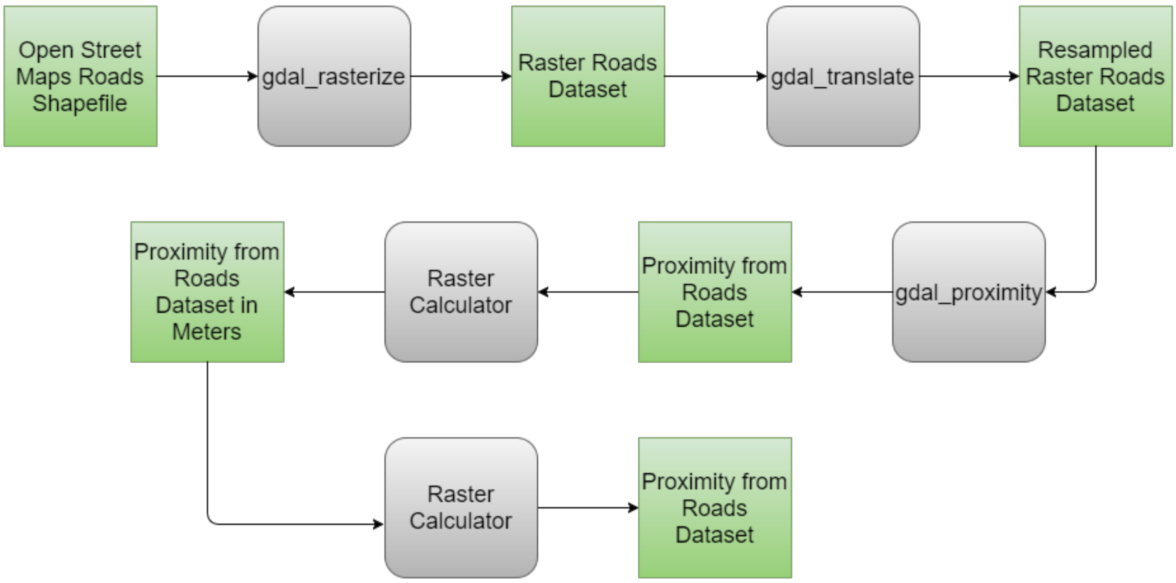

Figure 17: Process to Create Proximity to Roads Dataset.

4.2.1.6. Proximity to Human Settlements

The proximity to human settlements dataset used in the research as input to the fire potential indices was derived from the population dataset for South Africa, downloaded from WorldPop. The projection of the dataset is geographic, the horizontal datum is WGS84 which is the desired projection and datum for the research. The dataset was resampled to 30 metre spatial resolution using nearest neighbour interpolation with the GDAL warp tool.

The population dataset was then used to create a proximity to human settlements dataset with the GDAL proximity tool. The 'distunits' flag was set to pixels so that the proximity can be calculated in terms of distance in pixels and not in degrees. The dataset was created with the WGS84 datum and the data unit is degrees. We know the cell size to be around 0.000277778 degrees or 30 metres. The output from the proximity tool, with values in terms of number of pixels (distance) from human settlements, served as input to the QGIS raster calculator. The pixel values (number of pixels from human settlements) were multiplied with 30 to produce values that serve as the proximity to human settlements in meters at 30 metre spatial resolution.

The dataset was clipped to the boundaries of the two study areas. Therefore, two proximity to human settlements datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 18.

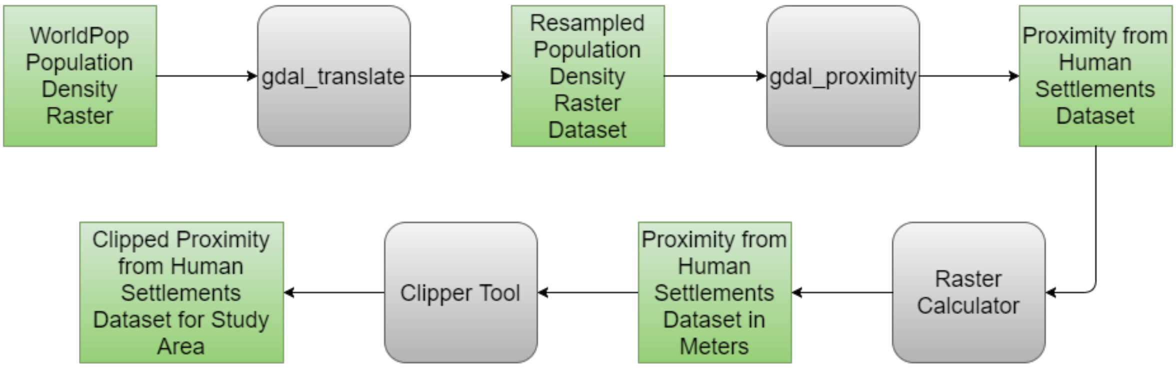

Figure 18: Process to Create Proximity to Human Settlements Dataset.

4.2.1.7. Proximity to Roads and Buildings

The proximity to roads and buildings dataset used in the research as input to the fire potential indices was derived from Open Street Maps roads and buildings vector datasets. The projection of the dataset is geographic, the horizontal datum is WGS84 which is the desired projection and datum for the research. The GDAL rasterise tool was used to rasterise the roads and buildings shapefiles, respectively. A value of 200 was burned into the GeoTIFF image where roads and buildings were present in the shapefiles and a value of 0 was assigned to all other pixels. Both datasets were then resampled to a 30 metre spatial resolution with GDAL warp. The raster calculator in QGIS was then used to create a sum of the two input raster layers.

The combined roads and buildings GeoTIFF dataset was then used to create a proximity to roads and buildings dataset with the GDAL proximity tool. The 'distunits' flag was set to pixels so that the proximity can be calculated in terms of distance in pixels and not in degrees. The dataset was created with the WGS84 coordinate reference system and the units are degrees. We know the cell size to be around 0.000277778 degrees or 30 metres. The output from the proximity tool, with values in terms of number of pixels (distance) from roads and buildings, served as input to the QGIS raster calculator. The pixel values (number of pixels from roads and buildings) were multiplied with 30 to produce values that serve as the proximity to roads and buildings in meters at 30 metre spatial resolution.

The dataset was clipped to the boundaries of the two study areas. Therefore, two proximity to roads and buildings datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 19.

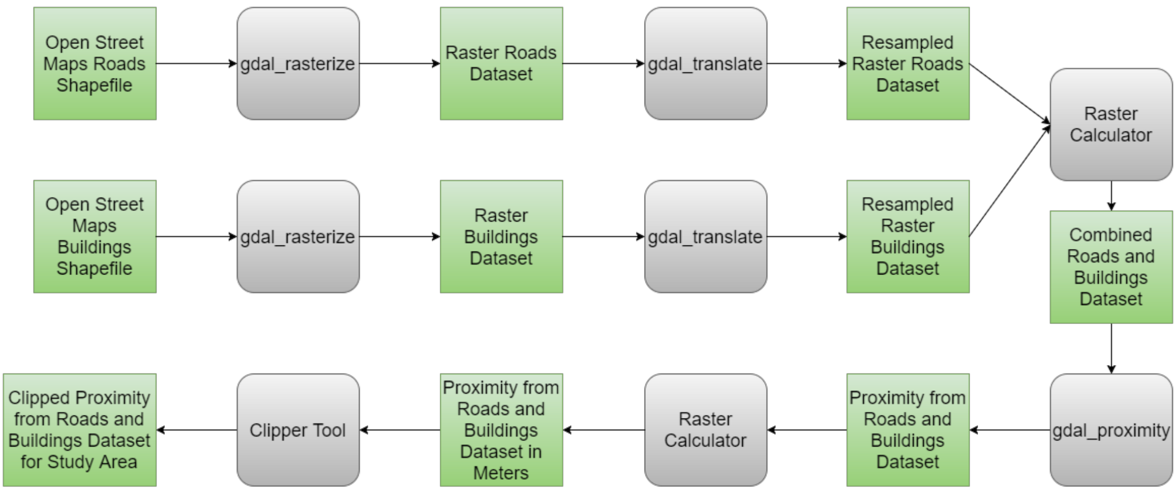

Figure 19: Process to Create Proximity to Roads and Buildings Dataset.

4.2.1.8. Proximity to Agricultural Fields

The proximity to agricultural fields dataset used in the research as input to the fire potential indices was derived from the 2013-2014 Land Cover dataset. The projection of the dataset is geographic, the horizontal datum is WGS84 which is the desired projection and datum for the research. The dataset was created to provide the proximity from agricultural fields to any other land cover class. The dataset was reclassified to include a value of 200 for all classes that are 'agricultural field' related and the other classes were reclassified to a value of 0 with the use of the r.reclass tool from GRASS. The dataset was then resampled to a 30 metre spatial resolution with GDAL warp. The agricultural fields GeoTIFF dataset was then used to create a proximity to agricultural fields dataset with the GDAL proximity tool. The 'distunits' flag was set to pixels so that the proximity can be calculated in terms of distance in pixels and not in degrees. The dataset was created with the WGS84 coordinate reference system and the units are degrees. We know the cell size to be around 0.000277778 degrees or 30 metres. The output from the proximity tool, with values in terms of number of pixels (distance) from agricultural fields, served as input to the QGIS raster calculator. The pixel values (number of pixels from agricultural fields) were multiplied with 30 to produce values that serve as the proximity to agricultural fields in meters at 30 metre spatial resolution.

The dataset was clipped to the boundaries of the two study areas. Therefore, two proximity to agricultural fields datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 20.

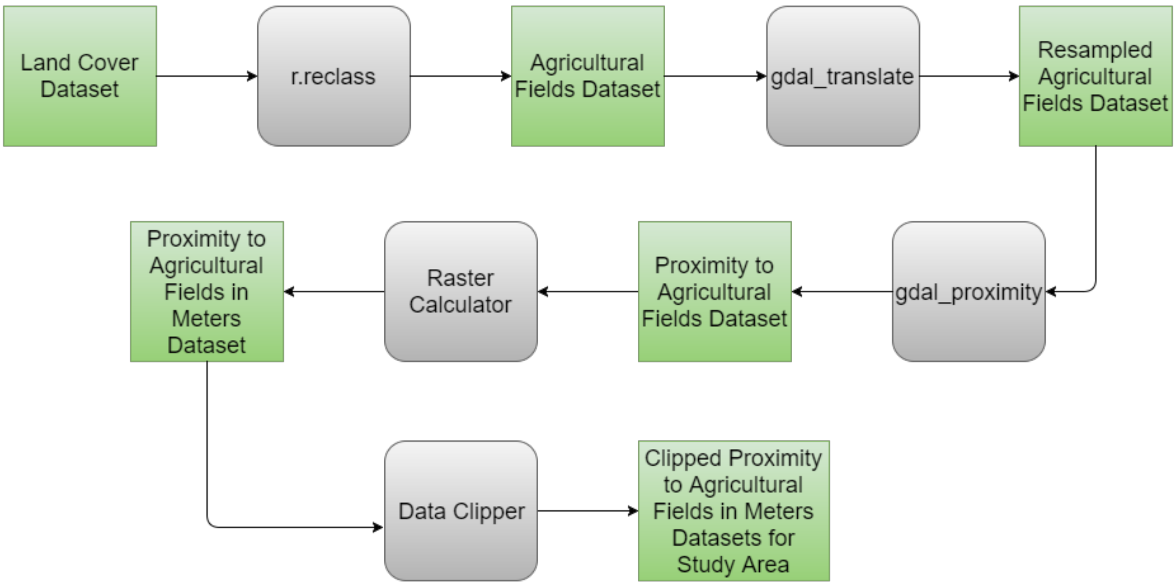

Figure 20: Process to Create Proximity to Agricultural Fields Dataset.

4.2.1.9. NDWI

The Normalised Difference Water Index (NDWI) dataset used in the research as input to the fire potential indices was derived from MODIS 500m, 16-day, BRDF-corrected, surface reflectance data (MCD43A4). Data was collected for the period of study in 2014 and 2015. The time period studied in the Western Cape was from August 2014 to June 2015 (including the summer fire season) and the time period studied in Mpumalanga was from February 2015 to December 2015 (including the winter fire season).

The HDF files were converted to GeoTIFF files using the GDAL translate tool. For band 2 and band 5, the four tiles for South Africa were merged into a single TIFF using the GDAL merge tool. The merged GeoTIFF files were used to calculate the NDWI. An NDWI value was calculated for each pixel. The data set was reprojected to WGS84 to match other fire potential index input datasets as the original dataset projection was a sinusoidal projection. The dataset was then resampled to 30 meter spatial resolution to match other fire potential index input datasets.

The dataset was clipped to the boundaries of the two study areas. Therefore, two NDWI datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 21.

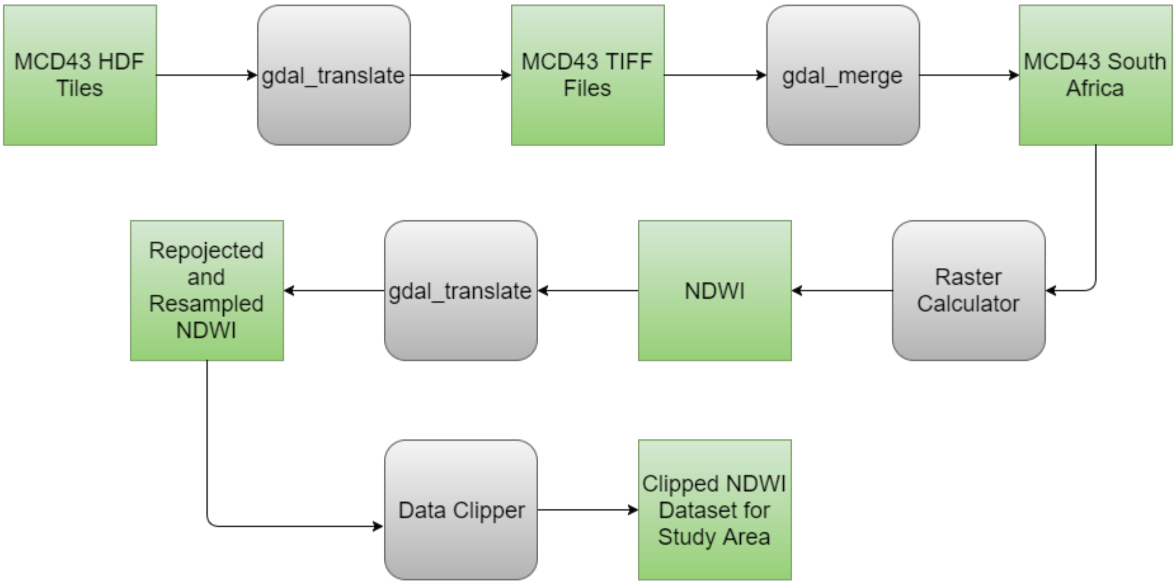

Figure 21: Process to Create NDWI Dataset.

Maximum NDWI

A maximum NDWI dataset was derived from all NDWI values from the first available MCD43A4 image to the end of the fire season for each of the study areas. The r.series function in GRASS was used to assign a maximum value to each pixel by taking all past values for a pixel into account.

The dataset was clipped to the boundaries of the two study areas. Therefore, two maximum NDWI datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 22.

Figure 22: Process to Create Maximum NDWI Dataset.

Minimum NDWI

A minimum NDWI dataset was derived from all NDWI values from the first available MCD43A4 image to the end of the fire season for each of the study areas. The r.series function in GRASS was used to assign a minimum value to each pixel by taking all past values for a pixel into account.

The dataset was clipped to the boundaries of the two study areas. Therefore, two minimum NDWI datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 23.

Figure 23: Process to Create Minimum NDWI Dataset.

4.2.1.10. Relative Humidity

The relative humidity dataset used in the research as input to the fire potential indices was created using ECMWF forecast data. ECMWF data was exported from a database hosted in the Earth Observation Science and Information Technology (EOSIT) competence area at the Council for Scientific and Industrial Research (CSIR) Meraka. The projection of the dataset is geographic, the horizontal datum is WGS84 which is the desired projection and datum for the research. Only the data for the two relevant fire seasons studied in South Africa was exported from the database. A table with the same definition was created on a local database. The data was then imported on the local database. The use of the local database made it easier to access the data while not on the network at the CSIR. The GDAL translate tool was used to export the data from the database to GeoTIFF files. The dataset datum was WGS84. The dataset was resampled to a 30 meter spatial resolution to match other fire potential index input datasets.

The dataset was clipped to the boundaries of the two study areas. Therefore, two relative humidity datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 24.

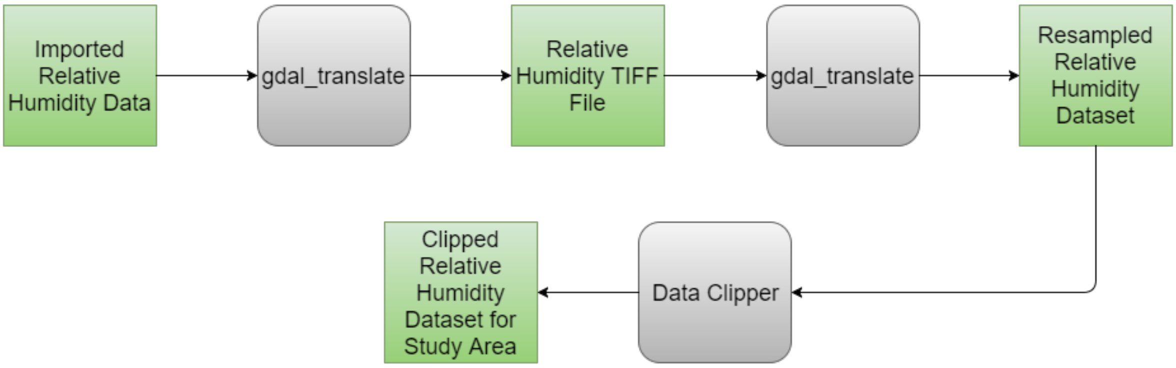

Figure 24: Process to Create Relative Humidity Dataset.

4.2.1.11. Temperature

The temperature dataset used in the research as input to the fire potential indices was created using ECMWF forecast data. ECMWF data was exported from a database hosted in the EOSIT competence area at CSIR Meraka. The projection of the dataset is geographic, the horizontal datum is WGS84 which is the desired projection and datum for the research. Only the data for the two relevant fire seasons studied in South Africa was exported from the database. A table with the same definition was created on a local database. The data was then imported on the local database. The use of the local database made it easier to access the data while not on the network at the CSIR. The GDAL translate tool was used to export the data from the database to GeoTIFF files. The dataset datum was WGS84. The dataset was resampled to a 30 meter spatial resolution to match other fire potential index input datasets.

The dataset was clipped to the boundaries of the two study areas. Therefore, two temperature datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 25.

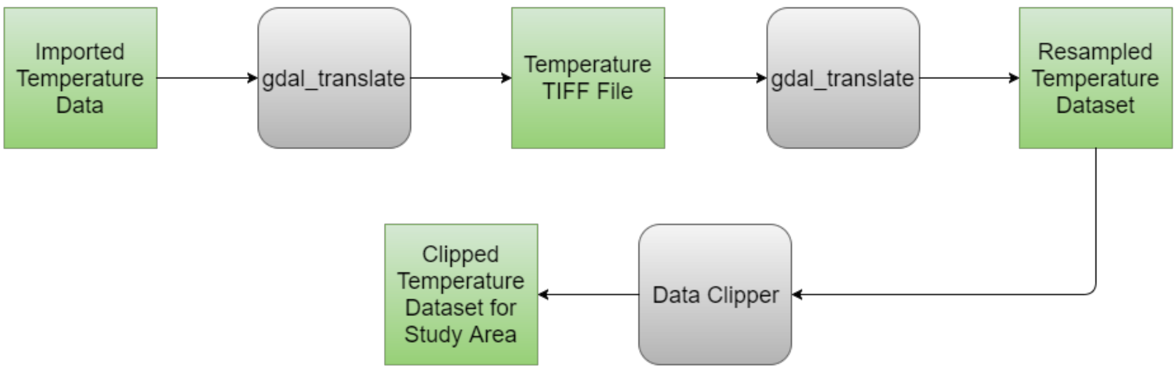

Figure 25: Process to Create Temperature Dataset.

4.2.1.12. Rainfall

The rainfall dataset used in the research as input to the fire potential indices was derived from NASA Global Precipitation Measurement data. The datasets provide rainfall amounts in millimetres. The dataset was reprojected to WGS84 to match other fire potential index input datasets. The dataset was resampled to a 30 meter spatial resolution to match the other input datasets.

The dataset was clipped to the boundaries of the two study areas. Therefore, two rainfall datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 26.

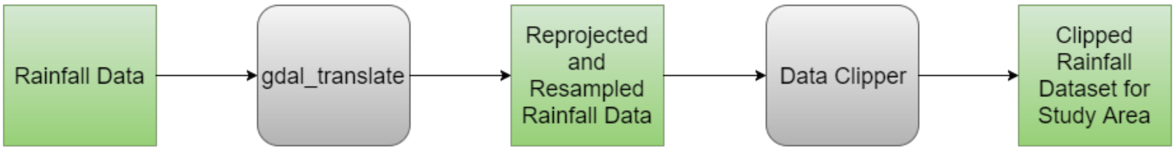

Figure 26: Process to Create Rainfall Dataset.

4.2.1.13. Cloud Cover

The cloud cover dataset used in the research as input to the fire potential indices was MODIS Cloud Fraction data. The data was downloaded from the NASA Earth Observation website. Only the data for the two relevant fire seasons studied in South Africa was downloaded. The raster calculator on QGIS was used to produce percentage cloud cover ((pixel value/255) * 100) because the dataset contained values in the range of 0 to 255. The dataset was reprojected to WGS84. The dataset was resampled to a 30 meter spatial resolution to match other fire potential index input datasets.

The dataset was clipped to the boundaries of the two study areas. Therefore, two cloud cover datasets were created based on the extent of each of the study areas. For the implementation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 27.

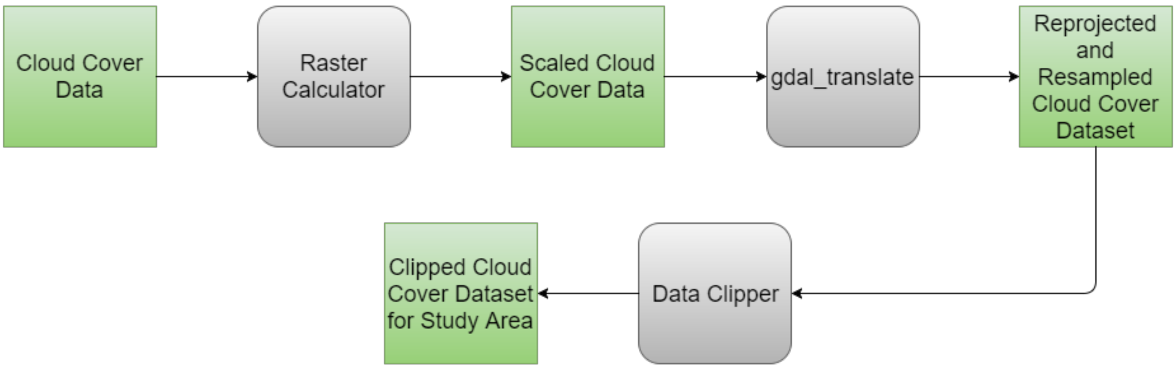

Figure 27: Process to Create Cloud Cover Dataset.

4.2.1.14. Active Fires

The active fires dataset used in the research as input to the validation of the fire potential indices was derived from Suomi National Polar-orbiting Partnership (NPP) Visible Infrared Imaging Radiometer Suite (VIIRS) data. The relevant vector data points were retrieved from an in-house database at the CSIR Meraka Institute. The data is stored in WGS84. The query used to retrieve the active fire data is provided in Figure 28. The retrieved data was then returned in a dictionary. The dictionary was used to create insert queries that would later be used to insert the data into a local database.

```
SELECT fires.gid, fires.brightness, fires.acqdate, fires.acqtime, fires.satellite, fires.confidence, fires.the_geom,
fires.obs_time_stamp, adm.province, adm.district, adm.localmunic
FROM af_v375 as fires
JOIN ba_admin as adm
ON ST_Intersects(adm.the_geom,fires.the_geom)
WHERE adm.country_code = 'ZA'
AND acqdate >= '2015-05-30'
```

Figure 28: Select Query for Active Fire Data.

A table was created on a local database for the purpose of importing the data into the table. The use of the local database made it easier to access the data while not on the network at the CSIR. The query used to create the table on the local database is provided in Figure 29.

```
CREATE TABLE public.v375_active_fires
(
gid integer NOT NULL,
brightnessi4 double precision,
brightnessi5 double precision,
acqdate date,
acqtime time without time zone,
satellite character varying(1),
confidence integer,
the_geom geometry,
obs_time_stamp timestamp without time zone,
province text,
district text,
localmunic text,
CONSTRAINT v375_active_fires_pkey_ PRIMARY KEY (gid),
CONSTRAINT enforce_dims_the_geom_ CHECK (st_ndims(the_geom) = 2),
CONSTRAINT enforce_geotype_the_geom_ CHECK (geometrytype(the_geom) = 'POINT'::text OR the_geom IS NULL),
CONSTRAINT enforce_srid_the_geom_ CHECK (st_srid(the_geom) = 4326)
)
WITH (
OIDS=FALSE
);
```

Figure 29: Statement Used to Create Table on Local Database.

A vector grid was used for the purpose of binning the active fire points to a spatial resolution of 12.5 kilometres. A vector grid was created with QGIS at a spatial resolution of 12.5 kilometres. The spatial resolution was chosen based on the fact that the coarsest dataset used in this research had a spatial resolution of 12.5 kilometres. The vector grid was imported into the database.

A pixel id was then assigned to every active fire point in the active fire table for the 12.5 kilometre grid. The data was exported on a 12.5 kilometre spatial resolution grid. The count value was calculated for every pixel and the values were stored in the grid. This was done for every day in the fire seasons.

The grid was then exported with the shp2pgsql UI that provides pgsql2shp functionality. GDAL rasterise was used to export the data to GeoTIFF files. A file was created containing the number of active fire counts per 12.5 kilometre pixel. The data projection of the file was geographic and the datum was WGS84.

The dataset was clipped to the boundaries of the two study areas. Therefore, two active fires datasets were created based on the extent of each of the study areas. For the evaluation of the models, the input datasets have to contain the same number of pixels (rows and columns). The data preparation process is illustrated in Figure 30.

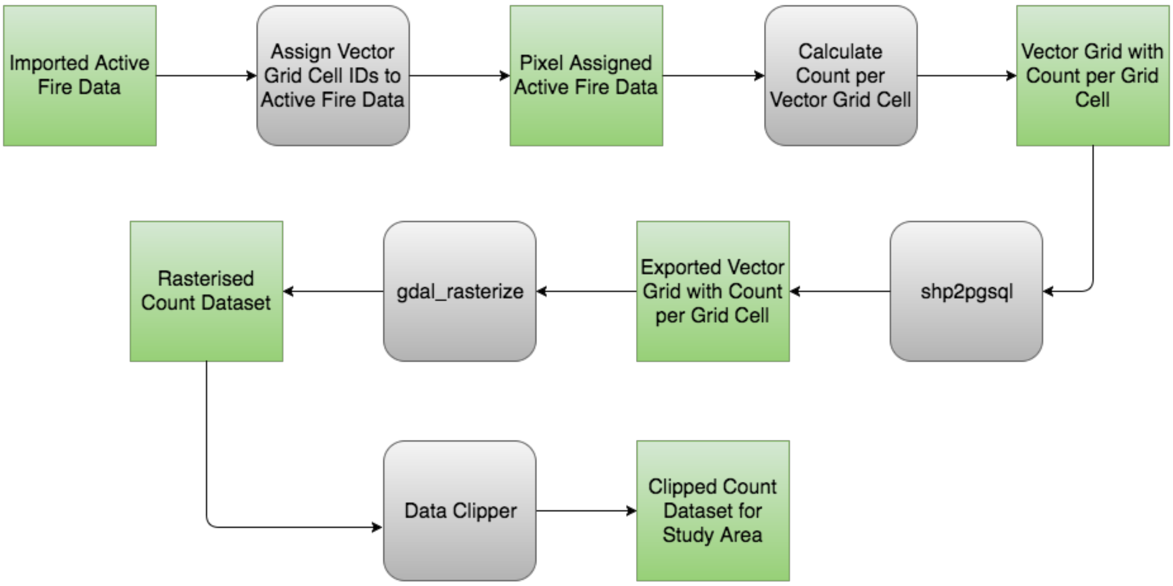

Figure 30: Process to Create Active Fire Count Datasets.

4.3. Fire Potential Index Implementation

Seven candidate fire potential indices were implemented for evaluation in the research. The implementations of each of the candidate fire potential indices are discussed below. All of the models were implemented on a raster, per pixel, basis. Most of the ratings assigned to almost all of the models (except for the Fire Potential Index (FPI)) were taken from Adab et al. (2013).

4.3.1. Hybrid Fire Index (Adab et al. 2011)

The Hybrid Fire Index was developed by Adab et al. in 2011. This fire potential index takes elevation, slope, aspect, proximity to roads, proximity to human settlements and vegetation moisture into account when determining the fire potential for an area.

4.3.1.1. Required Data

Table 12 provides details on the datasets used as input to the Hybrid Fire Index.

Parameters	Dataset Used	Description
Elevation	SRTM 30m	Data describing the height above sea level of the terrain in an area.
Slope	Derived from SRTM 30m	Data describing the rising and falling of the terrain in an area.
Aspect	Derived from SRTM 30m	Data describing the positioning of the terrain in an area in a particular direction.
Proximity to Roads	Derived from Open Street Maps Roads	Data describing the distance of an area to roads.
Proximity to Human Settlements	Derived from Worldpop South Africa Population	Data describing the distance of an area to human settlements.
Vegetation Moisture	NDWI Derived from MODIS MCD43A4	Data describing the moisture content of vegetation in an area.

Table 12: Datasets Required for Hybrid Fire Index.

4.3.1.2. Implementation

The Hybrid Fire Index was implemented in Python. The datasets mentioned in Table 12 were used in the implementation.

For a date range (including the fire season) and a study area (Mpumalanga or Western Cape) the implementation opened and read all of the necessary dataset files to create the fire potential index output file, per day. The Hybrid Fire Index was processed for every eight days, which is the temporal frequency of the vegetation moisture data used as input to the model.

The data files are opened and read into arrays. The data arrays serve as input to functions specifically written, for each dataset, to assign a potential rating to a pixel (array entry) based on its input value. The ratings assigned to the pixels, per dataset is available in Table 13.

Parameters	Classes	Rating of Hazard	Fire Sensitivity
Vegetation Moisture	> 0.36	1	Very Low
	0.26-0.36	2	Low
	0.16-0.26	3	Medium
	0-0.16	4	High
	0	5	Very High
Elevation	> 2000	1	Very Low
	1000-2000	2	Low
	500-1000	3	Medium
	200-500	4	High
	< 200	5	Very High
Slope	< 5 %	1	Very Low
	5-10 %	2	Low
	10-25 %	3	Medium
	25-35 %	4	High
	>35 %	5	Very High

Parameters	Classes	Rating of Hazard	Fire Sensitivity
Aspect	South	2	Low
	East	3	Medium
	West	4	High
	North	5	Very High
Proximity to Roads	> 400m	1	Very Low
	300-400 m	2	Low
	200-300 m	3	Medium
	100-200 m	4	High
	< 100 m	5	Very High
Proximity to Settlements	> 2000 m	1	Very Low
	1500-2000 m	2	Low
	1000-1500 m	3	Medium
	500-1000 m	4	High
	< 500 m	5	Very High

Table 13: Ratings Assigned to Datasets for Hybrid Fire Index.

The rating arrays are then provided as input to the function that calculates the fire potential index value for each pixel in the raster dataset. The final fire potential index array is then written to a GeoTIFF file. The process of creating the Hybrid Fire Index output is shown in Figure 31. The squares show the model parameters, the ovals contain the datasets used as model parameter input and the equation that the input parameters are provided to is contained in the rectangle.

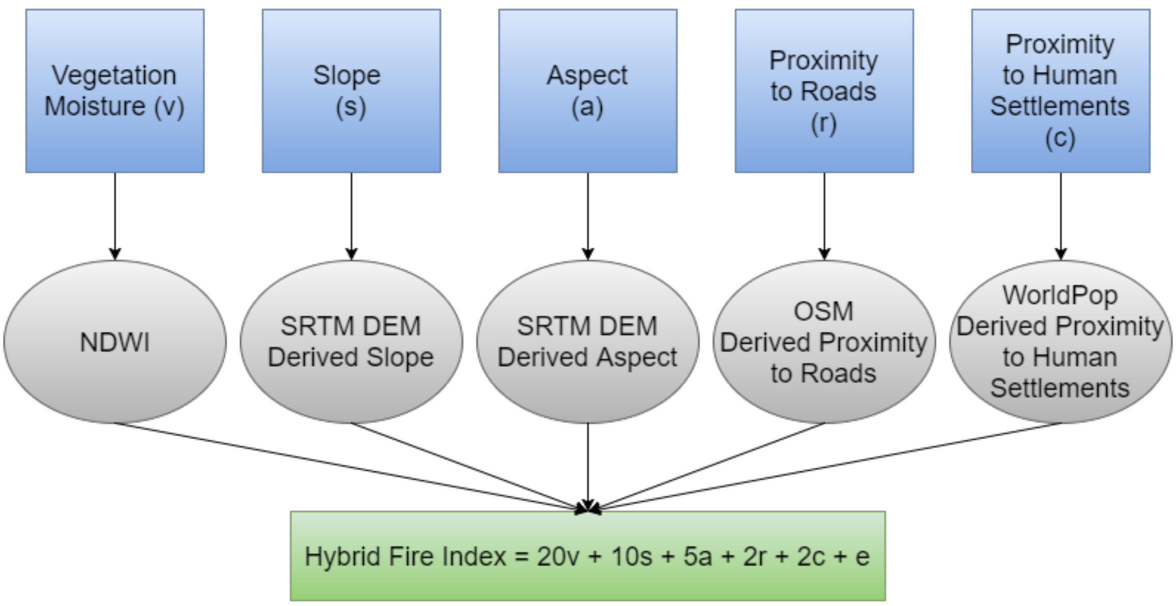

Figure 31: Process to Create Hybrid Fire Index.

4.3.2. Forest Fire Risk Index (Ertena et al. 1994)

The Forest Fire Risk Index was developed by Ertena et al. in 1994. This fire potential index takes slope, aspect, proximity to roads, proximity to human settlements and vegetation moisture into account when determining the fire potential for an area.

4.3.2.1. Required Data

Table 14 provides details on the datasets used as input to the Forest Fire Risk Index.

Parameters	Dataset Used	Description
Slope	Derived from SRTM 30m	Data describing the rising and falling of the terrain in an area.
Aspect	Derived from SRTM 30m	Data describing the positioning of the terrain in an area in a particular direction.
Proximity to Roads	Derived from Open Street Maps Roads	Data describing the distance of an area to roads.
Proximity to Human Settlements	Derived from Worldpop South Africa Population	Data describing the distance of an area to human settlements.
Vegetation Moisture	NDWI Derived from MODIS MCD43A4	Data describing the moisture content of vegetation in an area.

Table 14: Datasets Required for Forest Fire Risk Index.

4.3.2.2. Implementation

The Forest Fire Risk Index was implemented in Python. The datasets mentioned in Table 14 were used in the implementation.

The Forest Fire Risk Index is a structural fire potential index. For the purpose of making the fire potential indices dynamic and more useful in a time sensitive way and for making comparison between the candidate fire potential indices researched more suitable, the static vegetation type dataset was replaced with vegetation moisture which is a dynamic variable.

For a date range (including the fire season) and a study area (Mpumalanga or Western Cape) the implementation opened and read all of the necessary dataset files to create the fire potential index output file, per day. The Forest Fire Risk Index was processed for every eight days, which is the temporal frequency of the vegetation moisture data used as input to the model.

The data files are opened and read into arrays. The data arrays serve as input to functions specifically written, for each dataset, to assign a potential rating to a pixel (array entry) based on its input value. The ratings assigned to the pixels, per dataset is available in Table 15.

Parameters	Classes	Rating of Hazard	Fire Sensitivity
Vegetation Moisture	> 0.36	1	Very Low
	0.26-0.36	2	Low
	0.16-0.26	3	Medium
	0-0.16	4	High
	0	5	Very High
Slope	< 5 %	1	Very Low
	5-10 %	2	Low
	10-25 %	3	Medium

Parameters	Classes	Rating of Hazard	Fire Sensitivity
	25-35 %	4	High
	>35 %	5	Very High
Aspect	South	2	Low
	East	3	Medium
	West	4	High
	North	5	Very High
Proximity to Roads	> 400m	1	Very Low
	300-400 m	2	Low
	200-300 m	3	Medium
	100-200 m	4	High
	< 100 m	5	Very High
Proximity to Settlements	> 2000 m	1	Very Low
	1500-2000 m	2	Low
	1000-1500 m	3	Medium
	500-1000 m	4	High
	< 500 m	5	Very High

Table 15: Ratings Assigned to Datasets for Forest Fire Risk Index.

The rating arrays are then provided as input to the function that calculates the fire potential index value for each pixel in the raster dataset. The final fire potential index array is then written to a GeoTIFF file. The process of creating the Forest Fire Risk Index output is shown in Figure 32. The squares show the model parameters, the ovals contain the datasets used as model parameter input and the equation that the input parameters are provided to is contained in the rectangle.

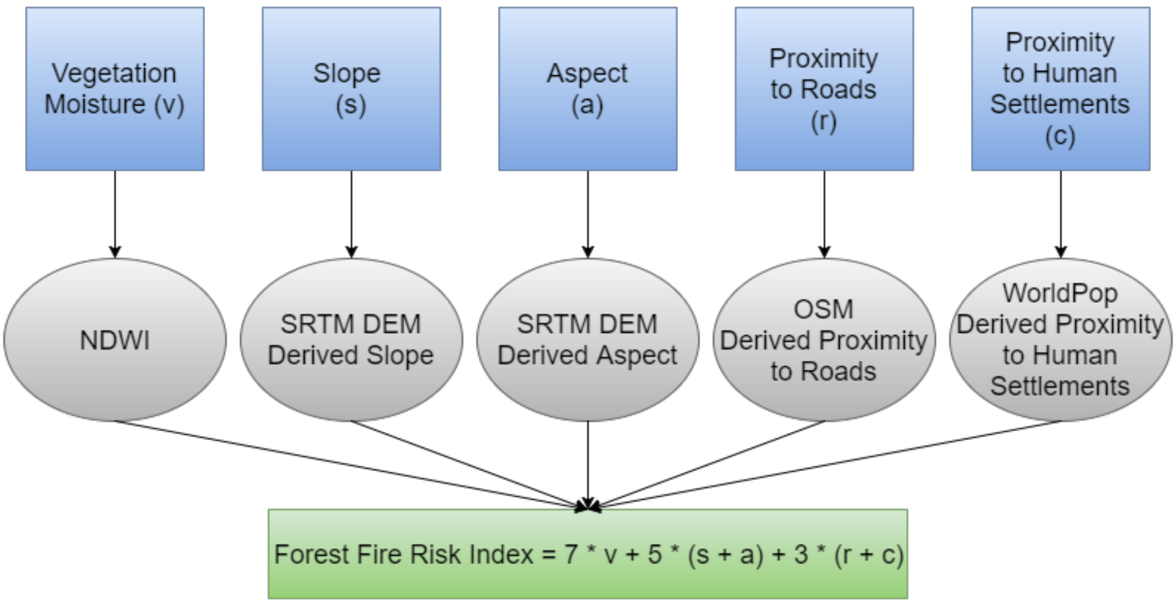

Figure 32: Process to Create Forest Fire Risk Index.

4.3.3. Fire Hazard Index (Chuvieco & Congalton 1989)

The Fire Hazard Index was developed by Chuvieco and Congalton et al. in 1989. This fire potential index takes elevation, slope, aspect, proximity to roads and vegetation moisture into account when determining the fire potential for an area.

4.3.3.1. Required Data

Table 16 provides details on the datasets used as input to the Fire Hazard Index.

Parameters	**Dataset Used**	**Description**
Elevation	SRTM 30m	Data describing the height above sea level of the terrain in an area.
Slope	Derived from SRTM 30m	Data describing the rising and falling of the terrain in an area.
Aspect	Derived from SRTM 30m	Data describing the positioning of the terrain in an area in a particular direction.
Proximity to Roads	Derived from Open Street Maps Roads	Data describing the distance of an area to roads.
Vegetation Moisture	NDWI Derived from MODIS MCD43A4	Data describing the moisture content of vegetation in an area.

Table 16: Datasets Required for Fire Hazard Index.

4.3.3.2. Implementation

The Fire Hazard Index was implemented in Python. The datasets mentioned in Table 16 were used in the implementation.

The Fire Hazard Index is a structural fire potential index. For the purpose of making the fire potential indices dynamic and more useful in a time sensitive way and for making comparison between the candidate fire potential indices researched more suitable, the static vegetation type dataset was replaced with vegetation moisture which is a dynamic variable.

For a date range (including the fire season) and a study area (Mpumalanga or Western Cape) the implementation opened and read all of the necessary dataset files to create the fire potential index output file, per day. The Fire Hazard Index was processed for every eight days, which is the temporal frequency of the vegetation moisture data used as input to the model.

The data files are opened and read into arrays. The data arrays serve as input to functions specifically written, for each dataset, to assign a potential rating to a pixel (array entry) based on its input value. The ratings assigned to the pixels, per dataset is available in Table 17.

Parameters	**Classes**	**Rating of Hazard**	**Fire Sensitivity**
Vegetation Moisture	> 0.36	1	Very Low
	0.26-0.36	2	Low
	0.16-0.26	3	Medium
	0-0.16	4	High
	0	5	Very High
Elevation	> 2000	1	Very Low
	1000-2000	2	Low

Parameters	Classes	Rating of Hazard	Fire Sensitivity
	500-1000	3	Medium
	200-500	4	High
	< 200	5	Very High
Slope	< 5 %	1	Very Low
	5-10 %	2	Low
	10-25 %	3	Medium
	25-35 %	4	High
	>35 %	5	Very High
Aspect	South	2	Low
	East	3	Medium
	West	4	High
	North	5	Very High
Proximity to Roads	> 400m	1	Very Low
	300-400 m	2	Low
	200-300 m	3	Medium
	100-200 m	4	High
	< 100 m	5	Very High

Table 17: Ratings Assigned to Datasets for Fire Hazard Index.

The rating arrays are then provided as input to the function that calculates the fire potential index value for each pixel in the raster dataset. The final fire potential index array is then written to a GeoTIFF file. The process of creating the Fire Hazard Index output is shown in Figure 33. The squares show the model parameters, the ovals contain the datasets used as model parameter input and the equation that the input parameters are provided to is contained in the rectangle.

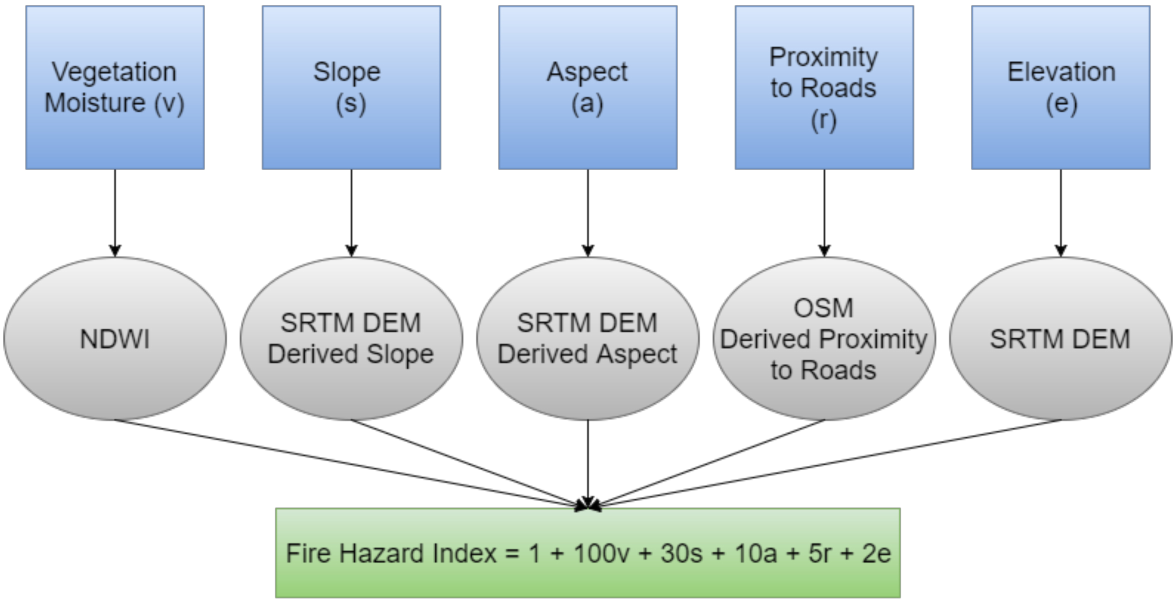

Figure 33: Process to Create Fire Hazard Index.

4.3.4. Structural Fire Index (Cipriani et al. 2011)

The Structural Fire Index was developed by Cipriani et al. in 2011. This fire potential index takes elevation, slope, aspect, proximity to roads and buildings and vegetation moisture into account when determining the fire potential for an area.

4.3.4.1. Required Data

Table 18 provides details on the datasets used as input to the Structural Fire Index.

Parameters	Dataset Used	Description
Elevation	SRTM 30m	Data describing the height above sea level of the terrain in an area.
Slope	Derived from SRTM 30m	Data describing the rising and falling of the terrain in an area.
Aspect	Derived from SRTM 30m	Data describing the positioning of the terrain in an area in a particular direction.
Proximity to Roads and Buildings	Derived from Open Street Maps Roads	Data describing the distance of an area to roads and buildings.
Vegetation Moisture	NDWI Derived from MODIS MCD43A4	Data describing the moisture content of vegetation in an area.

Table 18: Datasets Required for Structural Fire Index.

4.3.4.2. Implementation

The Structural Fire Index was implemented in Python. The datasets mentioned in Table 18 were used in the implementation.

The Structural Fire Index is a structural fire potential index. For the purpose of making the fire potential indices dynamic and more useful in a time sensitive way and for making comparison between the candidate fire potential indices researched more suitable, the static vegetation type dataset was replaced with vegetation moisture which is a dynamic variable.

For a date range (including the fire season) and a study area (Mpumalanga or Western Cape) the implementation opened and read all of the necessary dataset files to create the fire potential index output file, per day. The Structural Fire Index was processed for every eight days, which is the temporal frequency of the vegetation moisture data used as input to the model.

The data files are opened and read into arrays. The data arrays serve as input to functions specifically written, for each dataset, to assign a potential rating to a pixel (array entry) based on its input value. The ratings assigned to the pixels, per dataset is available in Table 19.

Parameters	**Classes**	**Rating of Hazard**	**Fire Sensitivity**
Vegetation Moisture	> 0.36	1	Very Low
	0.26-0.36	2	Low
	0.16-0.26	3	Medium
	0-0.16	4	High
	0	5	Very High
Elevation	> 2000	1	Very Low
	1000-2000	2	Low
	500-1000	3	Medium
	200-500	4	High
	< 200	5	Very High
Slope	< 5 %	1	Very Low
	5-10 %	2	Low
	10-25 %	3	Medium
	25-35 %	4	High
	>35 %	5	Very High
Aspect	South	2	Low
	East	3	Medium
	West	4	High
	North	5	Very High
Proximity to Roads and Buildings	> 400m	1	Very Low
	300-400 m	2	Low
	200-300 m	3	Medium
	100-200 m	4	High
	< 100 m	5	Very High

Table 19: Ratings Assigned to Datasets for Structural Fire Index.

The rating arrays are then provided as input to the function that calculates the fire potential index value for each pixel in the raster dataset. The final fire potential index array is then written to a GeoTIFF file. The process of creating the Structural Fire Index output is shown in Figure 34. The squares show the model parameters, the ovals contain the datasets used as model parameter input and the equation that the input parameters are provided to is contained in the rectangle.

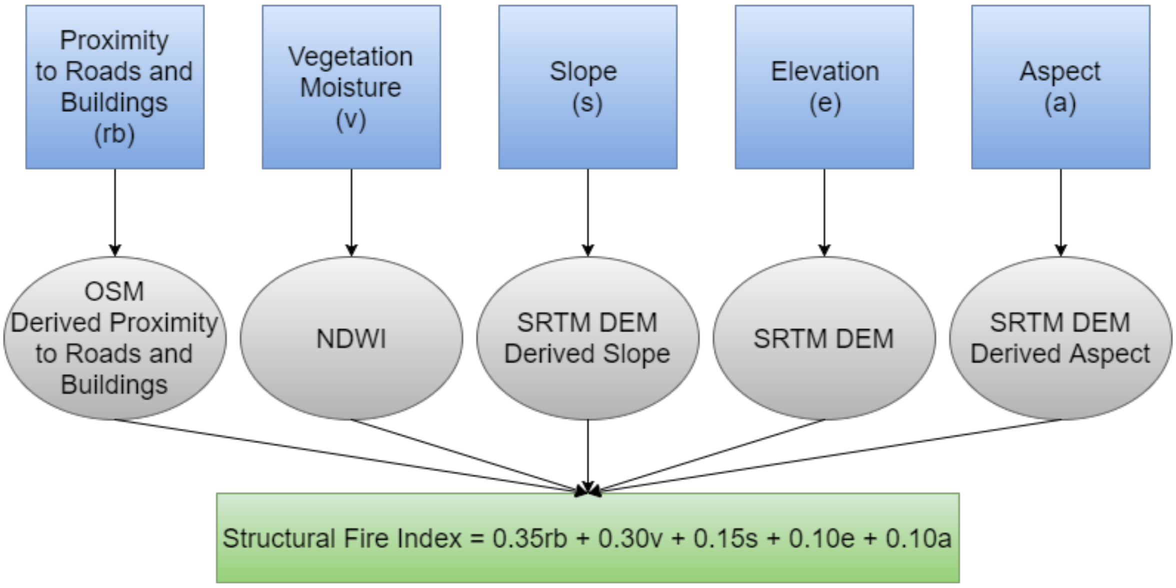

Figure 34: Process to Create Structural Fire Index.

4.3.5. Fire Risk Index (Jaiswal et al. 2002)

The Fire Risk Index was developed by Jaiswal et al. in 2002. This fire potential index takes slope, proximity to roads, proximity to human settlements and vegetation moisture into account when determining the fire potential for an area.

4.3.5.1. Required Data

Table 20 provides details on the datasets used as input to the Fire Risk Index.

Parameters	Dataset Used	Description
Slope	Derived from SRTM 30m	Data describing the rising and falling of the terrain in an area.
Proximity to Roads	Derived from Open Street Maps Roads	Data describing the distance of an area to roads.
Proximity to Human Settlements	Derived from Worldpop South Africa Population	Data describing the distance of an area to human settlements.
Vegetation Moisture	NDWI Derived from MODIS MCD43A4	Data describing the moisture content of vegetation in an area.

Table 20: Datasets Required for Fire Risk Index.

4.3.5.2. Implementation

The Fire Risk Index was implemented in Python. The datasets mentioned in Table 20 were used in the implementation.

The Fire Risk Index is a structural fire potential index. For the purpose of making the fire potential indices dynamic and more useful in a time sensitive way and for making comparison between the candidate fire potential indices researched more suitable, the static vegetation type dataset was replaced with vegetation moisture which is a dynamic variable.

For a date range (including the fire season) and a study area (Mpumalanga or Western Cape) the implementation opened and read all of the necessary dataset files to create the fire potential index output file, per day. The Fire Risk Index was processed for every eight days, which is the temporal frequency of the vegetation moisture data used as input to the model.

The data files are opened and read into arrays. The data arrays serve as input to functions specifically written, for each dataset, to assign a potential rating to a pixel (array entry) based on its input value. The ratings assigned to the pixels, per dataset is available in Table 21.

Parameters	**Classes**	**Rating of Hazard**	**Fire Sensitivity**
Vegetation Moisture	> 0.36	1	Very Low
	0.26-0.36	2	Low
	0.16-0.26	3	Medium
	0-0.16	4	High
	0	5	Very High
Slope	< 5 %	1	Very Low
	5-10 %	2	Low
	10-25 %	3	Medium
	25-35 %	4	High
	>35 %	5	Very High
Proximity to Roads	> 400m	1	Very Low
	300-400 m	2	Low
	200-300 m	3	Medium
	100-200 m	4	High
	< 100 m	5	Very High
Proximity to Settlements	> 2000 m	1	Very Low
	1500-2000 m	2	Low
	1000-1500 m	3	Medium
	500-1000 m	4	High
	< 500 m	5	Very High

Table 21: Ratings Assigned to Datasets for Fire Risk Index.

The rating arrays are then provided as input to the function that calculates the fire potential index value for each pixel in the raster dataset. The final fire potential index array is then written to a GeoTIFF file. The process of creating the Fire Risk Index output is shown in Figure 35. The squares show the model parameters, the ovals contain the datasets used as model parameter input and the equation that the input parameters are provided to is contained in the rectangle.

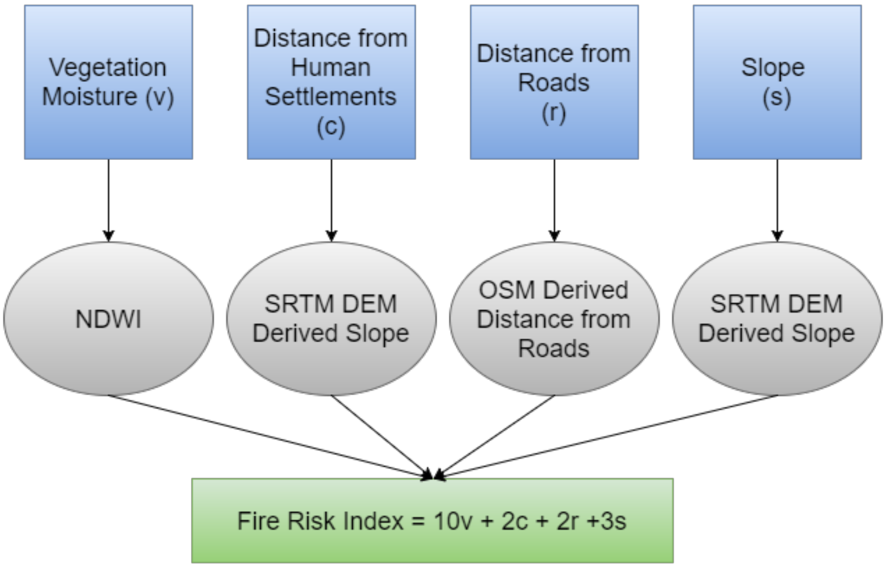

Figure 35: Process to Create Fire Risk Index.

4.3.6. Fire Risk Index (Saglam et al. 2008)

The Fire Risk Index was developed by Saglam et al. in 2008. This fire potential index takes slope, aspect, proximity to agricultural fields, proximity to human settlements and vegetation moisture into account when determining the fire potential for an area.

4.3.6.1. Required Data

Table 22 provides details on the datasets used as input to the Fire Risk Index.

Parameters	**Dataset Used**	**Description**
Slope	Derived from SRTM 30m	Data describing the rising and falling of the terrain in an area.
Aspect	Derived from SRTM 30m	Data describing the positioning of the terrain in an area in a particular direction.
Proximity to Agricultural Fields	Derived from DEA 2014 South African National Land cover	Data describing the distance from agricultural fields.
Proximity to Human Settlements	Derived from Worldpop South Africa Population	Data describing the distance of an area to human settlements.
Vegetation Moisture	NDWI Derived from MODIS MCD43A4	Data describing the moisture content of vegetation in an area.

Table 22: Datasets Required for Fire Risk Index.

4.3.6.2. Implementation

The Fire Risk Index was implemented in Python. The datasets mentioned in Table 22 were used in the implementation.

The Fire Risk Index is a structural fire potential index. For the purpose of making the fire potential indices dynamic and more useful in a time sensitive way and for making comparison between the candidate fire potential indices researched more suitable, the static vegetation type dataset was replaced with vegetation moisture which is a dynamic variable.

For a date range (including the fire season) and a study area (Mpumalanga or Western Cape) the implementation opened and read all of the necessary dataset files to create the fire potential index output file, per day. The Fire Risk Index was processed for every eight days, which is the temporal frequency of the vegetation moisture data used as input to the model.

The data files are opened and read into arrays. The data arrays serve as input to functions specifically written, for each dataset, to assign a potential rating to a pixel (array entry) based on its input value. The ratings assigned to the pixels, per dataset is available in Table 23.

Parameters	**Classes**	**Rating of Hazard**	**Fire Sensitivity**
Vegetation Moisture	> 0.36	1	Very Low
	0.26-0.36	2	Low
	0.16-0.26	3	Medium
	0-0.16	4	High
	0	5	Very High
Slope	< 5 %	1	Very Low
	5-10 %	2	Low
	10-25 %	3	Medium
	25-35 %	4	High
	>35 %	5	Very High
Aspect	South	2	Low
	East	3	Medium
	West	4	High
	North	5	Very High
Proximity to Agricultural Fields	> 400m	1	Very Low
	300-400 m	2	Low
	200-300 m	3	Medium
	100-200 m	4	High
	< 100 m	5	Very High
Proximity to Settlements	> 2000 m	1	Very Low
	1500-2000 m	2	Low
	1000-1500 m	3	Medium
	500-1000 m	4	High
	< 500 m	5	Very High

Table 23: Ratings Assigned to Datasets for Fire Risk Index.

The rating arrays are then provided as input to the function that calculates the fire potential index value for each pixel in the raster dataset. The final fire potential index array is then written to a GeoTIFF file. The process of creating the Fire Risk Index output is shown in Figure 36. The squares show the model parameters, the ovals contain the datasets used as model parameter input and the equation that the input parameters are provided to is contained in the rectangle.

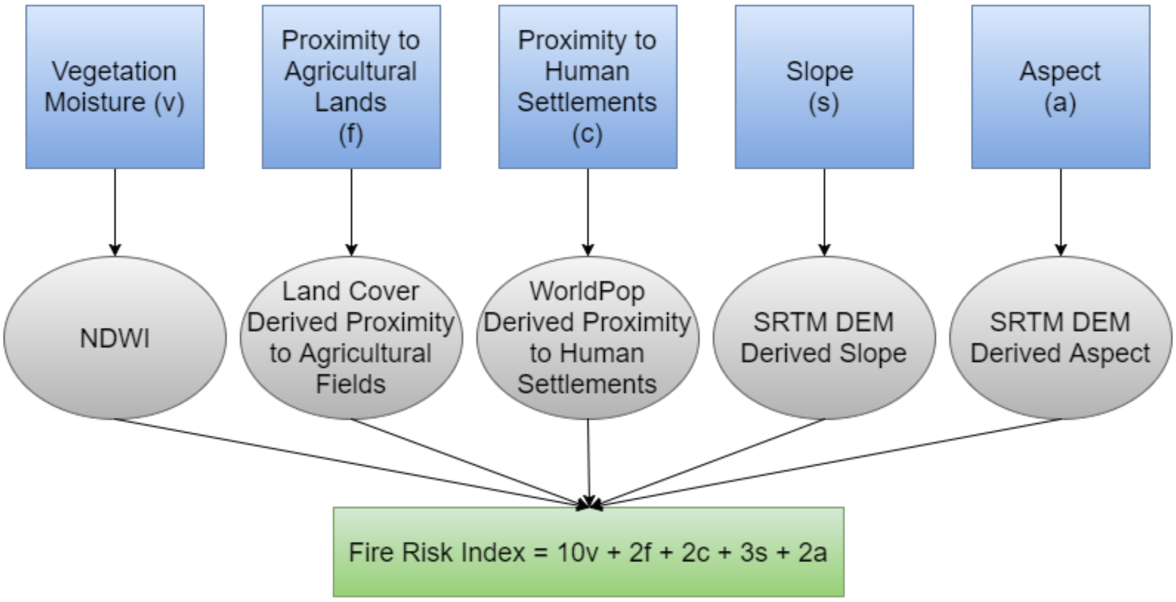

Figure 36: Process to Create Fire Risk Index.

4.3.7. Fire Potential Index (Burgan et al. in 1998)

The Fire Potential Index was developed by Burgan et al. in 1998. The Fire Potential Index takes vegetation moisture, land cover, extinction moisture, temperature, relative humidity, rainfall and cloud cover into account when determining the fire potential for an area.

4.3.7.1. Required Data

Table 24 provides details on the datasets used as input to the Fire Potential Index.

Parameters	**Dataset Used**	**Description**
Vegetation Moisture	NDWI Derived from MODIS MCD43A4	Data describing the moisture content of vegetation in an area.
Land Cover	DEA 2014 South African National Land cover	Data describing the land cover type in an area. In this context it provides information on vegetation types and other land cover types that should be excluded from the models.
Extinction Moisture	Derived from Land Cover	Data describing the extinction moisture of vegetation in an area.
Temperature	ECMWF Forecast Model	Data describing the air temperature in an area.
Relative Humidity	ECMWF Forecast Model	Data describing the relative humidity in an area.

Parameters	Dataset Used	Description
Cloud Cover	MODIS Cloud Fraction (MODAL2)	Data describing the cloud cover in an area.
Rainfall	NASA GPM	Data describing the rainfall in an area.

Table 24: Datasets Required for Fire Potential Index.

4.3.7.2. Implementation

The Fire Potential Index was implemented in Python. The datasets mentioned in Table 24 were used in the implementation.

For a date range (including the fire season) and a study area (Mpumalanga or Western Cape) the implementation opened and read all of the necessary dataset files to create the Fire Potential Index output file, per day. The Fire Potential Index was processed for every day, which is the temporal frequency of the rainfall, temperature, relative humidity and cloud cover data used as input to the model.

The data files are opened and read into arrays. The data arrays serve as input to functions written to calculate values per pixel based on a number of equations to serve as input to the final Fire Potential Index equation.

The temperature data provides temperatures in Kelvin and these temperatures are converted to Fahrenheit. The rainfall data provides rainfall in centimetres and these rainfall measurements are converted to inches.

The maximum live ratio is calculated for every pixel based on the historical maximum NDWI value obtained for the pixel.

The relative greenness is calculated for every pixel based on the maximum and minimum historical NDWI values as well as the current NDWI value for the process date of the model. The relative greenness calculation is done to determine how green the pixel is in relation to the historical minimum and maximum values of the pixel.

The ten-hour fuel moisture is calculated based on temperature, relative humidity, cloud cover, rainfall and extinction moisture of the vegetation fuel. Equilibrium moisture content is calculated per pixel based on the relative humidity, temperature and cloud cover input datasets. The equilibrium moisture content is used to calculate the ten-hour fuel moisture per pixel. The ten-hour fuel moisture is used along with the rainfall and extinction moisture to calculate a final ten-hour fuel moisture value. The ten-hour fuel moisture values are then smoothed.

Finally, the Fire Potential Index value for every pixel in the raster is calculated by taking all of the output from previously executed functions as input and calculating a value based on the final Fire Potential Index equation. The process of creating the Fire Potential Index output is shown in Figure 37. The squares show the model parameters and input datasets, the ovals contain intermediate steps in the model process and the final model equation is contained in the rectangle.

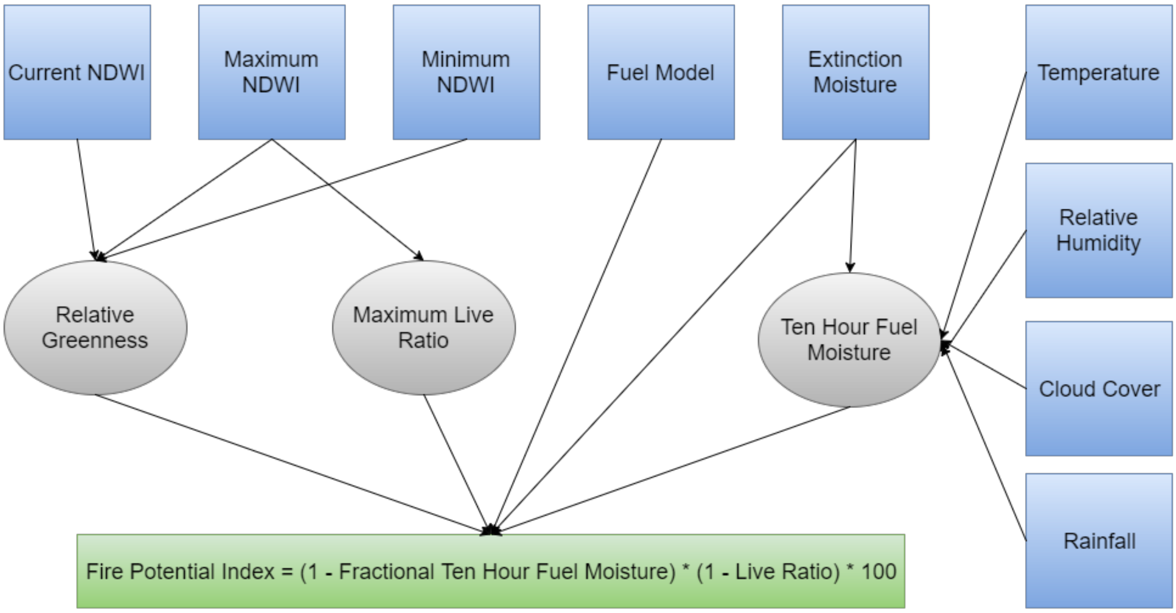

Figure 37: Process to Create Fire Potential Index.

4.4. Chapter Summary

This chapter discussed the implementation of the candidate fire potential indices chosen for the research. Seven fire potential indices were implemented. Each index uses different datasets as input to determine the fire potential in an area. The datasets used and the implementation of the indices in Python were discussed. The following chapter provides examples of the candidate fire potential indices, and the results of the evaluation of the candidate fire potential indices using a number of metrics that were discussed in chapter three.

5. Chapter Five: Results and Discussion

5.1. Chapter Overview

The previous chapter provided information on the data preparation and implementation of the candidate fire potential indices. This chapter provides examples of the executed candidate fire potential indices. The results of the candidate fire potential index evaluation process are also presented. The results of the metrics used are discussed and the fire potential indices are ranked based on performance in the evaluation process.

5.2. Results

5.2.1. Factors which Influence Fire Potential

A literature review was conducted to determine which factors influence the potential ignition of a wildfire if a suitable ignition source is available. From the literature review a number of influencing factors were identified. Some of these factors include proximity to human settlements, proximity to roads, slope, aspect, elevation and vegetation moisture.

Based on these factors a search was conducted to find fire potential indices that could provide an estimate of fire potential based on some of the influencing factors. A number of candidate fire potential indices were then selected and implemented as described in chapter three and chapter four.

The following candidate fire potential indices were implemented and included in the evaluation process. As mentioned in chapter three, along with the candidate fire potential indices, a number of fire danger indices used operationally to predict fire danger by the EOSIT competence area at the Meraka Institute CSIR were also included in the evaluation. More details on the fire danger index data is provided in section 3.6.3. of chapter three. Table 25 contains an alphabetical list of the implemented candidate fire potential indices identified through literature review and the fire danger indices used in the evaluation process.

Fire Potential Index	**Literature Source**	**Name in Evaluation Process**	**Index Source**
Canadian Fire Weather Index	Steenkamp et al. (2013)	FWI	Operational Fire Danger Index
Drought Code	Dimitrakopoulos et al. (2011)	DC	Operational Fire Danger Index
Duff Moisture Code	Dimitrakopoulos et al. (2011)	DMC	Operational Fire Danger Index

Fire Potential Index	Literature Source	Name in Evaluation Process	Index Source
Fine Fuel Moisture Code	Dimitrakopoulos et al. (2011)	FFMC	Operational Fire Danger Index
Fire Hazard Index	Chuvieco & Congalton (1989)	FHI	Candidate Fire Potential Index
Fire Potential Index	Burgan et al. (1998)	FPI	Candidate Fire Potential Index
Fire Risk Index	Jaiswal et al. (2002)	FRI (Jaiswal)	Candidate Fire Potential Index
Fire Risk Index	Saglam et al. (2008)	FRI (Saglam)	Candidate Fire Potential Index
Forest Fire Risk Index	Ertena et al. (1994)	FFR	Candidate Fire Potential Index
Hybrid Fire Index	Adab et al. (2011)	HFI	Candidate Fire Potential Index
Lowveld Fire Danger Index	Steenkamp et al. (2013)	LFDI	Operational Fire Danger Index
Structural Fire Index	Cipriani et al. (2011)	SFI	Candidate Fire Potential Index

Table 25: Candidate Fire Potential Indices and Fire Danger Indices Used in Evaluation.

5.2.2. Visual Results of Candidate Fire Potential Indices

This section provides visual examples of the implemented candidate fire potential indices on a single day for each of the two study areas – Mpumalanga and Western Cape. The examples are provided to give a visual impression of the results obtained for the candidate fire potential indices. The candidate fire potential indices are presented for a single day in each province. For Mpumalanga the fire potential indices represent the fire potential on 9 June 2015. This date was chosen because a fire ignited in the Kruger National Park in Mpumalanga and therefore fire potential should theoretically be high. For the Western Cape the fire potential indices represent the fire potential for 9 March 2015. This date was chosen because a fire ignited in the Jonkershoek area near Stellenbosch in the Western Cape and therefore, theoretically the fire potential should be high around that area.

'Zoomed' maps of the areas exposed to fire are presented below for each fire potential index for each one of the two provinces. This is provided to get a more detailed look into the fire potential index results in an area that was exposed to fire. The values of all of the candidate fire potential indices presented in the figures below range between zero and a hundred. A value of zero presents low fire potential and a value of a hundred presents high fire potential. The results shown in the maps below, with the province borders included on the map, provide the data for the entire province and is displayed at the same scale. This is done to best illustrate the results. More features stand out on the maps by including the entire area and it gives an idea of how the fire potential changes throughout a large area. The candidate fire potential indices perform differently and produce different results. Some of the indices take areas that are not part of South Africa into account and masked the areas out. Other indices take everything into account and assign fire potential values to areas that are not part of the terrestrial part of the provinces.

Hybrid Fire Index

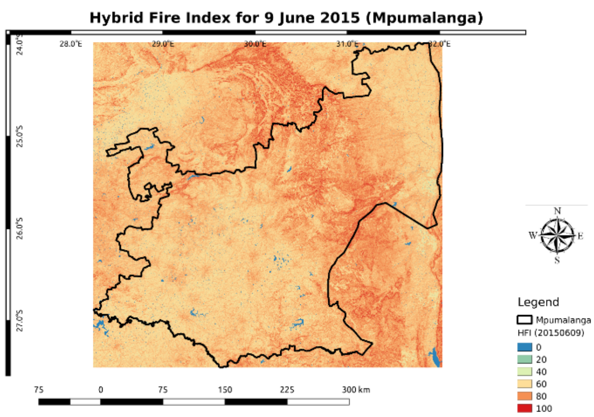

Figure 38: Hybrid Fire Index for Mpumalanga on 9 June 2015.

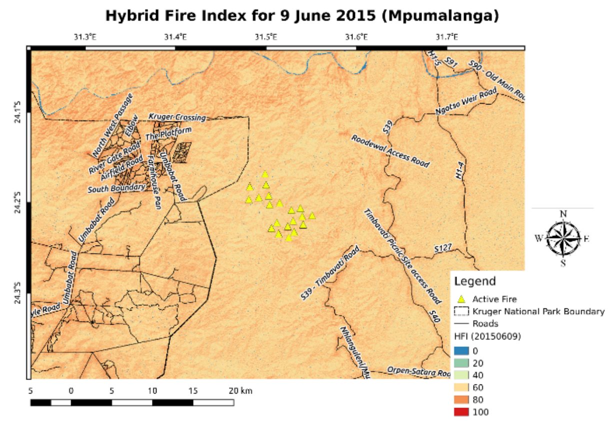

Figure 40: Hybrid Fire Index for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

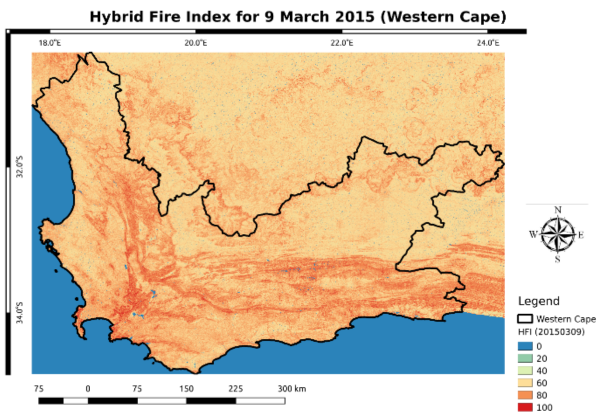

Figure 39: Hybrid Fire Index for Western Cape on 9 March 2015.

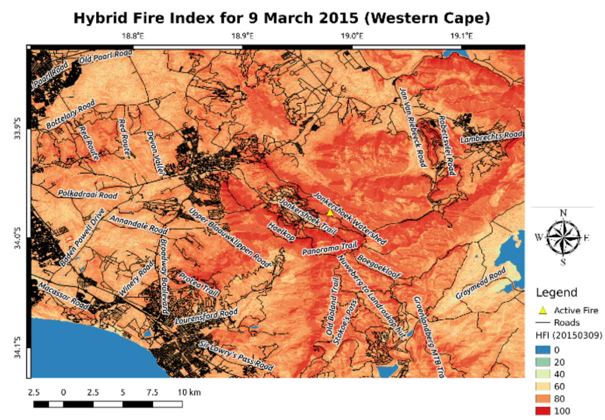

Figure 41: Hybrid Fire Index for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 38 provides the Hybrid Fire Index, as described in section 4.3.1 of chapter four, for Mpumalanga on 9 June 2015. Figure 39 provides the Hybrid Fire Index for the Western Cape on 9 March 2015. The areas where the slope changes have higher index values. This is due to the fact that slope has a high weight in the index calculation. Similar results are seen in both study areas. The areas that have slope changes can be identified by the darker colours and contour-like shapes.

Figure 40 shows the Hybrid Fire Index for a small area in the Kruger National Park in Mpumalanga. Figure 41 shows the Jonkershoek area near Stellenbosch in the Western Cape. The darker areas in Figure 41 shows higher variation in slope than the area displayed in Figure 40. Slope variation can be identified in Figure 40 and Figure 41 by 3-dimensional effect caused by the Hybrid Fire Index values. Figure 40 does not show high fire potential for the area exposed to fire on 9 June 2015, however Figure 41 shows high fire potential around the areas exposed to fire near the Panorama Trail.

Forest Fire Risk Index

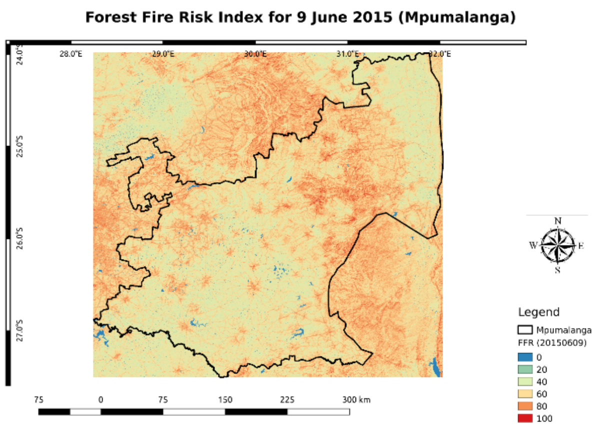

Figure 42: Forest Fire Risk Index for Mpumalanga on 9 June 2015.

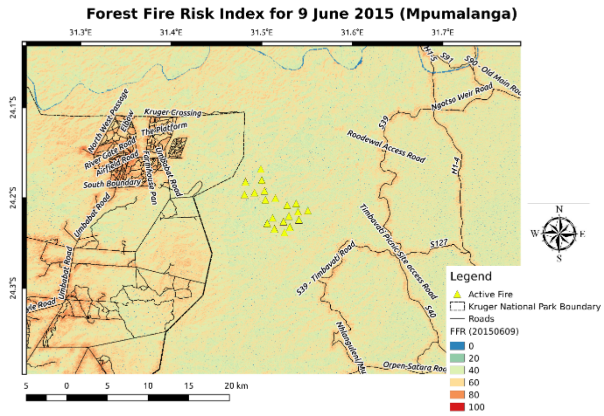

Figure 44: Forest Fire Risk Index for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 March 2015.

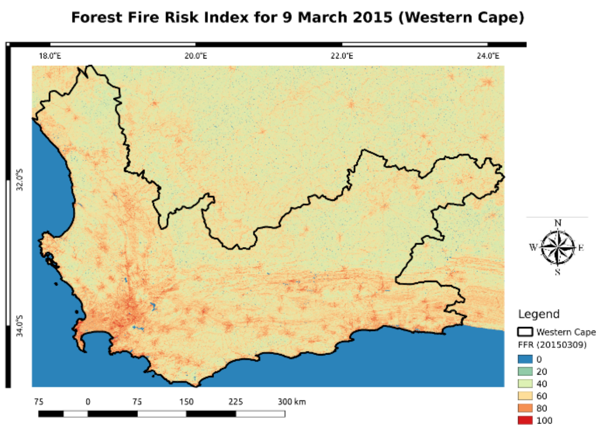

Figure 43: Forest Fire Risk Index for Western Cape on 9 March 2015.

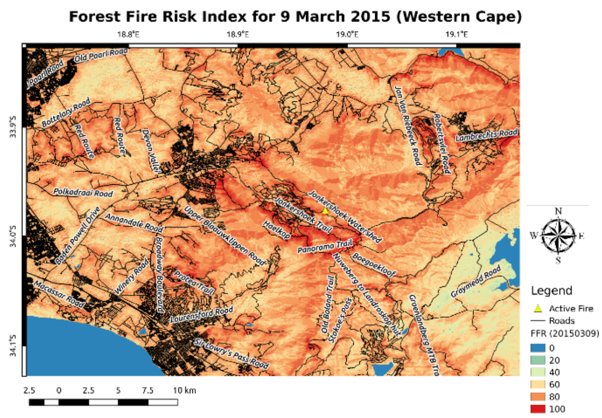

Figure 45: Forest Fire Risk Index for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 42 provides the Forest Fire Risk Index, as described in section 4.3.2 of chapter four, for Mpumalanga on 9 June 2015. Figure 43 provides the Forest Fire Risk Index for the Western Cape on 9 March 2015. The locations of the roads are visible in the values and appear to be much higher than the non-road neighbouring pixels. Roads can be identified by the dark line feature effect caused by the Forest Fire Risk Index values. This is due to the fact that a higher potential value is assigned to pixels close to roads. Areas where the slope changes also appear to have higher values. This is because the index assigns a high weight to slope changes. Slope variation can be identified by the thicker, dark contour-like features visible on the map. Similar results are seen in both study areas.

Figure 44 shows the Forest Fire Risk Index for a small area in the Kruger National Park in Mpumalanga. Figure 45 shows the Jonkershoek area near Stellenbosch in the Western Cape. The darker areas in Figure 45 shows higher variation in slope than the area displayed in Figure 44. Slope variation can be identified in Figure 44 and Figure 45 by 3-dimensional effect caused by the Hybrid Fire Index values. Figure 44 does not show high fire potential for the area exposed to fire on 9 June 2015, however Figure 45 shows high fire potential for parts of the area exposed to fire near the Panorama Trail on 9 March 2015.

Fire Hazard Index

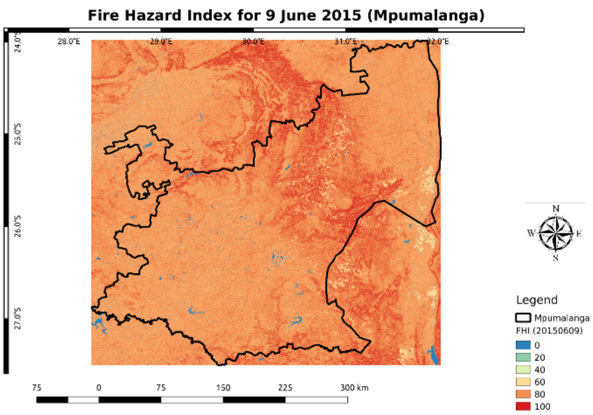

Figure 46: Fire Hazard Index for Mpumalanga on 9 June 2015.

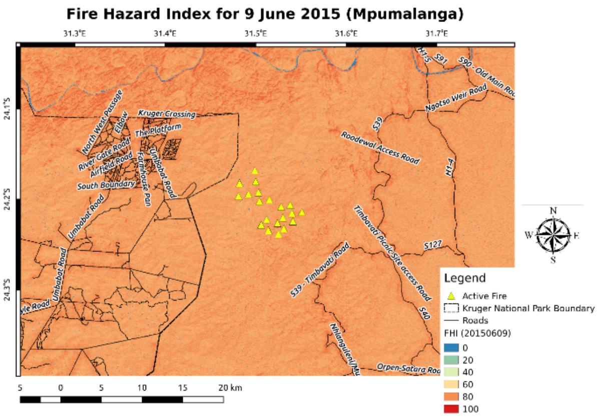

Figure 48: Fire Hazard Index for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

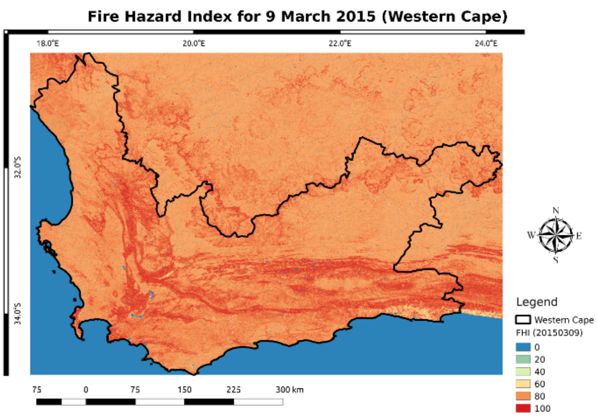

Figure 47: Fire Hazard Index for Western Cape on 9 March 2015.

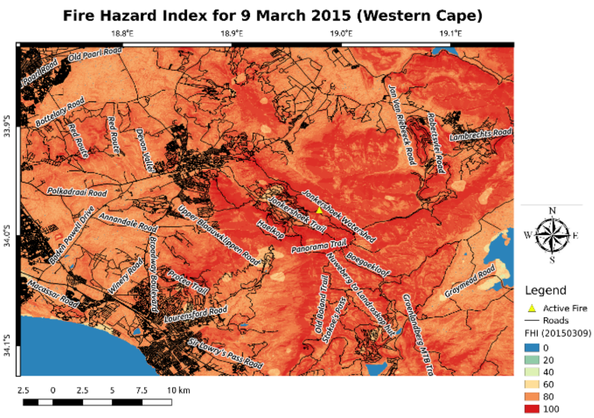

Figure 49: Fire Hazard Index for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 46 provides the Fire Hazard Risk Index, as described in section 4.3.3 of chapter four, for Mpumalanga on 9 June 2015. Figure 47 provides the Fire Hazard Risk Index for the Western Cape on 9 March 2015. The areas where the slope changes have higher values. This is due to the fact that slope has a high weight in the index calculation. Similar results are seen in both study areas.

Figure 48 shows the Fire Hazard Index for a small area in the Kruger National Park in Mpumalanga. Figure 49 shows the Jonkershoek area near Stellenbosch in the Western Cape. Figure 49 shows high fire potential for the area affected by the fire, however Figure 48 does not show very high fire potential for the area affected by the fire. The variation in slope can be identified in Figure 48 and Figure 49 by the 3-dimensional effect caused by the Fire Hazard Index values. Some areas appear darker than other areas and these areas are present where a steep slope is present.

Structural Fire Index

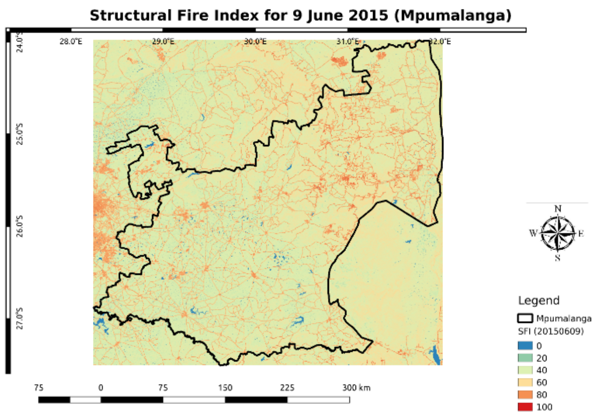

Figure 50: Structural Fire Index for Mpumalanga on 9 June 2015.

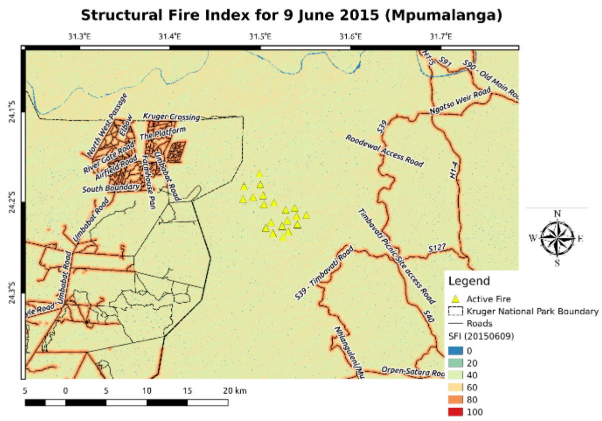

Figure 52: Structural Fire Index for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

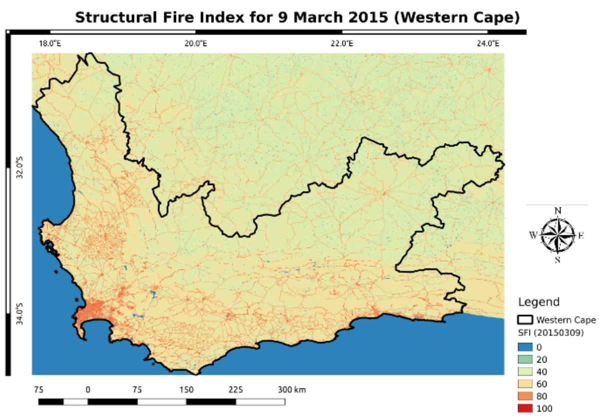

Figure 51: Structural Fire Index for Western Cape on 9 March 2015.

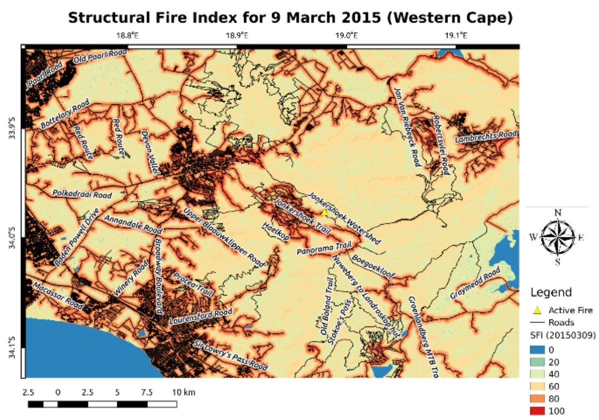

Figure 53: Structural Fire Index for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 50 provides the Structural Fire Index, as described in section 4.3.4 of chapter four, for Mpumalanga on 9 June 2015. Figure 51 provides the Structural Fire Index for the Western Cape on 9 March 2015. The values of the index range between zero and a hundred. The locations of the roads are visible in the values and appear to be much higher than the non-road neighbouring pixels. The roads can be identified by the road like line feature visible on the maps. This is due to the fact that the index assigns higher fire potential values close to roads and proximity to roads has a high weight in the index. Similar results are seen in both study areas.

Figure 52 shows the Structural Fire Index for a small area in the Kruger National Park in Mpumalanga. Figure 53 shows the Jonkershoek area near Stellenbosch in the Western Cape. The areas near roads can be identified in Figure 53 where a 'buffer' effect is created by the Structural Fire Index values around the road features on the map.

Fire Risk Index (Jaiswal)

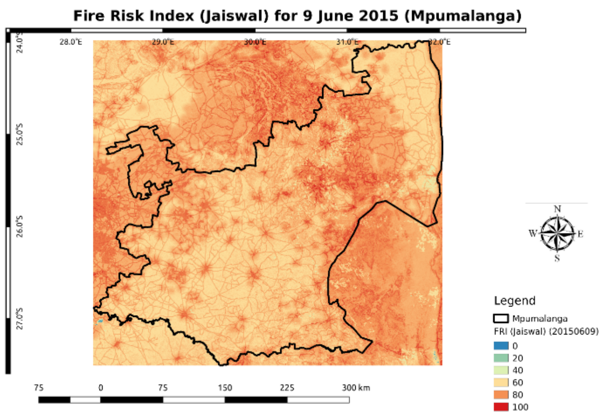

Figure 54: Fire Risk Index (by Jaiswal et al.) for Mpumalanga on 9 June 2015.

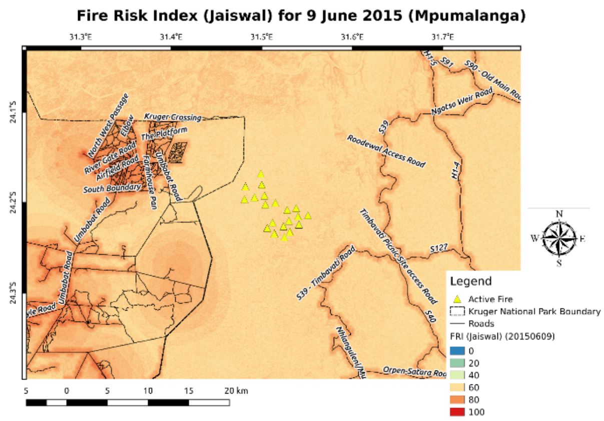

Figure 56: Fire Risk Index (Jaiswal) for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

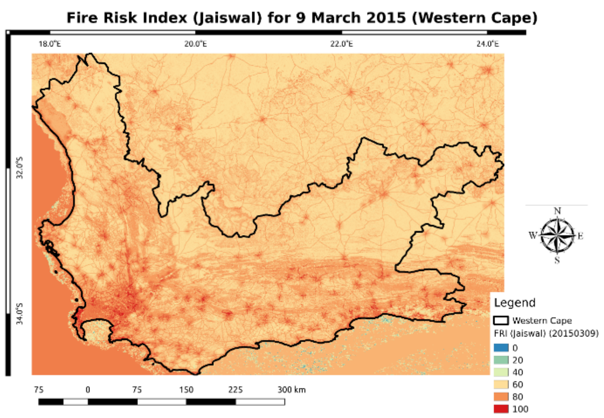

Figure 55: Fire Risk Index (by Jaiswal et al.) for Western Cape on 9 March 2015.

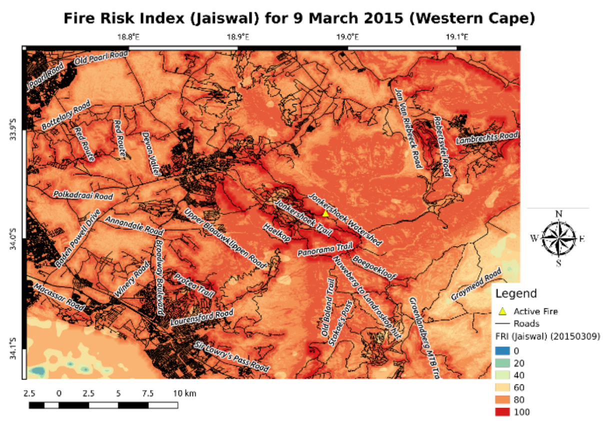

Figure 57: Fire Risk Index (Jaiswal) for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 54 provides the Fire Risk Index (Jaiswal), as described in section 4.3.5 of chapter four, for Mpumalanga on 9 June 2015. Figure 55 provides the Fire Risk Index (Jaiswal) for the Western Cape on 9 March 2015. The locations of the roads are visible in the values and appear to be much higher than the non-road neighbouring pixels. The roads can be identified by the road-like line feature visible on the map. This is due to the fact that the index assigns higher fire potential values close to roads. Similar results are seen in both study areas.

Figure 56 shows the Fire Risk Index (Jaiswal) for a small area in the Kruger National Park in Mpumalanga. Figure 57 shows the Jonkershoek area near Stellenbosch in the Western Cape. A 'buffer' effect can be seen around the road features in Figure 56 and Figure 57. This effect is caused because the Fire Risk Index values are higher close to roads.

Fire Risk Index (Saglam)

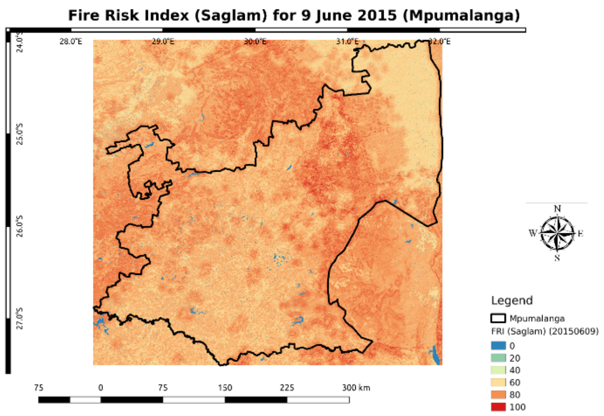

Figure 58: Fire Risk Index (by Saglam et al.) for Mpumalanga on 9 June 2015.

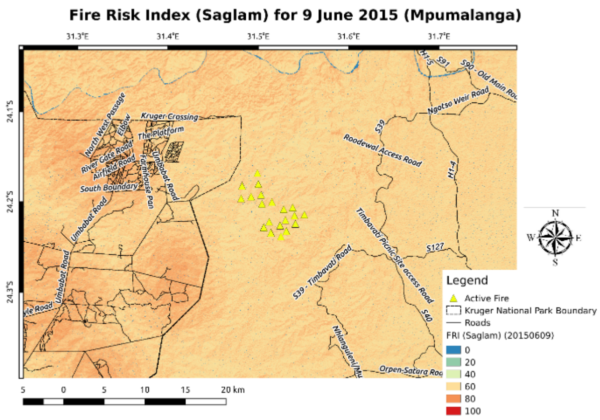

Figure 60: Fire Risk Index (Saglam) for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

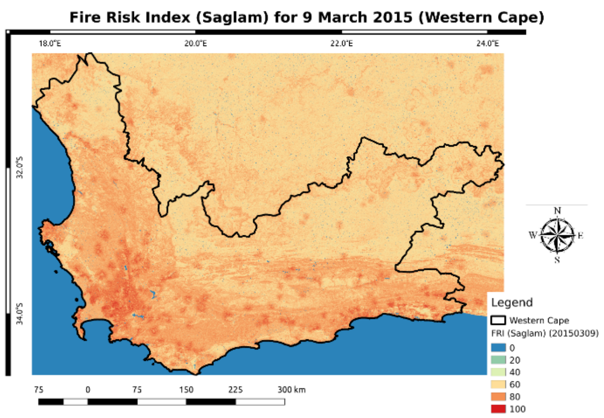

Figure 59: Fire Risk Index (by Saglam et al.) for Western Cape on 9 March 2015.

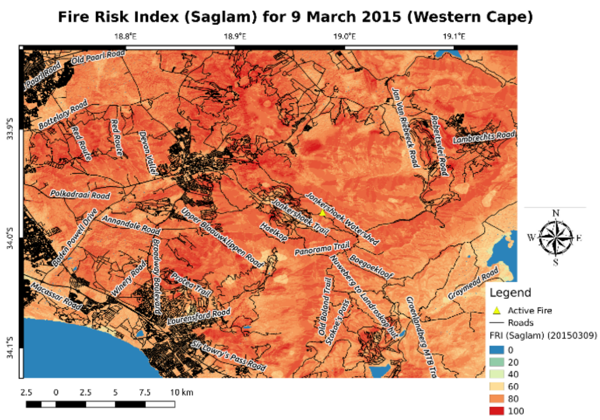

Figure 61: Fire Risk Index (Saglam) for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 58 provides the Fire Risk Index (Saglam), as described in section 4.3.6 of chapter four, for Mpumalanga on 9 June 2015. Figure 59 provides the Fire Risk Index (Saglam) for the Western Cape on 9 March 2015. The values of the index range between zero and a hundred. Locations close to roads have higher fire potential values than the pixels further away from roads. Spots can be seen in the results where roads cross each other or where a lot of roads are present in a small area. These areas can be identified by the dark spots on the maps. Similar results are seen in both study areas.

Figure 60 shows the Fire Risk Index (Saglam) for a small area in the Kruger National Park in Mpumalanga. Figure 61 shows the Jonkershoek area near Stellenbosch in the Western Cape. The fire potential values are higher in Figure 61 than in Figure 60. The variation in Hybrid Fire Index values is not high in Figure 60 and more variation is visible around the Panorama Trail in Figure 61.

Fire Potential Index

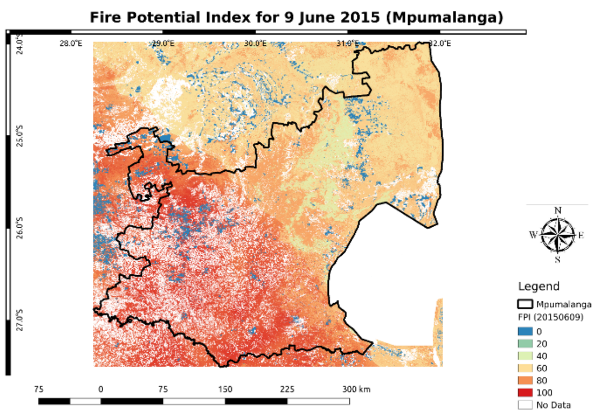

Figure 62: Fire Potential Index for Mpumalanga on 9 June 2015.

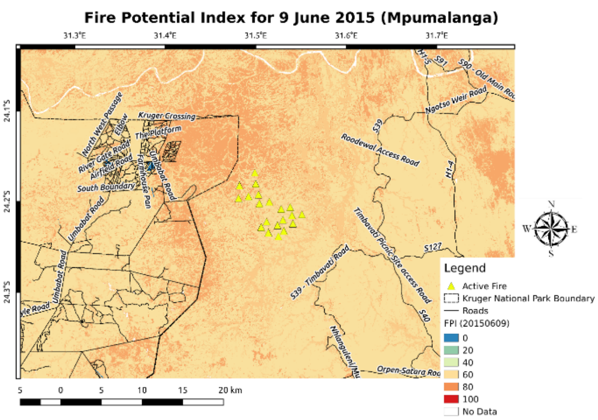

Figure 64: Fire Potential Index for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

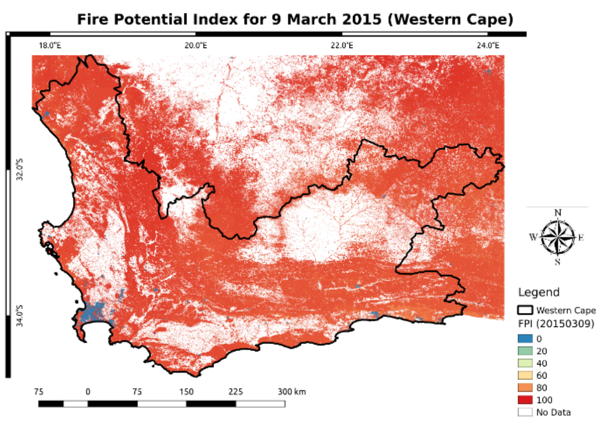

Figure 63: Fire Potential Index for Western Cape on 9 March 2015.

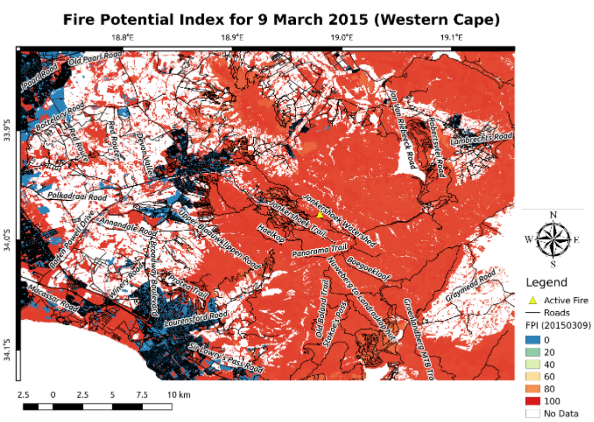

Figure 65: Fire Potential Index for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 62 provides the Fire Potential Index, as described in section 4.3.7 of chapter four, for Mpumalanga on 9 June 2015. Figure 63 provides the Fire Potential Index for the Western Cape on 9 March 2015. The values of the index range between zero and a hundred. The light areas present the areas that were determined not to have fire potential according to the index. This can be areas where water is present or where there is no vegetation to ignite. The index provides very high fire potential to a large part of the Western Cape. The variation in the Western Cape results is less than the variation in the Mpumalanga results. This is because of the input data and the different conditions present on the different days in the different areas.

Figure 64 shows the Fire Potential Index for a small area in the Kruger National Park in Mpumalanga. Figure 65 shows the Jonkershoek area near Stellenbosch in the Western Cape. The Fire Potential Index values are higher in Figure 65 than in Figure 64. Specific features cannot easily be identified in the Fire Potential Index values.

Fire Weather Index

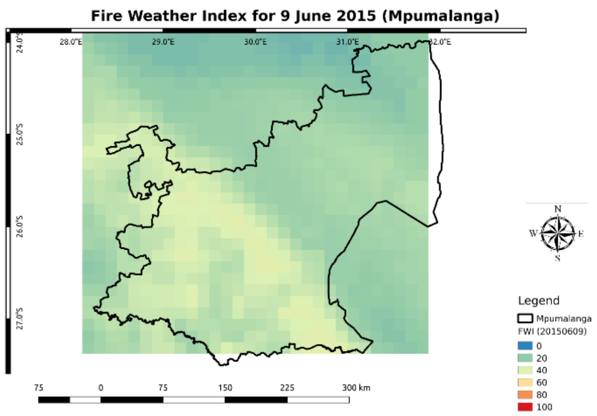

Figure 66: Fire Weather Index for Mpumalanga on 9 June 2015.

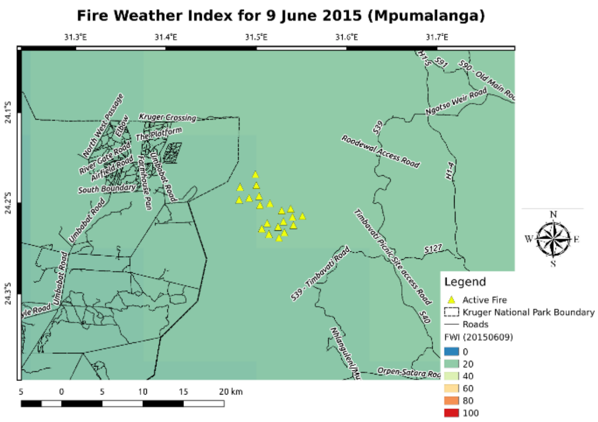

Figure 68: Fire Weather Index for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

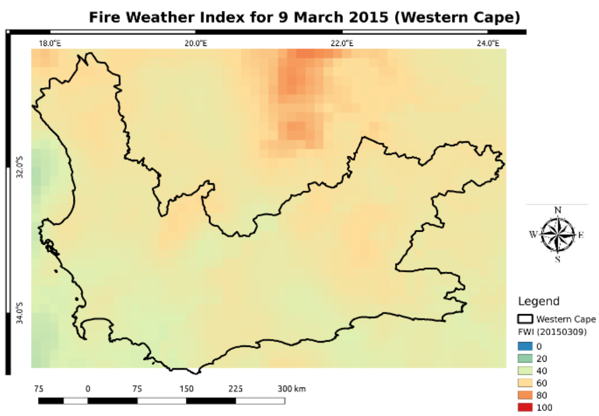

Figure 67: Fire Weather Index for Western Cape on 9 March 2015.

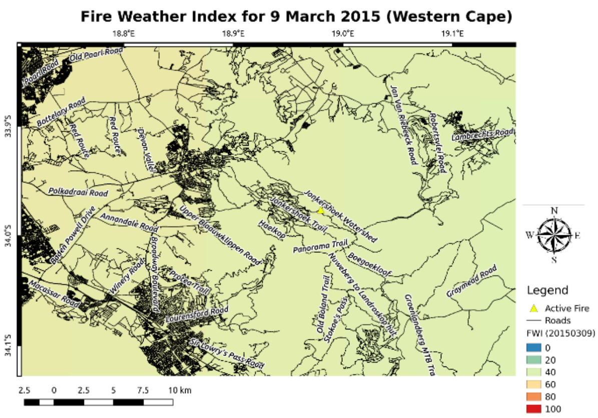

Figure 69: Fire Weather Index for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 66 provides the Fire Weather Index for Mpumalanga on 9 June 2015. Figure 67 provides the Fire Weather Index for the Western Cape on 9 March 2015. The values are calculated based on weather variables and no patterns are visible in the figures.

Figure 68 shows Fire Weather Index for a small area in the Kruger National Park in Mpumalanga. Figure 69 shows the Jonkershoek area near Stellenbosch in the Western Cape. No distinct patterns are visible between the index values near the active fire points and the index values further away from the active fire points.

Fine Fuel Moisture Code

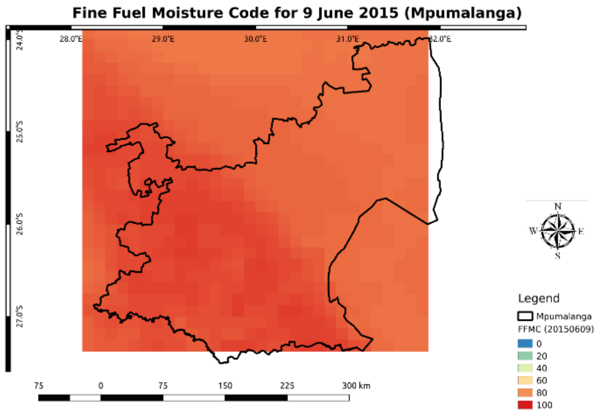

Figure 70: Fine Fuel Moisture Code for Mpumalanga on 9 June 2015.

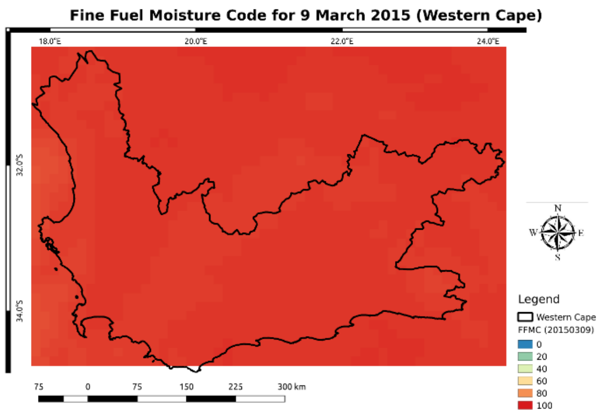

Figure 71: Fine Fuel Moisture Code for Western Cape on 9 March 2015.

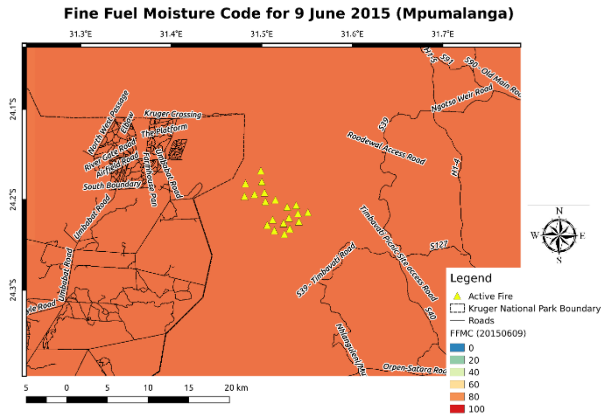

Figure 72: Fine Fuel Moisture Code for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

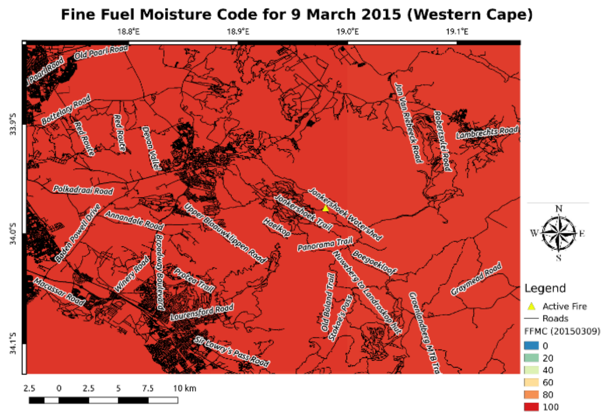

Figure 73: Fine Fuel Moisture Code for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 70 provides the Fine Fuel Moisture Code for Mpumalanga on 9 June 2015. Figure 71 provides the Fine Fuel Moisture Code for the Western Cape on 9 March 2015. The values are calculated based on weather variables and no patterns are visible in the figures.

Figure 72 shows Fine Fuel Moisture Code for a small area in the Kruger National Park in Mpumalanga. Figure 73 shows the Jonkershoek area near Stellenbosch in the Western Cape. No distinct patterns are visible between the index values near the active fire points and the index values further away from the active fire points.

Duff Moisture Code

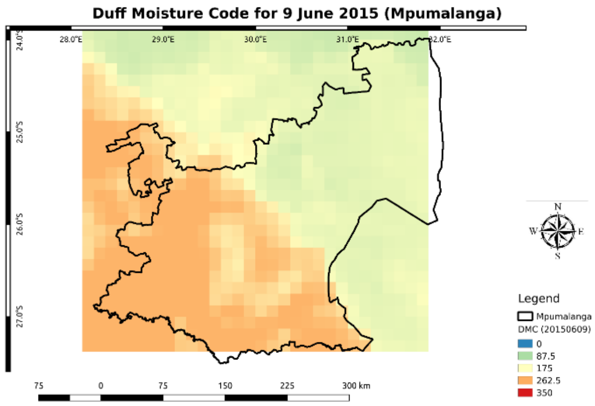

Figure 74: Duff Moisture Code for Mpumalanga on 9 June 2015.

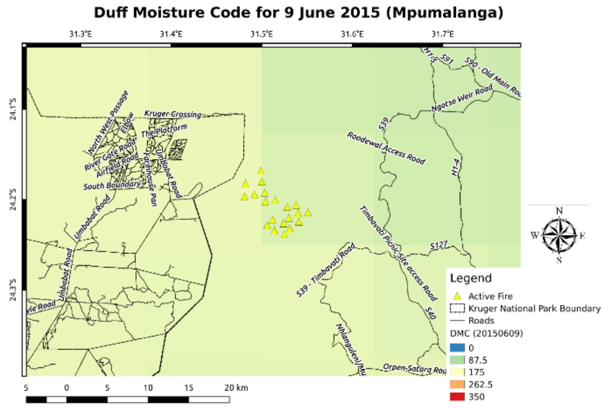

Figure 76: Duff Moisture Code for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

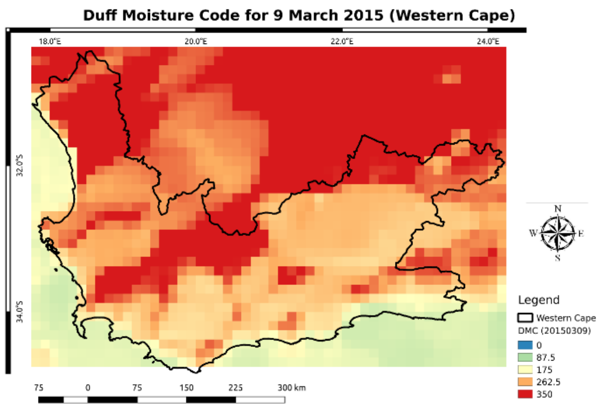

Figure 75: Duff Moisture Code for Western Cape on 9 March 2015.

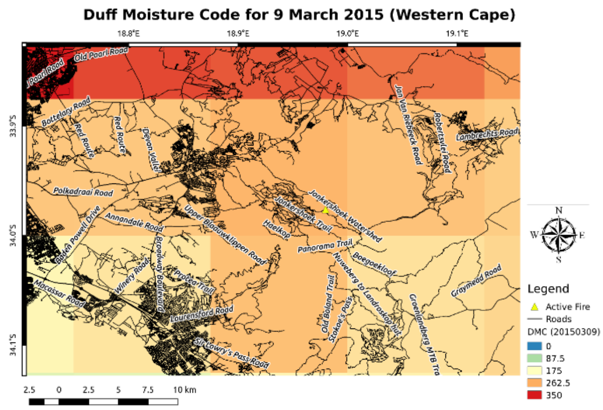

Figure 77: Duff Moisture Code for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 74 provides the Duff Moisture Code for Mpumalanga on 9 June 2015. Figure 75 provides the Duff Moisture Code for the Western Cape on 9 March 2015. The values are calculated based on weather variables and no patterns are visible in the figures.

Figure 76 shows Duff Moisture Code for a small area in the Kruger National Park in Mpumalanga. Figure 77 shows the Jonkershoek area near Stellenbosch in the Western Cape. No distinct patterns are visible between the index values near the active fire points and the index values further away from the active fire points.

Drought Code

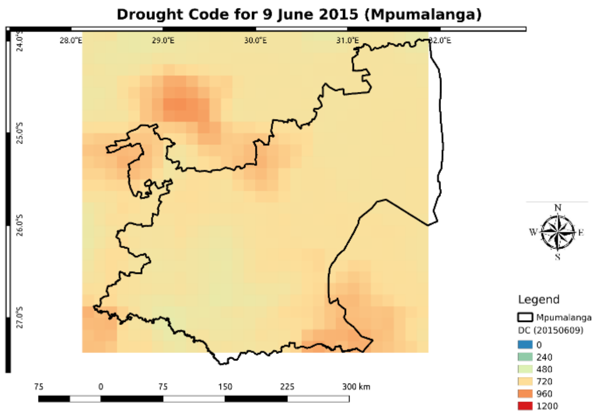

Figure 78: Drought Code for Mpumalanga on 9 June 2015.

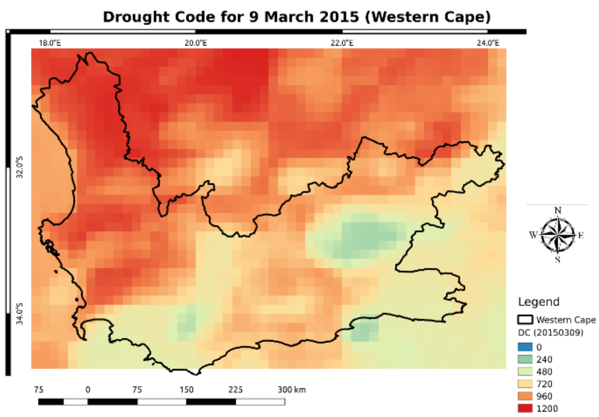

Figure 79: Drought Code for Western Cape on 9 March 2015.

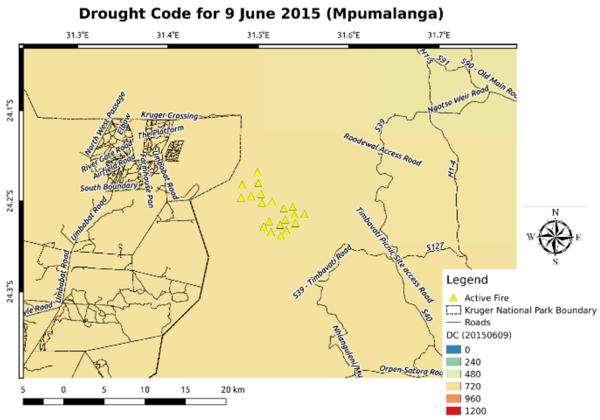

Figure 80: Drought Code for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

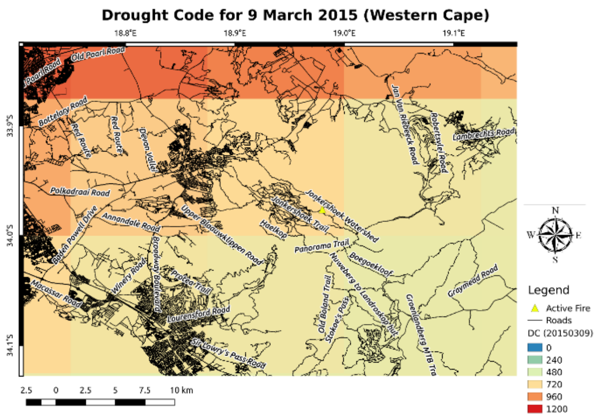

Figure 81: Drought Code for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 78 provides the Drought Code for Mpumalanga on 9 June 2015. Figure 79 provides the Drought Code for the Western Cape on 9 March 2015. The values are calculated based on weather variables and no patterns are visible in the figures.

Figure 80 shows Drought Code for a small area in the Kruger National Park in Mpumalanga. Figure 81 shows the Jonkershoek area near Stellenbosch in the Western Cape. No distinct patterns are visible between the index values near the active fire points and the index values further away from the active fire points.

Lowveld Fire Danger Index

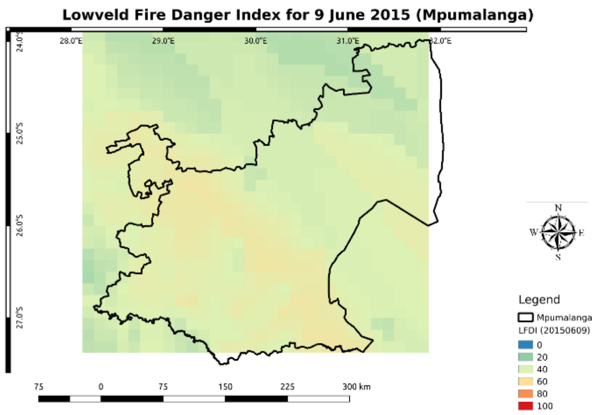

Figure 82: Lowveld Fire Danger Index for Mpumalanga on 9 June 2015.

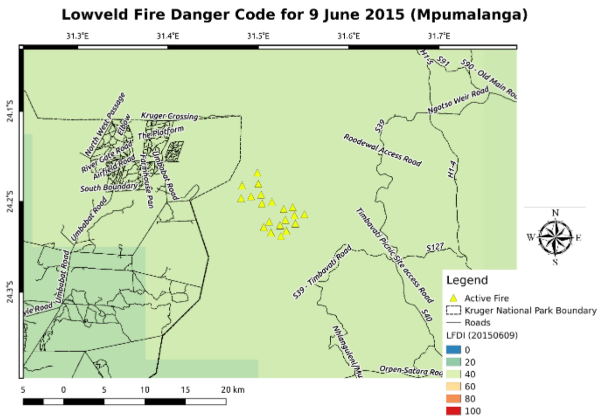

Figure 84: Lowveld Fire Danger Index for Part of Kruger National Park Near Northern Mpumalanga Boundary on 9 June 2015.

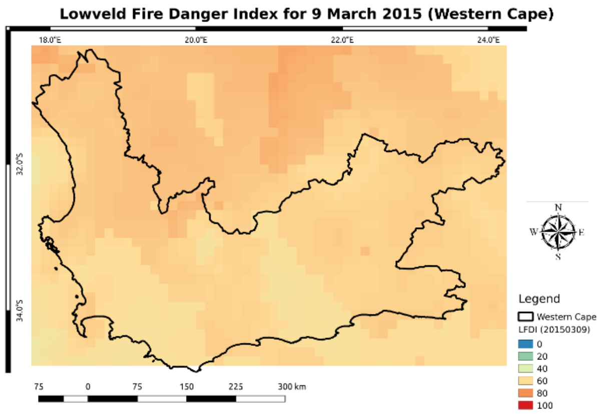

Figure 83: Lowveld Fire Danger Index for Western Cape on 9 March 2015.

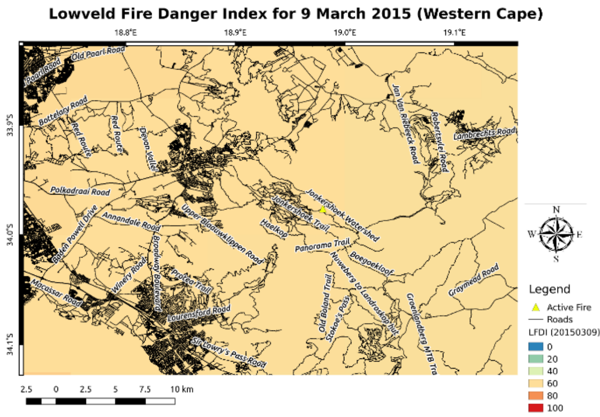

Figure 85: Lowveld Fire Danger Index for Jonkershoek Area in the Western Cape on 9 March 2015.

Figure 82 provides the Drought Code for Mpumalanga on 9 June 2015. Figure 83 provides the Drought Code for the Western Cape on 9 March 2015. The values are calculated based on weather variables and no patterns are visible in the figures.

Figure 84 shows Drought Code for a small area in the Kruger National Park in Mpumalanga. Figure 85 shows the Jonkershoek area near Stellenbosch in the Western Cape. No distinct patterns are visible between the index values near the active fire points and the index values further away from the active fire points.

5.3. Evaluation of Candidate Fire Potential Index and Fire Danger Index Results

Details on the evaluation process is provided in section 3.6.3. of chapter three. The process followed as well as details on the fire danger index data used in the evaluation process is included in section 3.6.3.

5.3.1. Pseudo R^2

Table 26 provides the ranges of the Pseudo R^2 obtained from all valid pixels per index and per study area as well as the average and median values. The Pseudo R^2 is calculated from a logistic regression model. The Pseudo R^2 in logistic regression is calculated as SSR_1/SSR_2 where SSR_1 is the sum of squares residual of the logistic regression model and SSR_2 is the sum of squares residual for the saturated model. The closer the R^2 is to one, the better the logistic model fits the data.

The minimum R^2 value obtained by pixels for an index throughout the fire season in a study area was -1.0 for all of the indices. The maximum R^2 value obtained by the FHI, HFI, FRI (Saglam) and the SFI was 1.0 in the Mpumalanga and the FFR and SFI had a maximum R^2 value of 1.0 in the Western Cape. The best performers in terms of maximum R^2 value obtained in Mpumalanga was the FHI, HFI, FRI (Saglam) and SFI. The best performers in terms of maximum R^2 value obtained in the Western Cape was the FFR, SFI, FRI (Saglam) and FHI. The average R^2 value obtained in both provinces by the FRI (Jaiswal) was -1.0. The median R^2 value obtained in both provinces by the HFI, FFR, FRI (Saglam), FRI (Jaiswal) and SFI was -1.0. The FHI, HFI, FRI (Saglam) and SFI showed the best average R^2 performance in Mpumalanga. The FFR, SFI, FRI (Saglam) and the FHI showed the best average R^2 performance in the Western Cape. In terms of the median of the R^2 the FWI was the best performer in both provinces.

Index	Minimum (MP)	Maximum (MP)	Average (MP)	Median (MP)	Minimum (WC)	Maximum (WC)	Average (WC)	Median (WC)
FPI	-1.00	0.23	-0.81	-0.28	-1.00	0.10	-0.80	-0.75
FHI	-1.00	1.00	1.00	-0.93	-1.00	0.88	-1.00	-1.00
HFI	-1.00	1.00	1.00	-1.00	-1.00	0.87	-1.00	-1.00
FFR	-1.00	0.51	-1.00	-1.00	-1.00	1.00	1.00	-1.00
FRI (Saglam)	-1.00	1.00	1.00	-1.00	-1.00	0.97	-1.00	-1.00
FRI (Jaiswal)	-1.00	0.58	-1.00	-1.00	-1.00	0.15	-1.00	-1.00
SFI	-1.00	1.00	1.00	-1.00	-1.00	1.00	1.00	-1.00
LFDI	-1.00	0.17	-0.49	-0.26	-1.00	0.23	-0.59	-0.56
FWI	-1.00	0.30	-0.44	-0.20	-1.00	0.31	-0.53	-0.52
FFMC	-1.00	0.29	-0.53	-0.23	-1.00	0.23	-0.68	-0.63
DMC	-1.00	0.44	-0.52	-0.30	-1.00	0.31	-1.00	-0.83
DC	-1.00	0.48	-0.61	-0.33	-1.00	0.35	-1.00	-1.00

Table 26: Pseudo R^2 Range Values, Averages and Medians for all Indices.

The poor performance of the indices in the Pseudo R^2 metric can be due the fact that the indices might be poor predictors of fire potential or it can be because the potential in an area was high but no active fire was detected or present in the area.

The performance of the fire potential indices and fire danger indices is significantly different between the two provinces. This can be attributed to different conditions of the study areas during the time periods used in the evaluation. Based on the above mentioned facts and the average results it appears that the SFI, FHI and FRI (Saglam) performed well in both provinces in the evaluation.

5.3.2. Percentile Shift

Percentile shift is calculated to determine the distribution shifts in a dataset. The distribution shift is calculated on the indices based on days that fires occurred and all days in the fire season. The percentile shift was calculated by creating a sum of the differences between the 25th, 50th and 90th percentiles between the two datasets. The larger the distribution shift, the better the index performance.

The minimum, maximum, average and median percentile shift obtained in the pixels of the indices are presented in Table 27. The minimum percentile shift calculated for all indices was very low. In terms of maximum percentile shift the FPI, LFDI, FWI, FFMC, DMC and DC performed the best in Mpumalanga. The best performers in terms of maximum percentile shift in the Western Cape was the FPI, FHI, HFI, FFR, FRI (Saglam), SFI, LFDI, FWI, FFMC, DMC and DC. The maximum percentile shift of the FRI (Jaiswal) was the lowest in both provinces. The FPI, FFMC, FWI and LFDI showed the best average percentile shift performance in Mpumalanga. The FPI, FWI, LFDI and FFMC showed the best average percentile shift performance in the Western Cape. The average percentile shift performance of the FPI was the best in both provinces. The worst performers in the average percentile shift in both provinces were the FFR and SFI.

Index	**Minimum (MP)**	**Maximum (MP)**	**Average (MP)**	**Median (MP)**	**Minimum (WC)**	**Maximum (WC)**	**Average (WC)**	**Median (WC)**
FPI	-135.00	165.00	39.49	47.61	-135.00	165.00	10.32	15.00
FHI	-135.00	65.00	4.02	15.00	-135.00	165.00	-63.02	-46.11
HFI	-135.00	65.00	4.02	15.00	-135.00	165.00	-63.05	-46.81
FFR	-135.00	65.00	-27.59	-20.71	-135.00	165.00	-68.05	-55.00
FRI (Saglam)	-135.00	65.00	4.17	15.00	-135.00	165.00	-60.02	-44.09
FRI (Jaiswal)	-135.00	65.00	6.84	15.00	-135.00	65.00	-55.42	-35.00
SFI	-135.00	65.00	-59.56	-75.00	-135.00	165.00	-79.53	-85.00
LFDI	-135.00	165.00	11.70	11.67	-135.00	165.00	-7.14	-10.00
FWI	-135.00	165.00	12.29	15.00	-135.00	165.00	2.86	5.00
FFMC	-135.00	165.00	17.23	21.25	-135.00	165.00	-23.90	-35.00
DMC	-135.00	165.00	-3.86	-1.67	-135.00	165.00	-32.42	-35.00
DC	-135.00	165.00	4.49	7.86	-135.00	165.00	-25.76	-35.00

Table 27: Percentile Shift Range Values, Averages and Medians for all Indices.

The low percentile shift present in some pixels may be due to the fact that fire potential in an area may have been high but no ignition source was present to start a fire or no active fire was detected for the pixels. The higher percentile shift seen in the FPI, LFDI, FWI and FFMC shows that the indices are better indicators of fire potential than the FFR and SFI in both study areas. The best performer of all of the indices in terms of percentile shift is the FPI.

5.3.3. C-Index

The C-Index is used to compare and rank fire potential indices. The C-Index calculation follows the calculation of the area under the receiver operating characteristic curve. A C-Index value of less than 0.5 shows a random prediction, while a C-Index close to 1 shows an ideal prediction.

Table 28 contains the mean C-Index values obtained in all valid pixels per index per province. The FPI, FFR, FRI (Saglam), FRI (Jaiswal) and LFDI have C-Index values of less than 0.5 in Mpumalanga indicating random prediction. None of the indices have C-Index values of less than 0.5 in the Western Cape and therefore they do not indicate random prediction. The best performers in terms of C-Index values in Mpumalanga are the FWI, HFI, SFI and DC. The FFMC, FPI, FFR and FHI show the best C-Index performance in the Western Cape. The results show that the indices perform differently in the two provinces.

Index	Mean (MP)	Mean (WC)
FPI	0.23	0.90
FHI	0.63	0.85
HFI	0.67	0.80
FFR	0.40	0.88
FRI (Saglam)	0.39	0.65
FRI (Jaiswal)	0.29	0.84
SFI	0.67	0.67
LFDI	0.48	0.64
FWI	0.93	0.64
FFMC	0.62	0.91
DMC	0.63	0.55
DC	0.66	0.78

Table 28: C-Index Range Values, Averages and Medians for all Indices.

The different performance seen in the indices between the two provinces can be attributed to the fact that the provinces are very different in terms of vegetation, mountainous areas and weather. The best performers for this metric are the FWI for Mpumalanga and the FFMC for the Western Cape. Both of these indices are fire danger indices.

5.3.4. Bhattacharyya Coefficient

The Bhattacharyya Coefficient is used to calculate the overlap between two distributions. The two distributions taken into account in this metric is the fire potential index values on days with no fire activity and the fire potential index values on days with fire activity. Better performance is indicated by smaller values.

Table 29 contains the minimum, maximum, average and median Bhattacharyya Coefficient values obtained in all valid pixels per index per province. The best performers in terms of maximum Bhattacharyya Coefficient values in Mpumalanga include the DC, FFMC, FWI and FRI (Saglam). In the Western Cape the best maximum Bhattacharyya Coefficient performers are the DMC, FWI, DC and FFMC. The FWI, FFMC, FPI and LFDI show the best average performance for the Bhattacharyya Coefficient metric in Mpumalanga. The FFMC, LFDI, FWI and DMC show the best average performance for the Bhattacharyya Coefficient metric in the Western Cape.

Index	Minimum (MP)	Maximum (MP)	Average (MP)	Median (MP)	Minimum (WC)	Maximum (WC)	Average (WC)	Median (MP)
FPI	3.00	164.39	44.62	41.03	2.00	117.53	23.36	18.40
FHI	12.57	164.21	49.93	47.71	8.89	117.55	26.97	22.05
HFI	12.57	164.21	49.93	47.71	8.89	117.55	26.99	22.05
FFR	12.57	165.87	51.84	49.90	8.89	117.55	27.83	22.05
FRI (Saglam)	9.38	164.14	49.95	47.71	8.66	117.55	26.90	22.05
FRI (Jaiswal)	12.25	164.20	49.80	47.55	5.29	117.55	26.50	22.05
SFI	12.57	165.95	52.45	50.40	8.89	119.14	28.39	22.05
LFDI	1.41	164.18	44.65	41.15	1.41	117.88	20.50	14.49
FWI	2.45	164.00	43.92	39.92	1.00	113.56	20.85	15.16
FFMC	3.46	163.65	44.10	40.23	2.24	116.67	19.25	13.48
DMC	1.73	164.64	45.22	42.69	1.73	109.53	23.16	19.66
DC	2.00	163.32	44.79	41.69	3.00	115.59	24.55	20.82

Table 29: Bhattacharyya Coefficient Range Values, Averages and Medians for all Indices.

This metric shows poorer performance for the candidate fire potential indices than the fire danger indices included in the analysis. The FPI shows the best average performance of the candidate fire potential indices. The poor performance may be because of the fact that fire potential values were high but no ignition source was present to ignite a fire or no active fire was detected for the pixels.

5.3.5. Eastaugh's Two-Part Parametric

Eastaugh's Two-Part Parametric was developed to evaluate the performance of an index based on the slope of percentiles on fire days and the y-intercept of the slope. A slope of 1.0 and an intercept of zero shows ideal performance and a slope near zero and an intercept of 100 will show random performance.

Table 30 contains the minimum and maximum slope and matching intercept values obtained in all valid pixels per index per province. The best performers in terms of Eastaugh's Two-Part parametric in Mpumalanga include the DMC, DC and LFDI. In the Western Cape the best performers were the FFMC, DMC and DC. For the candidate fire potential indices, the FPI shows the best performance in both provinces. The DMC shows the best performance amongst the indices included in the analysis in both provinces.

Index	Best Slope (MP)	Best Matching Intercept (MP)	Worst Slope (MP)	Worst Matching Intercept (MP)	Best Slope (WC)	Best Matching Intercept (WC)	Worst Slope (WC)	Worst Matching Intercept (WC)
FPI	1.00	65.02	90.84	-87.54	0.99	76.62	-82.86	173.06
FHI	0.00	0.00	-50.00	126.28	0.00	0.00	-50.00	116.53
HFI	0.00	0.00	-50.00	126.28	0.00	0.00	-50.00	116.53
FFR	1.21	44.63	63.96	-51.65	0.00	0.00	-65.31	164.49
FRI (Saglam)	0.96	52.30	59.01	-42.94	0.00	0.00	-60.41	154.69
FRI (Jaiswal)	1.13	-8.32	71.02	-66.97	0.66	76.38	60.20	-53.88
SFI	1.07	50.17	-51.35	126.73	0.00	0.00	-60.41	154.69
LFDI	1.01	38.38	87.39	-80.93	1.06	43.96	-90.82	187.96
FWI	0.99	53.72	-87.39	183.33	1.04	42.46	-78.37	167.76
FFMC	0.99	66.39	-85.89	173.87	1.02	3.06	-82.86	180.20
DMC	1.03	10.87	-89.49	185.74	1.01	23.64	-70.20	144.69
DC	0.93	13.68	-74.47	151.65	0.92	15.20	-80.20	162.45

Table 30: Eastaugh's Two-Part Parametric Range Values for all Indices.

The DC and DMC displayed the best performance in both provinces based on the Eastaugh's Two-Part Parametric. The values obtained by the indices for the metric display good performance as a slope near 1 and an intercept near 0 represents an ideal index.

5.4. Ranking of candidate Fire Potential Indices According to Metric Performance

The metrics mentioned in the previous section were used to rank the performance of the fire potential indices and fire danger indices to determine which one of the indices perform the best in the study areas. The data required for the candidate fire potential indices is described in section 3.5.1 of chapter three and the implementation of the indices is described in chapter four. The data used for the fire danger indices is described in section 3.6.3 of chapter three. The ranking was done separately for

Mpumalanga and the Western Cape. Table 31 contains the ranking of the fire potential indices in Mpumalanga and Table 32 contains the ranking of the fire potential indices in the Western Cape.

The rankings in the tables show how many times an index placed first, second or any other position from one to twelve as twelve indices were included in the evaluation. For example, in Mpumalanga the FPI placed first 21.0% of the time and was placed second 9.8% of the time. The rankings were assigned to the metric values by processing all values for a single metric for all indices and assigning rankings to individual values. Percentages were calculated from these rankings and the final percentages were then ranked to indicate index performance.

The FWI was ranked first in 28.3% of the evaluated pixels for Mpumalanga, the FPI was ranked first in 21.0% and the DC was ranked first in 11.7% of the evaluated pixels for Mpumalanga. The DMC was ranked second in 28.2% of the evaluated pixels for Mpumalanga. The SFI was ranked last in 28.2% of the evaluated pixels for Mpumalanga and the FRI (Jaiswal) was ranked second to last in 34.4% of the evaluated pixels for Mpumalanga.

Index / Rank	FPI	FHI	HFI	FFR	FRI (Saglam)	FRI (Jaiswal)	SFI	LFDI	FWI	FFMC	DMC	DC
1	21.0	4.1	1.9	1.3	0.7	0.4	4.4	7.7	28.3	9.5	8.8	11.7
2	9.8	8.4	3.8	3.0	0.9	1.2	2.1	10.5	11.9	11.9	28.2	8.3
3	7.5	5.2	7.2	3.3	2.1	1.0	2.4	11.7	12.7	30.4	8.3	8.2
4	6.9	5.5	25.1	7.1	2.9	1.8	2.8	11.7	10.7	10.2	8.0	7.2
5	7.8	6.3	5.4	5.4	7.8	3.1	22.4	7.8	7.7	9.3	8.9	8.2
6	8.6	8.1	6.4	5.4	6.1	7.8	3.7	6.2	4.4	6.9	7.6	28.7
7	5.0	17.2	8.9	7.3	8.9	7.9	7.3	23.3	2.4	4.4	2.9	4.3
8	6.1	27.2	18.1	7.9	9.6	8.3	4.6	5.4	2.6	3.5	2.9	3.7
9	1.7	4.1	6.6	13.0	36.8	12.2	5.9	4.0	6.1	3.6	3.3	2.7
10	1.8	3.4	4.4	27.2	15.6	17.0	6.0	4.6	5.0	5.9	5.0	4.2
11	1.7	6.0	6.3	11.0	5.7	34.4	10.1	4.2	4.9	2.7	8.8	4.3
12	22.1	4.5	5.9	8.2	2.9	4.9	28.2	2.8	3.1	1.7	7.4	8.4

Table 31: Ranking of Performance of each Index over all Metrics for Mpumalanga by Percentage.

The FFMC was ranked first in 14.9% of the evaluated pixels for the Western Cape, the FPI was ranked first in 20.9% and the HFI was ranked first in 21.8% of the evaluated pixels for the Western Cape. The FHI was ranked second in 31.2% of the evaluated pixels for the Western Cape. The SFI was ranked last in 25.7% of the evaluated pixels for the Western Cape and the FWI was ranked second to last in 22.4% of the evaluated pixels for the Western Cape.

Index / Rank	FPI	FHI	HFI	FFR	FRI (Saglam)	FRI (Jaiswal)	SFI	LFDI	FWI	FFMC	DMC	DC
1	20.9	3.5	21.8	1.2	0.3	0.5	1.7	9.9	10.6	14.9	8.5	6.2
2	8.2	31.2	3.1	1.8	0.5	0.6	2.3	13.9	16.7	10.4	6.0	5.4
3	8.7	4.5	10.2	2.2	20.9	0.9	2.0	14.1	13.9	10.4	7.3	5.1
4	8.9	5.5	4.4	9.7	2.5	0.8	2.3	11.5	9.5	29.1	8.5	7.3
5	9.0	7.4	5.6	24.8	9.6	3.0	2.5	5.5	6.8	5.9	10.5	9.2
6	7.7	10.2	7.7	5.0	5.8	30.1	2.2	4.4	3.4	3.8	8.6	11.0
7	4.2	18.5	11.7	8.1	6.7	7.5	10.4	1.7	1.8	1.9	3.7	23.9
8	2.2	7.3	18.8	9.4	9.6	8.2	25.0	7.8	1.9	1.9	2.6	5.3
9	2.2	2.4	5.3	14.8	17.6	12.2	6.5	3.0	8.6	2.0	22.9	2.5
10	2.7	1.4	2.6	7.3	16.2	17.2	9.6	22.8	2.6	9.5	4.2	3.9
11	3.1	4.9	4.2	8.2	7.1	15.0	9.7	3.0	22.4	4.9	11.7	5.8
12	22.3	3.2	4.6	7.5	3.3	4.1	25.7	2.3	1.8	5.2	5.6	14.5

Table 32: Ranking of Performance of each Index over all Metrics for Western Cape by Percentage.

Based on the ranking of the performance of each index as shown in (Table 31) and (Table 32), the Spearman's rank correlation coefficient was calculated and is shown in (Table 33). The Spearman's rank correlation coefficient ranges from -1 to 1, with -1 indicating a perfect negative correlation, 1 indicating a perfect positive correlation, and 0 indicating random performance (no correlation). A positive correlation indicates that the index had higher percentages of being ranked highly and lower percentages of being ranked poorly. In Mpumalanga the FFMC showed the best performance with a coefficient of 0.902, the LFDI and the FWI with coefficients of 0.741 and 0.734, respectively. The FFR showed the worst performance with a coefficient of -0.916. In the Western Cape, the FFMC showed the best performance with a coefficient of 0.508, followed by the FWI with a coefficient of 0.448, while the SFI showed the worst performance with a coefficient of -0.825. The FPI showed the best performance of the candidate fire potential indices with coefficients of 0.462 for Mpumalanga and 0.244 for the Western Cape

Index / Study Area	Mpumalanga	Western Cape
FPI	0.462	0.244
FHI	0.175	0.420
HFI	-0.147	0.350
FFR	-0.916	-0.427
FRI (Saglam)	-0.587	-0.254
FRI (Jaiswal)	-0.846	-0.734

SFI	-0.734	-0.825
LFDI	0.741	0.315
FWI	0.734	0.448
FFMC	0.902	0.508
DMC	0.489	0.070
DC	0.483	0.007

Table 33: Spearman's Rank Correlation Coefficient for Each Index Within Each Province.

From the fire danger indices included in the index evaluation the FWI performs well in Mpumalanga and the FFMC performs well in the Western Cape. The candidate fire potential index that performs the best in both provinces the FPI. The SFI performed the worst in both provinces.

For all of the metrics it was seen that a fire danger index performed best in both provinces followed by a fire potential index. Ranking all of the fire potential indices based on performance in the metrics gives a clearer picture of the fire potential index performance. The FPI is the only candidate fire potential index that takes some of the weather parameters into account in the calculation. This could be why the FPI shows better performance than the other candidate fire potential indices that do not account for weather in their calculations.

5.5. Discussion

A single date was selected per province to provide visual results of the implemented candidate fire potential indices. The date selected for Mpumalanga was 9 June 2015 and the date selected for the Western Cape was 9 March 2015. These dates were selected because a fire occurred in each of the provinces on these dates.

The implemented candidate fire potential indices produce different results when visualised. Based on the visual results, the fire potential variation throughout all of the candidate fire potential indices seemed to be higher for the Western Cape than for Mpumalanga. This might be because of the differences in conditions (such as slope, aspect, fuel type and fuel moisture, and proximity to roads and settlements) in the provinces. The variation in slope is higher in the Western Cape than in Mpumalanga and that is visible in the visual fire potential index results. The Structural Fire Index, Forest Fire Risk Index and the Fire Risk Index (Jaiswal) prominently show locations close to roads. Slope is prominent when visualising the Fire Hazard Index and the Hybrid Fire Index. The indices present different ways of viewing and defining fire potential. Comparing the Western Cape data to the Mpumalanga data, the same features are present and prominent in the fire potential maps. Visually the fire potential indices for Mpumalanga do not show high fire potential for the area affected by fire in Mpumalanga compared to surrounding areas, whereas the fire potential indices show high fire potential for the area affected by fire in the Western Cape compared to surrounding areas. Therefore, the fire potential indices visually indicate fire potential variation in the Western Cape better than in Mpumalanga. The conditions in an area can therefore make it difficult to see where fire potential is high in small areas if the conditions across the entire area produce the same fire potential. This can be caused by the type of fuel and the fuel moisture, the variation in slope and the aspect in an area and the proximity to roads and settlements.

The fire potential indices were evaluated along with a number of fire danger indices to determine their usefulness as fire potential indices in Mpumalanga and the Western Cape in South Africa. A number of metrics were used in the index evaluation. The evaluation was done based on the fire potential index data (or the fire danger index data) and fire occurrence data. The Pseudo R^2 was calculated based on a logistic regression model fitted to the fire potential index data and the fire occurrence data. The other metrics used include Percentile Shift, Bhattacharyya Coefficient, C-Index, and Eastaugh’s Two-Part Parametric.

The candidate fire potential indices and fire danger indices included in the evaluation did not perform well in the Pseudo R^2 metric. This can however be attributed to the fact that even though the fire potential in an area is high a fire will only occur if an ignition source is present, which is not always the case. The SFI performed the best amongst the candidate fire potential indices in both provinces, while the FWI and the LFDI were the best performers amongst the fire danger indices in the evaluation. It is not possible to say, from this metric, whether indices including weather data perform better than the indices that do not include weather data because the performance of the indices in both provinces differ. Some of the indices that include weather data perform better than some of the indices that do not, but some of the indices that do not include weather data perform better than some of the indices that do include weather data.

In the Percentile Shift metric, the best performers were the FPI, LFDI, FWI and the FFMC. From this metric it can be seen that the indices that take weather into account outperform the indices that do not take weather into account.

The C-Index showed that the prediction power in Mpumalanga was not as high as in the Western Cape. The low prediction power can be attributed to the fact that high fire potential will only become a fire event if an ignition source is present. The C-Index performance of the indices were very different for the two provinces. This can be attributed to the environmental conditions of the study areas being better catered for in some of the indices than in others, thus showing differing levels of performance in the two provinces. In both provinces the best performing index in the C-Index evaluation was a fire danger index. The FWI was the best performer in Mpumalanga, while the FFMC was the best performer in the Western Cape.

The Bhattacharyya Coefficient displayed better performance in fire danger indices than in the candidate fire potential indices in both provinces. The FPI was the best performing fire potential index in the Bhattacharyya Coefficient metric. The other fire potential indices did not perform as well as the FPI or the fire danger indices. In this metric the indices that take weather into account outperformed the indices that do not take weather into account.

Eastaugh's Two-Part Parametric showed the best performance in the DMC and the DC across both provinces. The worst performers were FRI (Jaiswal) and FFR in Mpumalanga and the SFI, FHI, HFI, FFR and FRI (Saglam) in the Western Cape. All of the worst performing indices were candidate fire potential indices.

The above mentioned metrics were used to rank and compare the performance of the candidate fire potential indices and the fire danger indices included in the evaluation in both of the study areas – Mpumalanga and the Western Cape. The number of times a pixel achieved a first to last ranking was summed and percentages were assigned to determine the overall performance of a fire potential index.

In Mpumalanga the FWI displayed the best performance followed by the FPI. In the Western Cape the FFMC performed the best, followed by the FPI. Based on these results it is seen that the indices performed differently in the two study areas and this can be attributed to the fact that the time of year and seasons are different, and the environments are different with different types of vegetation and weather. The FPI is the best performer amongst the candidate fire potential indices and the FFMC and FWI are the best fire danger indices included in the evaluation. Once again, the indices that include weather data displayed better performance in the research than the indices that do not make use of weather data, even though they take fuel moisture into account. This means that in both provinces fire potential indices should be used which take weather data into account. The fire potential indices that do not take weather conditions into account are not as suitable as the fire potential indices that do take the conditions into account, but they can still be used as fire potential indices. The poor performance of the indices means that they may provide high fire potential that rarely realizes into an actual fire occurrence or the indices provide low fire potential in areas where fire events occur. The performance of fire potential indices is different because of the environmental conditions of an area.

Even though some of the indices do not show very good overall performance in these two provinces, it does not mean that they will not perform well in other areas.

The aim of the evaluation process was to determine if a fire potential index can predict the occurrence of a fire in an area. Even though the results of the metrics do not seem to indicate very powerful performance in any of the indices included in the evaluation it can be concluded that a fire potential index can be used to predict fire potential in an area, because a correlation was found between the indices and fire events. Even though there might be potential for fire, the absence of an ignition source means that no wildfires will break out. It is difficult to measure the performance of an index for the rare occurrence of fire potential which results in an actual fire event because of the need for an ignition source and the fact that ignition sources are not common. The fire danger indices included in the evaluation can also be used to predict fire potential in an area as also showed a correlation with fire events. However, the other candidate fire potential indices did not perform as well. This might be attributed to the fact that weather data was not taken into account or the weighting of the input variables of the indices might not give the highest priority to the most important variables. The performance of a fire potential index should be considered carefully because of the fact that fire potential is not always realised into an actual wildfire event due to the absence of an ignition source.

The evaluation was implemented as a standalone application, but integration with AFIS will be possible by making the raster outputs available to be ingested by the system, for example by importing the data into a database.

5.6. Chapter Summary

This chapter provided the results obtained from the research. Examples of the executed candidate fire potential indices were presented for both of the study areas. The results obtained from the fire potential index evaluation process was presented. Overall, some of the candidate fire potential indices did not perform as well as the fire danger indices included in the evaluation. The following chapter provides final conclusions, a summary of contributions and some recommendations for future work.

6. Chapter Six: Summary, Conclusions and Future Research

6.1. Chapter Overview

The previous chapter provided the results obtained from the fire potential index evaluation. The index performance was compared to determine which of the indices performed the best. This chapter provides a summary of the findings obtained in the research. Some final conclusions are provided and a summary of the contributions made by the research is provided. Lastly some recommendations are given for future work that can be conducted in the field of the research project.

6.2. Summary of Research

The aim of this research was to implement and evaluate different fire potential indices utilising geographic information, including remote sensing products, to predict fire potential in South Africa. This section provides a summary of how the research was conducted.

Literature Review

A literature review was conducted to identify the factors that influence fire potential. A search was conducted to find information on which factors have an influence on fire potential and how these factors influence fire potential. A number of influencing variables were identified including slope, aspect, weather, proximity to roads, proximity to settlements and vegetation moisture. A search was then conducted to identify a number of fire potential indices that could be considered for implementation, and many indices were found in the literature. The fire potential indices were investigated and a variety of input variables were found, and some indices were found to assign weights to the input variables in the final index calculation. Fire danger indices were found to be influenced by the same variables as fire potential indices. The literature review is provided in chapter two.

Requirements for a Fire Potential Index

In order to determine which of the fire potential indices identified in the literature review could be included as a candidate fire potential index, a list of variables by which the indices are influenced was required. A variety of variables were found to have an influence and those found to be most important and mentioned most frequently in literature were selected for use in this research. These variables are indicated in section 3.3 of chapter three. Seven fire potential indices that were found to be influenced by the list of variables were selected for implementation. Five fire danger indices were also selected for implementation.

Candidate Fire Potential Indices and Implementation

A list of the seven candidate fire potential indices is provided in section 3.5.3 of chapter three. The candidate fire potential indices were studied to determine how fire potential was described and estimated differently by each of the indices. This was necessary in order to be able to implement the fire potential indices in such a way that they can be compared to each other. It was found that the fire potential indices used different coefficients for the influencing factors and differed in which factors they included. The literature review of the fire potential indices is provided in section 2.4 of chapter two.

The candidate fire potential indices were implemented in a data rich environment, using the Python scripting language. The implementation of the candidate fire potential indices is described in section 4.3 of chapter four. Data was collected to execute the indices in two study areas in South Africa – Mpumalanga and the Western Cape. The fire seasons in the two study areas do not occur at the same time of the year. The Mpumalanga fire season is from June until October and the Western Cape fire season is from December until April. The data was collected for August 2014 to June 2015 for the Western Cape and for February 2015 to December 2015 for Mpumalanga. The data used in the fire potential index implementation is described in section 3.5.1 of chapter three. The preparation of the data for use in the fire potential index execution is described in section 4.2.1 of chapter four. It was found that the FPI process took a lot of time to complete compared to the other implemented models. This was because of the complexity of the FPI process.

Fire Potential Indices and Fire Danger Indices Evaluation

The fire potential index implementations were then executed for the two fire seasons and the data was prepared for the evaluation process. Details on the execution process is provided in section 3.5.4. of chapter three.

The fire potential indices and fire danger indices were then evaluated. The evaluation process is described in section 3.6.3 of chapter three. A visual evaluation was conducted to determine what features stand out in the fire potential indices and how the fire potential values for an area are presented. For example, it was found that roads and slope often stood out in the visual representation of the fire potential values. The results of the visual evaluation are provided in section 5.2.2 of chapter five. A statistical evaluation was then conducted. Fire potential index data or fire danger index data was used along with active fire data to determine the usefulness of the fire potential indices and the fire danger indices. The following metrics were used to evaluate the indices: Pseudo R^2, Percentile Shift, C-Index, Bhattacharyya Coefficient, Eastaugh's Two-Part Parametric.

The evaluation process results were then analysed and the results of the evaluation is provided in section 5.3 of chapter five and a discussion of the results is provided in section 5.5 of chapter five. It was found that the FPI performed the best in the Western Cape, followed by the FFMC. In Mpumalanga, it was found that the FWI performed the best. Of the candidate fire potential indices, the performance of the FPI was found to be best in the Western Cape, but random in Mpumalanga, while the performance of the FHI was found to be good in both provinces. Indices that take weather into account performed better than the indices that to not take weather into account.

6.3. Conclusions

Many fire potential indices have been developed, across the globe, but their suitability for South Africa has not been verified. The research project evaluated the usefulness of the indices in two study areas in South Africa – Mpumalanga and the Western Cape.

The implemented candidate fire potential indices show different results when visualized. Different features stand out in different fire potential indices. The features that stand out in a single fire potential index can be seen in the output for both of the study areas. The variation in fire potential values is different across the two study areas.

The fire potential indices and fire danger indices did not show very high performance in either one of the provinces. The fact that the performance was not very high does not mean that the indices are not suitable to predict fire potential in an area. This is because even though the fire potential is high in an area it does not mean that an ignition source will be present to realize that fire potential into an actual fire event.

The Fire Potential Index was the best performer among the candidate fire potential indices in both study areas. The Fine Fuel Moisture Code was the best performer amongst the fire danger indices in the Western Cape and the Fire Weather Index was the best performers amongst the fire danger indices in Mpumalanga. The fire potential indices and fire danger indices performed differently in the two study areas.

From the research project it was seen that some of the fire potential indices are not as suitable to predict fire potential in a study area as some of the other fire potential indices. It was also seen that the evaluated indices that take weather data into account performed better than the indices that do not take weather into account.

One of the goals for this research was to determine the best fire potential index for possible inclusion within AFIS. The outputs of the evaluation can be made available for ingestion by AFIS, thereby granting users of AFIS access to more information for their decision-making. As discussed in chapter 3, AFIS already incorporates the FWI and FFMC. Since the evaluation shows that these indices performed the best in the study areas, AFIS can continue using them to best meet the needs of its users.

The limited availability of weather data resulted in the use of a forecast model instead of actual weather readings from active weather stations. Weather forecast data is less reliable than active weather station data, and this has an impact on the final index values that were calculated.

The evaluation of the indices is made more difficult by the fact that that only a few fires occur in an area within a fire season. To try and overcome this problem, rare events logistic regression was used.

Calculating the fire potential index values can require large volumes of data. This could limit the applicability of the fire potential indices in an operational system. Processing data to smaller sizes based on the study area can help to ensure short processing times.

6.4. Recommendations for Future Work

Based on the research conducted a few questions were raised for future research. The performance of the fire potential indices differed between the two study areas. It would be useful to evaluate the fire potential indices in additional areas in South Africa. By repeating the research on more study areas in South Africa, differences between different vegetation types may be identified. It could be useful to determine for which conditions or fuel types a single fire potential index or fire danger index may be suitable. For example, weather conditions for flat areas do not differ across an area as much as with areas that have a lot of peaks and valleys. Therefore, some indices may be more suitable in some terrains than in others.

It would be useful if the evaluation can be done with higher spatial resolution active fire data where smaller fires will be included in the detections. More fire detections will mean that more pixels can be included in the evaluation which may provide a more accurate idea of the performance of a fire potential index or a fire danger index.

The fire potential indices were implemented with model forecast data which might not be as accurate as real-time weather station data. It would be useful to do the evaluation on fire potential indices based on real-time weather station data. If the weather data is more accurate, the fire potential assigned to an area may be more accurate and the performance of the index could be improved.

Additional variables can be added to fire potential indices to improve the performance of the index. For example, adding weather variables to the indices that do not make use of weather variables can significantly improve their performance as it was found that the indices that take weather into account perform better than those that do not.

To further test the usefulness and accuracy of the fire potential indices, the evaluation process can be conducted for additional fire seasons per study area. By running the evaluation process for more than one season, additional data can be included in the evaluation to improve the accuracy of the evaluation results.

It would be useful to examine and compare smaller areas within each region in terms of their performance per index. This could aid in identifying which variables and weights are responsible for better or poorer performance of the indices, and perhaps identifying the best indices per region or season.

In this research, the static vegetation type variable was replaced with the dynamic vegetation moisture variable for some of the indices (for example, the Fire Hazard Index). This was done to make the indices more comparable to the other indices, which used dynamic variables. It may be worth investigating the effect of combining both vegetation type and vegetation moisture.

It would be useful if a system can be created to define a number of new fire potential indices by providing a choice of variables and letting the user define an index. The user defined index can then be executed for a number of fire seasons and the index can then be evaluated by repeating the evaluation process used in this research. The index can be executed for the whole of South Africa. This type of system will require high performance computing if the index should be executed for the whole of South Africa.

References

Adab, H., Kanniah, K.D., & Solaimani, K. 2011. GIS-Based Probability Assessment of Fire Risk in Grassland and Forested Landscapes of Golestan Province, Iran. *2011 International Conference on Environmental and Computer Science*. *Online*, pp. 170-175.

AFIS. 2016. AFIS Viewer. [Online] Available: http://southernafrica.afis.co.za/ [Accessed on 20 June 2016].

Ager, A.A., Vaillant, N.M., Finney, M.A. 2010. A Comparison of Landscape Fuel Treatment Strategies to Mitigate Wildland Fire Risk in the Urban Interface and Preserve Old Forest Structure. *Forest Ecology and Management*. *Online*, pp. 1556-1570.

Ager, A.A., Vaillant, N.M., Finney, M.A. 2011. Integrating Fire Behavior Models and Geospatial Analysis for Wildland Fire Risk Assessment and Fuel Management Planning. *Journal of Combustion*. *Online*, pp. 1-19.

Alexander, M.E. & Cruz, M.G. 2013. Are the Applications of Wildland Fire Behaviour Models Getting Ahead of their Evaluation Again? *Environmental Modelling & Software*. *Online*, 41, pp. 65-71.

Anderson, H.E. 1982. Aids to Determining Fuel Models for Estimating Fire Behavior. [Online] Available: http://campus.extension.org/pluginfile.php/22004/mod_resource/content/0/Fire_Characteristics_and_Behavior/AidstoDeterminingFuelModelsforEstimatingFireBehavior.pdf [Accessed on 15 June 2015].

Andrews, P.L., Loftsgaarden, D.O., & Bradshaw, L.S. 2003. Evaluation of Fire Danger Rating Indexes Using Logistic Regression and Percentile Analysis. *International Journal of Wildland Fire*. *Online*, 12, pp. 213-226.

Andrews, P.L. 2014. Current Status and Future Needs of the BehavePlus Fire Modeling System. *International Journal of Wildland Fire*. *Online*, 23, pp. 21-33.

Archibald, S., Roy, D.P., van Wilgen, B.W., Scholes, R. J. 2008. What Limits Fire? An Examination of Drivers of Burnt Area in Southern Africa. *Global Change Biology*. *Online*, pp. 1-18.

Aricak, B., Kucuk, O., Enez, K. 2014. Determining a Fire Potential Map Based on Stand Age, Stand Closure and Tree Species, Using Satellite Imagery (Kastamonu Central Forest Directorate Sample). *Croatian Journal for Forest Engineering*. *Online*, 35, 1, pp. 101-108.

Baral, S.S., Das, J., Saraf, A.K., Borgohain, S., Singh, G. 2016. Comparison of Cartosat, ASTER and SRTM DEMs of Different Terrains. *Asian Journal of Geoinformatics*. *Online*, 16, 1, pp. 1-7.

Bastarrika, A., Chuvieco, E., Martin, M. P. 2011. Automatic Burned Land Mapping from MODIS Time Series Images: Assessment in Mediterranean Ecosystems. *IEEE Transactions on Geoscience and Remote Sensing*. *Online*, 49, 9, pp. 3401-3413.

Bastarrika, A., Chuvieco, E., Martín, M. P. 2011. Mapping Burned Areas from Landsat TM/ETM+ Data with a Two-Phase Algorithm: Balancing omission and Commission Errors. *Remote Sensing of Environment*. *Online*, 115, pp. 1003-1012.

Bogdos, N., Manolakos, E.S. 2013. A Tool for Simulation and Geo-Animation of Wildfires with Fuel Editing and Hotspot Monitoring Capabilities. *Environmental Modelling and Software*. *Online*, 46, pp. 182-195.

Burgan, R.E., Klaver, R.W., Klaver, J.M. 1998. Fuel Models and Fire Potential from Satellite and Surface Observations. In *International Journal of Wildland Fire*, 8 (3), pp. 159-170.

Caetano, M.R. 2004. Fire Risk Mapping by Integration of Dynamic and Structural Variables. In *Remote Sensing in Transition*. Edited by Goossens, R. Rotterdam: Millpress, pp. 319-326.

Chuvieco, E. & Congalton, R.G. 1989. Application of Remote Sensing and Geographic Information Systems to Forest Fire Hazard Mapping. *Remote Sensing of Environment*. *Online*, 29, pp. 147-159.

Chuvieco, E., Cocero, D., Riaño, D., Martin, P., Martínez-Vega, J., De La Riva, J., Pérez, F. 2004. Combining NDVI and Surface Temperature for Estimation of Live Fuel Moisture Content in Forest Fire Danger Rating. *Remote Sensing of Environment*. *Online*, 92, pp. 322-331.

Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martín, M.P., Zamora, R. 2010. Development of a Framework for Fire Risk Assessment Using Remote Sensing and Geographic Information System Technologies. *Ecological Modelling*. *Online*, 221, pp. 46-58.

Cipriani, H.N., Pereira, J.A.A. and Silva, R.A. and De Freitas, S.G., De Oliveira, L.T. 2011. Fire Risk Map for the Serra De Sao Domingos Municipal Park, Pocos De Caldas, MG. *Cerne*. *Online*, 17, 1, pp. 77-83.

Curt, T., Borgniet, L., Bouillon, C. 2013. Wildfire Frequency Varies with the Size and Shape of Fuel Types in Southeastern France: Implications for Environmental Management. *Journal of Environmental Management*. *Online*, 117, pp. 150-161.

Danson, F.M. & Bowyer, P. 2004. Estimating Live Fuel Moisture Content from Remotely Sensed Reflectance. *Remote Sensing of Environment*. *Online*, 92, pp. 309-321.

Dimitrakopoulos, A.P. 2011. Evaluation of the Canadian Fire Weather Index System in an Eastern Mediterranean Environment. *Meteorological Applications*. *Online*, 18, pp. 83-93.

Dowdy, A.J., Mills, G.A., Finkele, K., de Groot, W.J. 2010. Index Sensitivity Analysis Applied to the Canadian Forest Fire Weather Index and the McArthur Forest Fire Danger Index. *Meteorological Applications*. *Online*, 17, pp. 298-312.

Eastaugh, C.S., Arpaci, A., Vacik, H. 2012. A Cautionary Note Regarding Comparisons of Fire Danger Indices. *Natural Hazards and Earth System Sciences*. *Online*, 12, pp. 927-934.

ECMWF. 2015. User Guide to ECMWF Forecast Products. [Online] Available: http://www.ecmwf.int/sites/default/files/User_Guide_V1.2_20151123.pdf [Accessed on 6 May 2016].

Ertena, E., Kurgun, V., Musaoglu, N. 1994. Forest Fire Risk Zone Mapping from Satellite Imagery and GIS: A Case Study. *Proc. ISPRS Archives - Volume XXXV Part B8*. *Online*, pp. 1-6.

ESRI. 2017. Aspect. [Online] Available: http://support.esri.com/en/other-resources/gis-dictionary/term/aspect [Accessed on 9 July 2017].

Flannigan, M., Cantin, A.S., De Groot, W.J., Wotton, M., Newbery, A., Gowman, L.M. 2013. Global Wildland Fire Season Severity in the 21st Century. *Forest Ecology and Management*. *Online*, 294, pp. 54-61.

Forsyth, G.G., Kruger, F.J., Le Maitre, D.C. 2010. *National Veldfire Risk Assessment: Analysis of Exposure of Social, Economic and Environmental Assets to Veldfire Hazards in South Africa*. CSIR Report No: CSIR/NRE/ECO/ER/2010/0023/C.

Fosberg, M.A., Deeming, J.E. 1971. Derivation of the 1- and 10-hour timelag fuel moisture calculation for fire danger rating. USDA Forest Service. *Rocky Mountain Forest and Range Experiment Station. Research Paper RM-207*. *Online*, p. 10.

García, M., Riaño, D., Chuvieco, E., Salas, J., Danson, F.M. 2011. Multispectral and LiDAR Data Fusion for Fuel Type Mapping Using Support Vector Machine and Decision Rules. *Remote Sensing of Environment*. *Online*, 115, pp. 1369-1379.

GDAL.org. 2016. GDAL DEM. [Online] Available: http://www.gdal.org/gdaldem.html [Accessed on 1 July 2016].

GDAL.org. 2016. Geospatial Abstraction Library. Version 1.10.1. [Online] Available: http://www.gdal.org/ [Accessed on 28 June 2016].

GDAL.org. 2017. gdal_translate. [Online] Available: http://www.gdal.org/gdal_translate.html [Accessed on 8 July 2017].

GDAL.org. 2017. gdalwarp. [Online] Available: http://www.gdal.org/gdalwarp.html [Accessed on 8 July 2017].

GeoTerraImage. 2015. 2013-2014 South African National Land-Cover Dataset: Data User Report and MetaData. [Online] Available: http://bgis.sanbi.org/Account/LogIn?ReturnUrl=~%2FDocument%2FDownload%2F78 [Accessed on 11 May 2016].

Grégoire, J.M., Eva, H.D., Belward, A.S., Palumbo, I., Simonetti, D., Brink, A. 2013. Effect of land-cover change on Africa's Burnt Area. *International Journal of Wildland Fire*. *Online*, 22, pp. 107-120.

Guns, M. & Vanacker, V. 2012. Logistic Regression Applied to Natural Hazards: Rare Event Logistic Regression with Replications. *Natural Hazards and Earth System Sciences*. *Online*, 12, pp. 1937-1947.

Hantson, S., Padilla, M., Corti, D., Chuvieco, E. 2013. Strengths and Weaknesses of MODIS hotspots to characterize global fire occurrence. *Remote Sensing of Environment*. *Online*, 131, pp. 152-159.

Hardy, C.C. 2005. Wildland Fire Hazard and Risk: Problems, Definitions, and Context. *Forest Ecology & Management*. *Online*, 211, pp. 73-82.

Hernandez-Leal, P.A., Arbelo, M., Gonzalez-Calvo, A. 2006. Fire Risk Assessment Using Satellite Data. *Advances in Space Research*. *Online*, 37, pp. 741-746.

Hernandez-Leal, P.A., Gonzalez-Calvo, A., Arbelo, M, Barreto, A, Alonso-Benito, A. 2008. Synergy of GIS and Remote Sensing Data in Forest Fire Danger Modelling. *IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing*. *Online*, 1, 4, pp. 240-247.

Huesca, M., Litago, J., Palacios-Orueta, A., Montes, F., Sebastián-López, A., Escribano, P. 2009. Assessment of Forest Fire Seasonality using MODIS Fire Potential: A Time Series Approach. *Agricultural and Forest Meteorology*. *Online*, 149, pp. 1946-1955.

Huesca, M., Litago, J., Merino-de-Miguel, S., Cicuendez-López-Ocaña, V., Palacios-Orueta, A. 2014. Modeling and Forecasting MODIS-based Fire Potential Index on a Pixel Basis Using Time Series Models. *International Journal of Applied Earth Observation and Geoinformation*. *Online*, 26, 1993 pp. 363-376.

ISO/TC 211. 2017. Multi-Lingual Glossary of Terms. [Online] Available: https://committee.iso.org/files/live/sites/tc211/files/documents/TC211_Multi-Lingual_Glossary-2016-06-28_Published.xls [Accessed 9 July 2017].

Jaiswal, R. K., Mukherjee, S., Raju, K. D., Saxena, R. 2002. Forest Risk Zone Mapping from Satellite Imagery and GIS. *International Journal of Applied Earth Observation and Geoinformation*. *Online*, 4, pp. 1-10.

Jurdao, S., Yebra, M., Guerschman, J. P., Chuvieco, E. 2013. Regional Estimation of Woodland Moisture Content by Inverting Radiative Transfer Models. *Remote Sensing of Environment*. *Online*, 132, pp. 59-70.

Jurdao, S., Chuvieco, E., Arevalillo, J. M. 2012. Modelling Fire Ignition Probability from Satellite Estimates of Live Fuel Moisture Content. *Fire Ecology*. *Online*, 8, 1, pp. 77-97.

Kalabokidis, K., Athanasis, N., Vasilakos, C., Palaiologou, P. 2014. Porting of a Wildfire Risk and Fire Spread Application into a Cloud Computing Environment. *International Journal of Geographical Information Science*. *Online*, 28, 3, pp. 541-552.

Kanga, S., Sharma, L., Pandey, PC., Nathawat, M.S. 2014. GIS Modelling Approach for Forest Fire Risk Assessment and Management. *International Journal of Advancements in Remote Sensing, GIS and Geography*. *Online*, 2, 1, pp. 30-44.

Keane, R.E. & Reeves, M. 2012. Use of Expert Knowledge to Develop Fuel Maps for Wildland Fire Management. In *Expert Knowledge and Its Applications in Landscape Ecology*. Edited by Perera A.H. et al. Springer Science & Business Media, pp. 211-228.

Keane, R.E., Drury, S.A., Karau, E.C., Hessburg, P.F., Reynolds, K.M. 2010. A Method for Mapping Fire Hazard and Risk Across Multiple Scales and Its Application in Fire Management. *Ecological Modelling*. *Online*, 221, pp. 2-18.

King, G. & Zeng, L. 2001. Logistic Regression in Rare Events Data. *Political Analysis*. *Online*, 9,2, pp. 137-163.

Klaver, J.W., Klaver, R.W., Burgan, R.E. 1997 Using GIS to Assess Forest Fire Hazard in the Mediterranean Region of the U.S. *Proceedings of 17th Annual ESRI Users Conference*. pp. 10, San Diego.

Lein, J.K. & Stump, N.I. 2009. Assessing Wildfire Potential Within the Wildland-Urban Interface: A Southeastern Ohio Example. *Applied Geography*. *Online*, 29, pp. 21-34.

Linard, C., Gilbert, M., Snow, R.W., Noor, A.M., Tatem, A.J. 2012. Population Distribution, Settlement Patterns and Accessibility across Africa in 2010. *PLoS ONE*. *Online*, 7, 2, pp. 1-8.

Lopéz, A., San-Miguel-Ayanz, J., Burgan, R.E. 2001. Integration of Satellite Sensor Data, Fuel Type and Meteorological Observations for Evolution of Forest Fire Risk at the Pan- European Scale. *International Journal of Remote Sensing*. p. 10.

LP DAAC. 2016. Nadir BRDF-Adjusted Reflectance 16-Day L3 Global 500m. [Online] Available: https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd43a4 [Accessed on 11 May 2016].

McCaffrey, S. 2004. Thinking of Wildfire as a Natural Hazard. *Society and Natural Resources*. *Online*, 17, pp. 509-516.

MODIS Land Team. 2009. Validation. [Online] Available: https://landval.gsfc.nasa.gov [Accessed on 4 October 2016].

MODIS Land Team. 2015. Status for: BRDF/Albedo (MCD43). [Online] Available: http://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD43 [Accessed on 12 May 2016].

Mouillot, F., Schultz, M. G., Yue, C., Cadule, P., Tansey, K., Ciais, P., Chuvieco, E. 2014. Ten Years of Global Burned Area Products from Spaceborne Remote Sensing - A Review: Analysis of User Needs and Recommendations for Future Developments. *International Journal of Applied Earth Observation and Geoinformation*. *Online*, 26, pp. 64-79.

Municipal Demarcation Board. 2012. South Africa Provinces. [Online] Available: http://www.demarcation.org.za/index.php/downloads/boundary-data/boundary-data-main-files/province [Accessed on 3 March 2015].

Narayanaraj, G. & Wimberly, M.C. 2012. Influences of Forest Roads on the Spatial Patterns of Human- and Lightning-caused Wildfire Ignitions. *Applied Geography*. *Online*, 32, pp. 878-888.

NASA. 2016. MCD14DL. [Online] Available: https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/c6-mcd14dl [Accessed on 11 May 2016].

NASA Earth Data. 2016. VIIRS I-Band 375 m Active Fire Data. [Online] Available: https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/viirs-i-band-active-fire-data [Accessed on 30 June 2016].

NASA Earth Observations. 2016. Cloud Fraction (1 Month – Aqua/MODIS). [Online] Available: http://neo.sci.gsfc.nasa.gov/view.php?datasetId=MYDAL2_M_CLD_FR [Accessed on 11 May 2016].

Nieto, H., Aguado, I., García, M., & Chuvieco, E. 2012. Lightning-caused Fires in Central Spain: Development of a Probability Model of Occurrence for Two Spanish Regions. *Agricultural and Forest Meteorology*. *Online*, 162-163, pp. 35-43.

Nikolakopoulos, K.G., Kamaratakis, E. K., Chrysoulakis, N. 2006. SRTM vs ASTER Elevation Products. Comparison for Two Regions in Crete, Greece. *International Journal of Remote Sensing*. *Online*, 27, 21, pp. 4819-4838.

OpenStreetMap. 2016. About OpenStreetMap. [Online] Available: https://www.openstreetmap.org/about [Accessed on 11 May 2016].

Oxford Dictionary. 2016. Aspect. [Online] Available: http://www.oxforddictionaries.com/definition/english/aspect [Accessed on 23 March 2016].

Oxford Dictionary. 2016. Climate Change. http://www.oxforddictionaries.com/definition/english/climate-change?q=climate+change [Accessed on 23 March 2016].

Oxford Dictionary. 2016. Elevation. [Online] Available: http://www.oxforddictionaries.com/definition/english/elevation [Accessed on 23 March 2016].

Oxford Dictionary. 2016. Potential. [Online] Available: http://www.oxforddictionaries.com/definition/english/potential [Accessed on 24 March 2016].

Oxford Dictionary. 2016. Precipitation. [Online] Available: http://www.oxforddictionaries.com/definition/english/precipitation [Accessed on 24 March 2016].

Oxford Dictionary. 2016. Relative Humidity. [Online] Available: http://www.oxforddictionaries.com/definition/english/relative-humidity?q=relative+humidity [Accessed on 24 March 2016].

Oxford Dictionary. 2016. Slope. [Online] Available: http://www.oxforddictionaries.com/definition/english/slope [Accessed on 23 March 2016].

Oxford Dictionary. 2016. Temperature. [Online] Available: http://www.oxforddictionaries.com/definition/english/temperature [Accessed on 24 March 2016].

Oxford Dictionary. 2016. Topography. [Online] Available: http://www.oxforddictionaries.com/definition/english/topography [Accessed on 23 March 2016].

Oxford Dictionary. 2016. Wind. [Online] Available: http://www.oxforddictionaries.com/definition/english/wind [Accessed on 23 March 2016].

PostGIS. 2017. http://postgis.refractions.net/documentation/manual-1.3/ch04.html [Accessed on 8 July 2017].

Pourtaghi, Z. S., Pourghasemi, H. R., Rossi, M. 2014. Forest Fire Susceptibility Mapping in the Minudasht Forests, Golestan Province, Iran. *Environmental Earth Sciences*. *Online*, July 2014, pp. 1-19.

Precipitation Measurement Missions. 2016. Global Precipitation Measurement. [Online] Available: http://pmm.nasa.gov/gpm [Accessed on 11 May 2016].

Python Software Foundation. 2016. GDAL. [Online] Available: https://pypi.python.org/pypi/GDAL/ [Accessed on 10 May 2016].

Python Software Foundation. 2016. Matplotlib. [Online] Available: https://pypi.python.org/pypi/matplotlib [Accessed on 10 May 2016].

Python Software Foundation. 2016. NumPy. [Online] Available: https://pypi.python.org/pypi/numpy [Accessed on 10 May 2016].

Python Software Foundation. 2016. Pandas. [Online] Available: https://pypi.python.org/pypi/pandas/0.18.1/ [Accessed on 10 May 2016].

Python Software Foundation. 2016. Patsy. [Online] Available: https://pypi.python.org/pypi/patsy [Accessed on 10 May 2016].

Python Software Foundation. 2016. Rasterio. [Online] Available: https://pypi.python.org/pypi/rasterio/0.26.0 [Accessed on 10 May 2016].

Python Software Foundation. 2016. Scikit-Learn. [Online] Available: https://pypi.python.org/pypi/scikit-learn/0.17.1 [Accessed on 10 May 2016].

Python Software Foundation. 2016. SciPy. [Online] Available: https://pypi.python.org/pypi/scipy/0.17.0 [Accessed on 10 May 2016].

Python Software Foundation. 2016. Statsmodels. [Online] Available: https://pypi.python.org/pypi/statsmodels [Accessed on 10 May 2016].

Python Software Foundation. 2017. Data Structures. [Online] Available: https://docs.python.org/3/tutorial/datastructures.html#dictionaries [Accessed on 8 July 2017].

Rexer, M., Hirt, C. 2014. Comparison of Free High Resolution Digital Elevation Data Sets (ASTER GDEM2, SRTM v2.1/v4.1) and Validation Against Accurate Heights from the Australian National Gravity Database. *Australian Journal of Earth Sciences*. *Online*, 61, 2, pp. 213-226.

Rokni, K., Ahmad, A., Hazini, S. 2015. Comparative Analysis of ASTER DEM, ASTER GDEM and SRTM DEM Based on Ground-Truth GPS Data. *Jurnal Teknologi*. *Online*, 76, 1, pp. 97-102.

Rothermel, R.C. 1983. How to Predict the Spread and Intensity of Forest and Range Fires. *United States Department of Agriculture Forest Service General Technical Report INT-143*. *Online*, pp. 1-161.

Saglam, B., Bilgili, E., Dincdurmaz, B., Kadiogulari, A. I., Kücük, Ö. 2008. Spatio-Temporal Analysis of Forest Fire Risk and Danger Using Landsat Imagery. *Sensors*. *Online*, 8, pp. 3970-3987.

SANBI. 2012. National Vegetation Map 2012 Beta version 2. [Online] Available: http://bgis.sanbi.org/SpatialDataset/Detail/18 [Accessed on 2 May 2016].

Schöning, R., Bachmann, A., Allgöwer, B. 1997. GIS-Based Framework for Wildfire Risk Assessment. *Final Report for MINERVE 2, Zurich, Switzerland*. *Online*, pp. 1-24.

SciPy.org. 2016. Statistical Functions. [Online] Available: http://docs.scipy.org/doc/scipy/reference/stats.html [Accessed on 10 May 2016].

Scott, J.H. & Burgan, R.E. 2015. Standard Fire Behavior Fuel Models: A Comprehensive Set for Use with Rothermel's Surface Fire Spread Model. [Online] Available: http://www.fs.fed.us/rm/pubs/rmrs_gtr153.pdf [Accessed on 15 June 2015].

Siachalou, S., Doxani, G., Tsakiri-Strati, M. 2009. Integrating Remote Sensing Processing and GIS to Fire Risk Zone Mapping: A Case Study for the Seih-Sou Forest of Thessaloniki. In *Proceeding of ICC*. Online, pp. 1-10.

South African Government. 2016. South Africa's Provinces. [Online] Available: http://www.gov.za/node/67 [Accessed on 9 May 2016].

South African National Biodiversity Institute. 2012. Vegetation Map App [Vector] 2012. [Online] Available: http://bgis.sanbi.org/SpatialDataset/Detail/595 [Accessed on 10 June 2016].

StatsSA. 2015. Mid-Year Population Estimates. [Online] Available: https://www.statssa.gov.za/publications/P0302/P03022015.pdf [Accessed on 25 June 2016].

Steenkamp, K.C., Wessels, K.J., van den Bergh, F., McFerren, G.A., Frost, P.E., Lai, C.W., Swanepoel, D. 2012. Quantitative Comparison of Fire Danger Index Performance Using Fire Activity. *IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Munich, Germany*. *Online*, 22-27 July 2012, pp.3375-3378.

Steenkamp, K.C., Wessels, K.J., van den Bergh, F., McFerren, G.A., Frost, P.E., Lai, C.W., Swanepoel, D. 2013. *Quantitative Comparison of Performance of Fire Danger Indices in South Africa Report*. CSIR Meraka Institute, Pretoria.

The Telegraph. 2015. Tokai Forest Wildfire. [Online] Available: http://i.telegraph.co.uk/multimedia/archive/03218/Tokai_forest_wildf_3218418k.jpg [Accessed on 27 September 2016].

Thompson, M.P. & Calkin, D.E. 2011. Uncertainty and Risk in Wildland Fire Management. A Review. *Journal of Environmental Management*. *Online*, 92, pp. 1895-1909.

Thompson, M.P., Haas, J.R., Finney, M.A., Calkin, D.E., Hand, M.S., Browne, M.J., Grenfell, I.C. 2015. Development and Application of a Geospatial Wildfire Exposure and Risk Calculation Tool. *Environmental Modelling & Software*. *Online*, 63, pp. 61-72.

Trollope, L.A., Trollope, W.S.W. Hartnett, D. 2002. Fire Behaviour a Key Factor in the Fire Ecology of African Grasslands and Savannas. *Forest Fire Research & Wildland Fire Safety*. Viegas (ed.). Millpress, Rotterdam.

University of West England Research Observatory. 2007. Positivist Scientific Research. [Online] Available: http://ro.uwe.ac.uk/RenderPages/RenderLearningObject.aspx?Context=7&Area=1&Room=3&Constellation=24&LearningObject=104 [Accessed on 27 June 2016].

USGS. 2015. Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global. [Online] Available: https://lta.cr.usgs.gov/SRTM1Arc [Accessed on 11 May 2016].

Van Den Eeckhaut, M., Vanwalleghem, T., Poesen, J., Govers, G., Verstraeten, G., Vandekerckhove, L. 2006. Prediction of Landslide Susceptibility Using Rare Events Logistic Regression: A Case-study in the Flemish Ardennes (Belgium). *Geomorphology*. *Online*, 76, pp. 392-410.

van Wilgen, B. W., Forsyth, G. G., de Klerk, H., Das, S., Khuluse, S., Schmitz, P. 2010. Fire Management in Mediterranean-climate Shrublands: A Case Study from the Cape Fynbos, South Africa. *Journal of Applied Ecology*. *Online*, 47, pp. 631-638.

Van Wilgen, B. W., Forsyth, G., Prins, P. 2012. The Management of Fire-Adapted Ecosystems in an Urban Setting: The Case of Table Mountain National Park, South Africa. *Ecology and Society*. *Online*, 17, 1, pp. 1-10.

Verbesselt, J., Jonsson, P., Lhermitte, S., van Aardt, J., Coppin, P. 2006. Evaluating Satellite and Climate Data-Derived Indices as Fire Risk Indicators in Savanna Ecosystems. *IEEE Transactions on Geoscience and Remote Sensing*. *Online*, 44, 6, pp. 1622-1632.

Wikipedia.org. 2000. Deer Fire. [Online] Available: https://upload.wikimedia.org/wikipedia/commons/b/b8/Deerfire.jpg [Accessed on 17 June 2016].

Wikipedia.org. 2013. Fire Danger Rating Sign. [Online] Available: https://upload.wikimedia.org/wikipedia/commons/0/01/Fire_danger_rating_sign.jpg [Accessed on 17 June 2016].

Wikipedia.org. 2011. Fire Slope. [Online] Available: https://upload.wikimedia.org/wikipedia/commons/7/7e/Fire-sav-S-slope-3720.jpg [Accessed on 17 June 2016].

Wikipedia.org. 2016. Landscape View of Wildfire Near Highway 63 in South Fort McMurray. [Online] Available: https://upload.wikimedia.org/wikipedia/commons/7/7b/Landscape_view_of_wildfire_near_Highway_63_in_south_Fort_McMurray_(cropped).jpg [Accessed on 17 June 2016].

Wikipedia.org. 2012. Trees Torching – High Park Wildfire. [Online] Available: https://upload.wikimedia.org/wikipedia/commons/3/33/Trees_torching_-_High_Park_Wildfire.jpg [Accessed on 20 June 2016].

Working on Fire. 2013. Fire in South Africa. [Online] Available: http://www.workingonfire.org/index.php/about-wof/fire-in-sa [Accessed on 22 March 2016].

World Meteorological Organisation. 2017. METEOTERM, Official Terminology Database. [Online] Available: http://wmo.multicorpora.net/MultiTransWeb/Web.mvc [Accessed on 9 July 2017].

WorldPop.org. 2016. Methods. [Online] Available: http://www.worldpop.org.uk/data/methods/ [Accessed on 11 May 2016].

Yebra, M., Chuvieco, E., & Riaño, D. 2008. Estimation of Live Fuel Moisture Content from MODIS Images for Fire Risk Assessment. *Agricultural and Forest Meteorology*. *Online*, 148, pp. 523-536.

Yebra, M., Dennison, P. E., Chuvieco, E., Riaño, D., Zylstra, P., Hunt, E. R., Jurdao, S. 2013. A Global Review of Remote Sensing of Live Fuel Moisture Content for Fire Danger Assessment: Moving Towards Operational Products. *Remote Sensing of Environment*. *Online*, 136, pp. 455-468.

Zhang, Q., Wollersheim, M., Griffiths, S., Maddox, I. 2014. National Fire Risk Map for Continental USA: Creation and Validation. *IOP Conference Series: Earth and Environmental Science*. *Online*, 18, pp. 1-6.

Appendix A

The code developed for the dissertation can be accessed on Dropbox by following the link: https://www.dropbox.com/sh/0pur2rs14c121sh/AAADajkNyZgJVyQhUzSk4jHra?dl=0

Appendix B

Approval was required from the Ethics committee of the Natural and Agricultural Sciences faculty at the University of Pretoria. Approval from the committee was received on 11 August 2016. The approval document can be found on the next page.

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Faculty of Natural and Agricultural Sciences
Ethics Committee

E-mail: ethics.nas@up.ac.za

Date: 11 August 2016

ETHICS SUBMISSION: LETTER OF APPROVAL

Name of Applicant	Prof Coetzee
Department	Geography, Geoinformatics and Meteorology
Reference number	EC160606-043
Title	Fire Potential Modelling in South Africa

Dear Prof Coetzee

The submission conforms to the requirements of the NAS EC. Any amendments must be submitted to the NAS EC on a relevant application form as used for the original application quoting the reference number and detailing the required amendment. An amendment would be for example differentiating within the research target population.

You are required to submit a progress report no later than two months after the anniversary of this application as indicated by the reference number. The progress report document is accessible of the NAS faculty's website: Research/Ethics Committee.

You are required to notify the NAS EC upon the completion or ending of the project using the form Project Completed. Completion will be when the data has been analysed and documented in a postgraduate student's thesis or dissertation, or in a paper or a report for publication.

The digital archiving of data is a requirement of the University of Pretoria. The data should be accessible in the event of an enquiry or further analysis of the data.

The NAS EC wishes you well with your research project.

Yours sincerely,

Chairperson
NAS Ethics Committee