# DEVELOPMENT OF FIRE POTENTIAL INDEX OVER GOLDEN GATE HIGHLANDS NATIONAL PARK USING REMOTE SENSING

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A dissertation submitted in accordance with the requirements for the degree Magister Scientiae in the Faculty of Natural and Agricultural Science, Department of Geography at the University of the Free State

August 2017

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# DECLARATION

The research work described in this dissertation was carried out in the Faculty of Natural and Agricultural Sciences, University of the Free State, Phuthaditjhaba from January 2015 to July 2017, under the supervision of Dr. Samuel Adewale Adelabu (Department of Geography).

I declare that the dissertation hereby submitted by me for the Magister Scientiae degree at the University of the Free State is my own independent work and has not previously been submitted by me at another university/faculty. I furthermore, cede copyright of this dissertation in favour of the University of the Free State.

Dipuo Olga Mofokeng: ____________________ Date: August 2017

As the candidate's supervisor, I certify the above statement and have approved this dissertation for submission

Dr. Samuel Adewale Adelabu Signed: ____________________ Date:_August 2017

# SUMMARY

Fire is a natural phenomenon in many ecosystems. The positive and negative impacts of fire on biodiversity and natural resources has been a centre of attention across the world particularly within protected areas. Fire risk assessment systems provide an integrated approach for managing resources at stake and reducing the negative impact of fire. Fire Risk Index is of great assistance in which estimates the probability of fire occurrence and areas are quantitatively divided into different zone classified based on similar characteristics, which influence fire behaviour. Fire risk have traditionally been measured from point data collected at sparse weather stations and field survey. The accuracy of assessment may be limited by density of point data and spatial interpolation method errors. Remote Sensing techniques provide a cost-effective way of assessing required parameters such as fuel characteristics (moisture & biomass) and weather conditions in near-real time. Moreover, RS techniques have the ability to reveal spatial pattern of fire risk in recurrent, consistent way over large, remotely inaccessible mountainous area.

This study focused on development of Fire Potential Index for mountainous Golden Gate Highlands National Park, Free State Province, South Africa using Geospatial techniques. MODIS products MOD11A1, MODO9GA for fire seasons of 2011 -2014; and 30m Advanced Spaceborne Thermal Emission and Reflection Radiometer -Digital Elevation Model (ASTER-DEM) were used for data retrieval. Land Surface Temperature (LST); Normalized Difference Water Index derived Relatively Greenness Index ($RGI_{ndwi}$); Normalized Multi-Drought Index (NMDI) and Elevation were selected based on their significance in fire risk assessment. Variables were used to estimate two critical parameters, Fuel Moisture Content ($RGI_{ndwi}$ & NMDI) and Potential Surface Temperature (LST & Elevation). GIS was used during index calculation, data processing and analysis among other processes. Conversion of parameter's values into common danger scale was conducted using Normalization Tool. Reclass Tool for classification each data layer into five classes using manual classification method based on its impact on increasing the fire potential. Pairwise comparison of Analytic Hierarchy Process for assigning weightages for the parameters. Weighted Overlay tool for integration these parameters into construction of FPI. The final FPI Map was categorized into five classes as insignificant, low, medium, high and extreme high based on the FPI values. Fire points were used to validate the FPI map applying Extract Values to Points Tool. Geographical Weighted Regression (GWR) analysis was used to measure FPI performance.

The results revealed that about 12% of the park area was identified as high to extreme high danger zone,13%- medium danger zone and 42% - low danger zone towards fire. Largest area coverage of high to extreme fire danger classes was observed during 2013 (17%), 2014 (16%), 2012 (8%), and 2011(6%). The area was observed during September (17%), August (11%) and July (6%). The model revealed an overall accuracy of 89% ranging from 33%-100% indicating that maximum of fires fell under low to extreme high fire danger classes. GWR analysis show a sound agreement between FPI and the fire danger with overall $R^2$ of 0,69 ranging from 0,17 to 0,98. Therefore, the results suggest that the constructed FPI can be useful for monitoring spatiotemporal distribution of susceptibility of vegetation to fire.

The use of image fusion techniques to improve spatial and temporal resolutions of sensors as they are many freely available sensors that are sufficient in spectral resolution but have poor spatial and temporal resolutions should be encouraged. Plans to prevent and control fire in GGHNP should be more orientated to high and extreme fire danger areas. It was recommended the prediction of the index may be increased by incorporating more parameters such as Land-Cover-Land-Use (LULC), fuel type map and meteorological variables (wind speed and direction & insolation).

**Keywords: Fire, Fire Risk Assessment; Fire Risk Index; Fire Danger; Fire Potential Index; Remote Sensing; GIS; Golden Gate Highlands National Park**

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I humbly present my gratitude to my family and almighty God, without whom my life would not have been successful.

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# DEDICATION

To my loving and caring family, my husband, children, grandmother and late mother.

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# ACRONYMS

| Acronym | Definition |
|---|---|
| AHP | Analytical Hierarchy Process |
| ALI | Advanced LandImager |
| ALS | Airborne laser scanner |
| ANN | Artificial Neural Network |
| ARC | Agricultural Research Council |
| ARNDVI | Accumulative Relative Normalized Difference Vegetation Index |
| ASTER | Advanced Spaceborne Thermal Emission and Reflection Radiometer |
| AVIRIS | Airborne Visible and Infrared Imaging Spectrometer |
| DAFF | Department of Agriculture, Forestry and Fisheries |
| DEM | Digitized Elevation Model |
| DFMC | Dead Fuel Moisture Content |
| DoY | Date of Year |
| DTM | Digital Terrain Models |
| EMC | Equilibrium Moisture Content |
| EOSDIS | Earth Observing System Data and Information System |
| ERS-1/2 | European Remote Sensing Satellite 1 |
| ESA | European Space Agency |
| ET | Evapotranspiration |
| EUMESAT | European Organisation for the Exploitation of Meteorological Satellites |
| EVI | Enhance Vegetation Index |
| EWT | Equivalent Water Thickness |
| FAO | Food and Agriculture Organization |
| fAPAR | fraction of Absorbed Photosynthetic Active Radiation |
| FDRS | Fire Danger Rating System |
| FMC | Fuel Moisture Content |
| FMI | Fuel Moisture Index |
| fPAR | fraction of Photosynthetically Active Radiation |
| FPI | Fire Potential Index |
| FWI | Fire Weather Index |
| GEMI | Global Environmental Monitoring Index |
| GGHNP | Golden Gate Highlands National Park |
| GIS | Geographic Information Systems |
| GVMI | Global Vegetation Moisture Index |

| | |
|---|---|
| GWR | Geographical Weighted Regression |
| HDF | Hierarchical Data Format |
| IPCC | Intergovernmental Panel On Climate Change |
| IR | Infrared |
| iTVDI | improved Temperature Vegetation Dryness Index |
| IUCN | International Union for Conservation of Nature |
| KBDI | Keetch-Byram Drought Index |
| LAI | Leaf Area Index |
| LANDSAT-TM | Land Remote Sensing Satellite- Thematic Mapper |
| LANDSAT-ETM | Land Remote Sensing Satellite Enhanced Thematic Mapper |
| LFMC | Live Fuel Moisture Content |
| LIDAR | Light Detection and Ranging |
| LSE | Land Surface Emissivity |
| LST | Land Surface Temperature |
| LULC | Land Use Land Classification |
| MODIS | Moderate-Resolution Imaging Spectroradiometer (EOS) |
| MSG- SEVIRI | Meteosat Second Generation - Spinning Enhanced Visible and Infrared Imager |
| MSI | Moisture Stress Index |
| NASA | National Aeronautics and Space Administration |
| NDMC | National Disaster Management Centre |
| NDMI | Normalized Dry Matter Index |
| NDVI | Normalized Difference Vegetation Index |
| NDWI | Normalized Difference Water Index |
| NIR | Near Infrared |
| NMDI | Normalised Multi-Band Drought Index |
| NOAA-AVHRR | National Oceanic and Atmospheric Administration -Advanced Very High Resolution Radiometer |
| NPV | Net Primary Production |
| PA | Protected Areas |
| PCA | Principal Component Analysis |
| RADAR | Radio Detecting and Ranging |
| RGB | Red Green Blue |
| RGI | Relatively Greenness Index |
| RH | Relative Humidity |
| RS | Remote Sensing |
| RWC | Relative Water Content |
| RSA | Republic of South Africa |

| | |
|---|---|
| SAR | Synthetic Aperture Radar |
| SAVI | Soil Adjusted Vegetation Index |
| SAWS | South African Weather Services |
| SDS | Scientific Data Systems |
| SMA | Spectral Mixing Analysis |
| SPOT | Systeme Pour L'observation De La Terre |
| SPOT-VGT | Systeme Pour L'observation De La Terre -VEGETATION |
| SR | Simple Ratio |
| SRWI | Simple Relation Water Index |
| SVM | Support Vector Machine |
| SWIR | Shortwave Infrared |
| TCP | Tasseled Cap Transformation |
| TVDI | Temperature Vegetation Dryness Index |
| TVWI | Temperature –Vegetation Wetness Index |
| USA | United States of America |
| USDA | United States Department of Agriculture |
| USGS | United States Geological Survey |
| UTM | Universal Transverse Mercator |
| VARI | Visible Atmospherically Resistant Index |
| VDI | Vegetation Dryness Index |
| VHR | Very High Resolution |
| VI | Vegetation Index |
| VIS | Visible/Infrared Imaging Spectrometer |
| VWC | Vegetation Water Content |
| WDI | Water Deficient Index |

# Chapter 1

# General Introduction

## 1.1 Background

Fire is an important natural ecological factor that has occurred since time immemorial on the global ecosystem. There is evidence that the earliest use of fire by humans occurred more than one million years ago (Pausas and Keeley, 2009). Fire has become an increasing threat responsible for burning about 350 million hectares (ha) annually on average-basis (Food and Agricultural Organisation, 2007). Although vegetation fire statistics may be highly inaccurate, at the continental scale, Africa is the largest contributor with approximately 64% of the global total burnt area (Tansey *et al.*, 2004) with Sub-Sahara region being the highest (168 million ha; 230 million ha) (Food and Agricultural Organisation, 2007) hence Africa is known as “Fire continent”. Australasia contributes 16 %, Asia 14 %, South America 3%, North America 2% and Europe 1% (Tansey *et al.*, 2004).

In addition, countries invest billions of dollars annually on fire-related activities such as prevention, prescribe burning and suppression. For instance, Canada has spent an average of between US$ 531 million annually whereas the US Department of Agricultural Forest service’s spent more than US$ 11.5 billion; South American countries Brazil, Argentina and Bolivia spent high as US$ 1.6 billion annually with Australia investing approximately US$ 5, 612 million (González-Cabán, 2013).

## 1.2 Wildfire Drivers

In order to understand the factors contributing to fire risk, it is significantly necessary to examine the fire environment. According to Countryman (2004), fire environment is the “surrounding conditions, influences and modify force” that determine the behaviour of fire. Several factors are responsible for fire occurrence as depicted in Figure 1.1. At local scale, the occurrence of fire needs three basic components, (depending on the so called “fire fundamentals triangle (see figure 1.1), fuel, ignition and oxygen (Bachmann and Allgower, 2001). A fire requires fuel to burn, air to supply oxygen and a heat source to bring the fuel up to ignition temperature. At landscape scale, the fire behaviour is determined by three principal environmental factors: fuel, weather and topography. At a regional or global fire is influenced by climate, vegetation and land-use (Jin, 2010).


Figure 1:1. Fire drivers at different scales (Jin, 2010)

## 1.3 Concepts of Fire Risk Assessment

The risk assessment exists in number of disciplines; hence, the history of its application is full of contestation. In the context of fire management, its conceptual definition should encompass the most relevant components associated with the fire process. However, the terminologies fire risk and fire hazard are still controversial especially when compared with those used in disaster management. Consistent with most common terminology used in fire management "complex defined by volume, type, condition arrangement and location that determine the degree of fire hazard is a fuel ignition and resistance to control" as defined by US National Wildfire Coordinating Group (Hardy, 2005). The concept of fire danger describes the factors affecting the inception, spread and resistant to control and subsequently fire damages, often expressed as index (Chuvieco *et al.*, 2014). Bachmann and Allgower (2001) defined fire risk as the probability of a wildland fire occurring at a specified location and under specific circumstances together with its expected outcome as defined by its impacts on the objects it affects.

The above definitions emphasized on the destructive and negative impacts of fire, however, Miller and Ager (2013) emphasised that within the context fire management both positive and negative outcomes can be realized from a given fire, especially where a fire is used as the ecological management tool. Therefore, negative connotation associated with fire as "catastrophic" should be minimized from the fire management vocabulary.

## 1.4 Role of Remote Sensing in Wildfire Risk Assessment

Remote Sensing (RS) is the science and art of obtaining information about an object, area or phenomenon through analysis of data acquired by device that is not in contact with object, area or phenomena under investigation (Flasse *et al.*, 2004). Since the launch of the first environmental remote sensing Landsat in 1972 (Roy *et al.*, 2013), RS has proven to be significant beneficial to many disciplines ranging from land cover mapping to hydrology management. Fire management also has its own share of benefits from RS. RS observation provides reliable information timeously and cost-effectively. Remote Sensing play pivotal role in providing fire event at different spatial and temporal scales. For example, monitoring burnt scar areas requires data at higher spatial resolution in order to distinguish burnt areas from other land cover types but may not require data on daily basis. However, mapping active fires needs monitoring systems with a capability to capture data on fire event at near real time hence RS data with daily revisit time is used.

RS data provides significant role in the near real time monitoring of vegetation water content. For instance, National Oceanic and Atmospheric Administration – Advanced Very High Resolution Radiometer (NOAA-AVHRR) which has coarse spatial resolution of 1km and high temporal resolution of 1 day provides a good platform for producing daily information on vegetation changes and moisture (Yebra *et al.*, 2013). Most of the approaches depend on satellite which integrate multispectral sensors that incorporate infrared and near-infrared bands to determine vegetation presence, changes or stress status (Herawati *et al.*, 2015). These include sensors such as Landsat, TM and ETM, National Oceanic and Atmospheric Administration – Advanced Very High Resolution Radiometer (NOAA-AVHRR) and Systeme Pour lÓbservation de la Terre (SPOT), Moderate Resolution Imaging Spectraradiometer (MODIS), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER).

RS also provides one of the only means of fuel classification and biomass by using or fusing Synthetic Aperture Radar (SAR) and laser scanning data. Airborne Light Detection and Ranging (LIDAR) is an instrument that provides three-dimensional information of the arrangement of number of features including vegetation and fuel distribution (Herawati *et al.*, 2015). An effective alternative for overcoming two main limitations of optical data (i.e. estimation of fuel height and surface fuels when covered by forest canopy (Arroyo *et al.*, 2008, Gonzalez-Olabarria *et al.*, 2012, Mutlu *et al.*, 2008, Riaño *et al.*, 2007). LIDAR provides topographical information which play important role in fire spreading (Burns, 2012). Similar to thermal spectroscopic sensors, SAR can penetrate cloud cover so it is useful for detecting changes in vegetation cover and obtaining information soil moisture and vegetation dryness through haze (Herawati *et al.*, 2015).

Other important role RS is that it can provide spatially distributed information about fuel temperature and other weather data at adequate spatial and temporal. Meteorological satellites in geo-stationary are able to collect images of a large area frequently (Flasse *et al.*, 2004). For example, Meteosat Second Generation (MSG) Spinning Enhanced Visible and Infrared Imager (SEVIRI) suitable for retrieval of environmental parameter that change rapidly in time and been used to measure Air temperature and Relative Humidity (Nieto *et al.*, 2010).

## 1.5 South African Environment and Fire

Wildfire (termed veldfire in South Africa) is a natural and inescapable ecological factor in South African (SA) landscape and is the inevitable consequence of fire-prone vegetation and warm, dry climate (Forsyth *et al.*, 2010). More than 60% of South Africa ecosystems are fire dependent, 32% are fire independent and the remainder are fire sensitive (Le Maitre *et al.*, 2014). Fire dependent ecosystem are where fire is necessary for regeneration of most of plant but where inappropriate fire regimes can alter the species composition, vegetation structure or ecosystem functions or combination of these. Two latter ecosystems do not require fires for regenerations however, fire sensitive ecosystems are fire prone and can be adversely affected by inevitable fires if fires are too frequently or severe while fire independent ecosystems occurs where fires are very rare or absent (Forsyth *et al.*, 2010).

Additionally, SA is strongly influenced by climatic conditions as a result the country has two fire–seasons both in summer and winter rainfall areas. All provinces except Western Cape fall under summer rainfall areas with fire season starting in May till September. Across SA, rainfall is key determinant of vegetation growth and thus accumulation of litter of fuel for fires. This variation in the rainfall has even greater effect on the annual net primary production (a measure of the biomass growth of the vegetation in a year) (Forsyth *et al.*, 2010) which in fact, the ultimate determinant of the available fuel in wildfires (Le Maitre *et al.*, 2014). For example, in the eastern and southern parts of the country which receive more than 650 mm per year, enough fuel is produced to sustain wildfires every year (Le Maitre *et al.*, 2014).

Based on projected climate changes impacts for mid to late 21st century, likely and very likely increased of wildfire was projected by (Intergovernmental Panel on Climate Change (IPCC), 2007) due to an increased warm spells and increase in drought affected areas. Moreover, it has been observed that warming rate over the past 15 years (1998 -2012) has increased by 0.05ºC (-0.05 to 0.15) per decade (IPCC, 2013). South Africa is no exception as statistical evidence has shown that over the past four decades (1960 -2003), average annual temperature increased by 0.13ºC per decade together with changing precipitation pattern within the country (Benhim, 2006). With these kinds of temperature rises that exceeded the rate of mean global temperature rise, increased in fire frequency has been observed in the winter rainfall biomes and significant decreases of precipitation in the north east of the country during El Nino years (Republic of South Africa, 2010).

Like elsewhere in the world, SA's wildfire risks are associated with human factors such as biomass burning for land clearing and people as an omnipresent ignition source (Forsyth *et al.*, 2010) either by accident, negligence or deliberately. Hence, with the combination of fuel availability, weather conditions and ignition, SA is suitable for periodic and frequent fire. Approximately 60% of the country fall under extreme and high veldfire risk classes as shown in Figure 1.2. Therefore a clear understanding of where, under what conditions fire are desirable and where and when they should be avoided is necessary in order to appropriate fire management (Forsyth *et al.*, 2010).

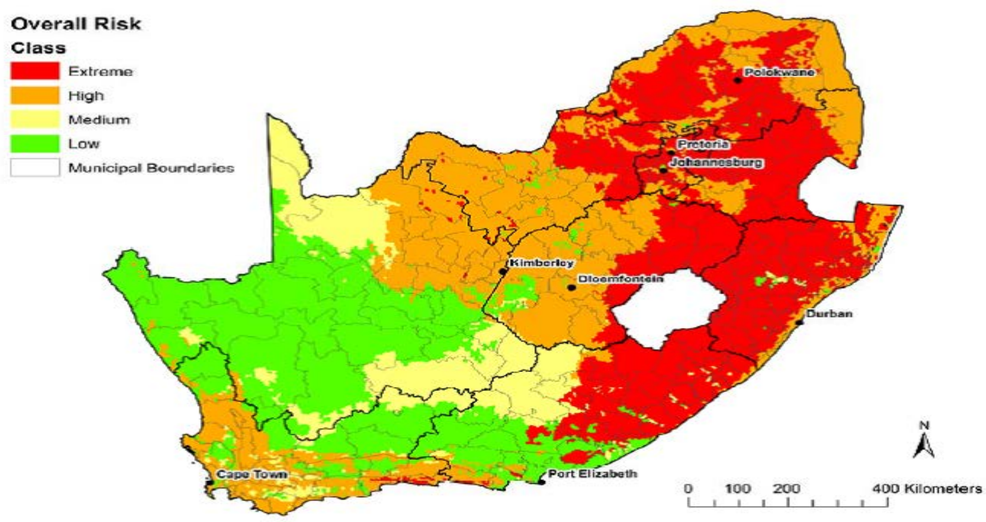



Figure 1:2. Overall assessment of veldfire risk level in South Africa (Forsyth et al., 2010)

South Africa has a long history in the management of veldfire, reflecting the need to balance ecological requirements of the natural vegetation and a risk-based approach to the management of veldfire. The two key Acts governing the administration of veldfire are the National Veld and Forest Fire Act, 1998 (Act no.101 of 1998) NFFVA, and the Disaster Management Framework (NDMC 2005) under the Disaster Management Act (Act no. 57 of 2002). NFFVA calls for integrated fire management recognising both the ecological role of fire for maintaining healthy ecosystem and the need to reduce risk posed by fire (Van Wilgen *et al.*, 2012). Chapter 2 of the act provides for the introduction of national fire danger rating system as a measure for the prevention of veldfire, early warning system of dangerous conditions and for the planning of veldfire operations; preparedness measures as well as for the management of risk to life and property (Bridgett *et al.*, 2003).

Disaster Management Act, 57 of 2002 and its associated National Disaster Management Framework (2005) provides for the establishment of National Disaster Management Centre (NDMC). NDMC has the objective of promoting an integrated and coordinated system of disaster management with special emphasis on prevention and mitigation, by organs of state in different spheres, statutory functionaries and the role players. The National Environmental Management Act, 1998 (Act no.107 of 1998) is another legislature that provide 20 principles and 8 constitutes sustainability development that must be considered when making decision concerning the protection of the environment and must guide the interpretation, administration and implementation of any law concerned with the protection and management of the environment. Principles pertaining to veld fires in the Act include those that require avoiding, minimizing of remedying. For instance, (i) disturbance to ecosystem or loss of biodiversity, (ii) pollution or degradation of environment, (iii) disturbance of landscapes and sites that constitutes the nation’s cultural heritage, and (iv) require caution when native impacts on the environment and people rights are possible.

While National Environmental Management: Protected Act, (Act no. 57 of 2003) and Biodiversity Act, (Act no.10 of 2010) simultaneously require the protection and conservation of the country’s exceptional biodiversity and ecological sensitive areas. NFFVA requires the development of standardised national Fire Danger Rating System (FDRS), a rigorous reliable and harmonised FDRS still not been formally adopted (United Nations Developement Program, 2011). In an attempt to standardise the FDRS, South Africa has adopted the Burning Index of United States National Fire Danger Rating System (US FDRS) (Bridgett *et al.*, 2003). However, the efficacy of US FDRS still requires accurate fuel models to calibrate the system. This is particularly problematic in South Africa, as the country does not yet have fuel models to use for different terrains and lack local fuel type, fire climatic and moisture conditions adopted (United Nations Developement Program, 2011). Furthermore, data based on lowland area can be misleading when applied in complex, elevated terrain. After attempting the Burning Index of US FDRS, the country adopted the Low-veld Fire Danger Rating System (FDRS) model.

## 1.6 Problem Statement

Despite progress in fire mitigation and management, the country still experiences many fire episodes annually particularly in mountainous regions (Strydom and Savage, 2016). Mountainous areas are more vulnerable due to its rugged terrain. Implementation of integrated fire management is complex and remains incomplete due to the lack or limited knowledge on the spatial and temporal dimensions of the fire risk conditions (Van Wilgen *et al.* (2012). Lowveld FDRS is based on meteorological variables measured from sparsely distributed weather stations located at the area that may not be very appropriate for fire risk estimation. The measurements are point based and do not have uniform and extensive spatial covered of the area. Model suffers from errors due to spatial interpolation techniques that may be unsuitable in areas of complex terrain. The model is ineffective for understanding the spatial and temporal behaviour of fire risk conditions because these conditions may change considerably over space and time. Therefore, the development of a better tool for fire prevention and mitigation strategies is critical.

Fire risk evaluation or assessment systems provide an integrated approach for managing resources at stake and reducing the negative impact of fire (Yebra *et al.*, 2008). These systems should include a wide range of factors that are related to fire ignition, probability and vulnerability (Chuvieco *et al.*, 2004). One of the approaches for fire risk evaluation involves indentifying the potentially contributing variables and integrate them into mathematical expression known as “index” (San-Miguel-Ayanz *et al.*, 2003). This index, therefore quantifies and indicates the level of risk. Short-term or Dynamic Index, Long-term or Short term Index and Integrated or Advance Index also known as Fire Potential Index have been developed for fire risk assessment (Adab *et al.*, 2016, San-Miguel-Ayanz *et al.*, 2003). Fire Potential Index (FPI) is regarded as fuel-moisture based index that used to identify areas susceptible to ignition (United States Geological Survey (USGS), 2016).

## 1.7 Study Aim and Objectives

The overall aim of this study is to develop Fire Potential Index (FPI) for fire risk assessment over the mountainous Golden Gate Highlands National Park (GGHNP), Eastern Free State Province of South Africa.

Objectives of the study included the:

1. Reviewing of previous studies regarding the successes and limitations of utilising remote sensing in monitoring wildfire risk conditions for fire risk assessment/mapping in protected area.
2. Calculate fuel moisture index (FMI) using satellite remote sensed derived variables (Relative Greenness Index derived from Normalized Difference Water Index (NDWI) and Normalized Multiband Drought Index (NDMI).
3. Determine the Potential Surface Temperature from Land Surface Temperature and Elevation.
4. Estimation of FPI by using data layers from (2 & 3)

## 1.8 Geographical location and description of the study area

GGHNP is conservation area located in Thabo-Mofutsanyane District Municipality, north-eastern of Free State Province in South Africa, in the foothills of the Maloti Mountains, (28°27'S – 28° 37'S and 28°33'E – 28°27'E). Topographically, GGHNP lies between 1654 m and 2815 m above sea level (Fig.1.3.). Initially, the park was proclaimed for conservation on the 13th September 1963, amalgamated of former farms (Glen Reeen, Wodehouse and Meslsetter) were 11 630 ha (Rademeyer and van Zyl, 2014, South African National Parks, 2013). In 1981, Noord Branbant farm was added to the park and was enlarged to 6 241 ha. The park was further extended to 11 630 ha with the addition of another eight (8) farmers during the period of 1988 and 1989 (Rademeyer and van Zyl, 2014). The former QwaQwa National park was incorporated into GGHNP on the 21 November 2008, thus increasing the park to its current size of 32 690 ha (Rademeyer and van Zyl, 2014, South African National Parks, 2013). The location map is shown in Fig.1.3.

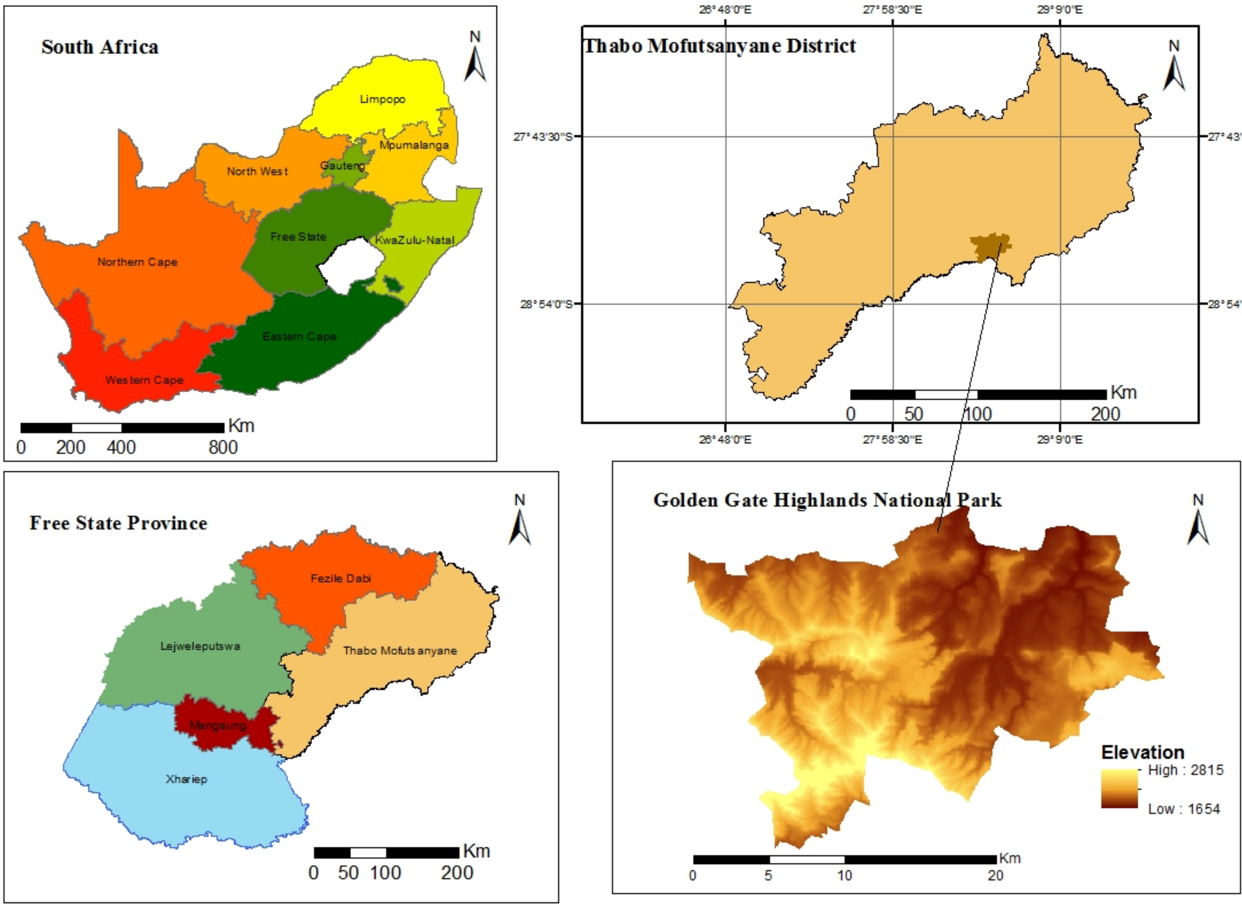



Figure 1:3. Location of study area (GGHNP) within Thabo Mofutsanyane District Municipality located in Free State, South Africa

GGHNP is situated in the summer-rainfall region characterized by rainfall season stretching from September to April with a mean annual ranging from 1 800 mm and 2 000 mm thus categorised as dry sub-humid region (South African National Parks, 2013). Summers are temperate with mean temperature ranges from 13 °C to 26 °C and Winters are cold (mean temperature ranges from 1 °C to 15 °) (South African National Parks, 2013). Frost is widespread during the winter months and snow occasionally falls on the higher peaks in the park (Grab *et al.*, 2011). An Agricultural Weather Station of Agricultural Research Council (ARC) located within the park between Latitude: -28.50381 and Longitude 28.5838DD; altitude 1849mm recorded the monthly average of max-min of Temperature & Relative Humidity as shown in Fig. 1.4. The rainfall pattern of the study area is shown in Fig 1.5.

The vegetation of GGHNP falls in the Grassland Biome of South Africa and represents the Drakensberg grassland bioregion and the Mesic highland grassland bioregion (South African National Parks, 2013)

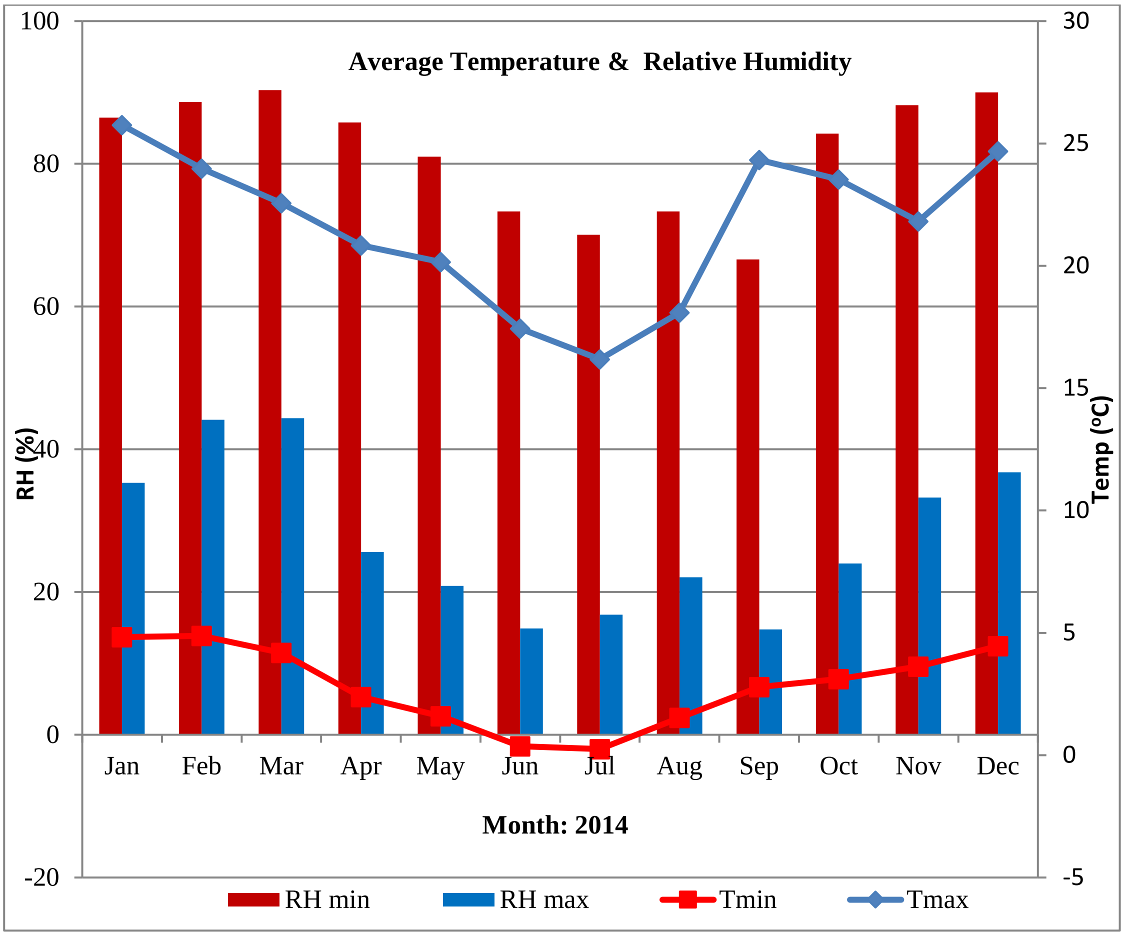



Figure 1:4 Monthly average Temperature and Relative Humidity at Clarens Golden Gate Agricultural Weather Stations

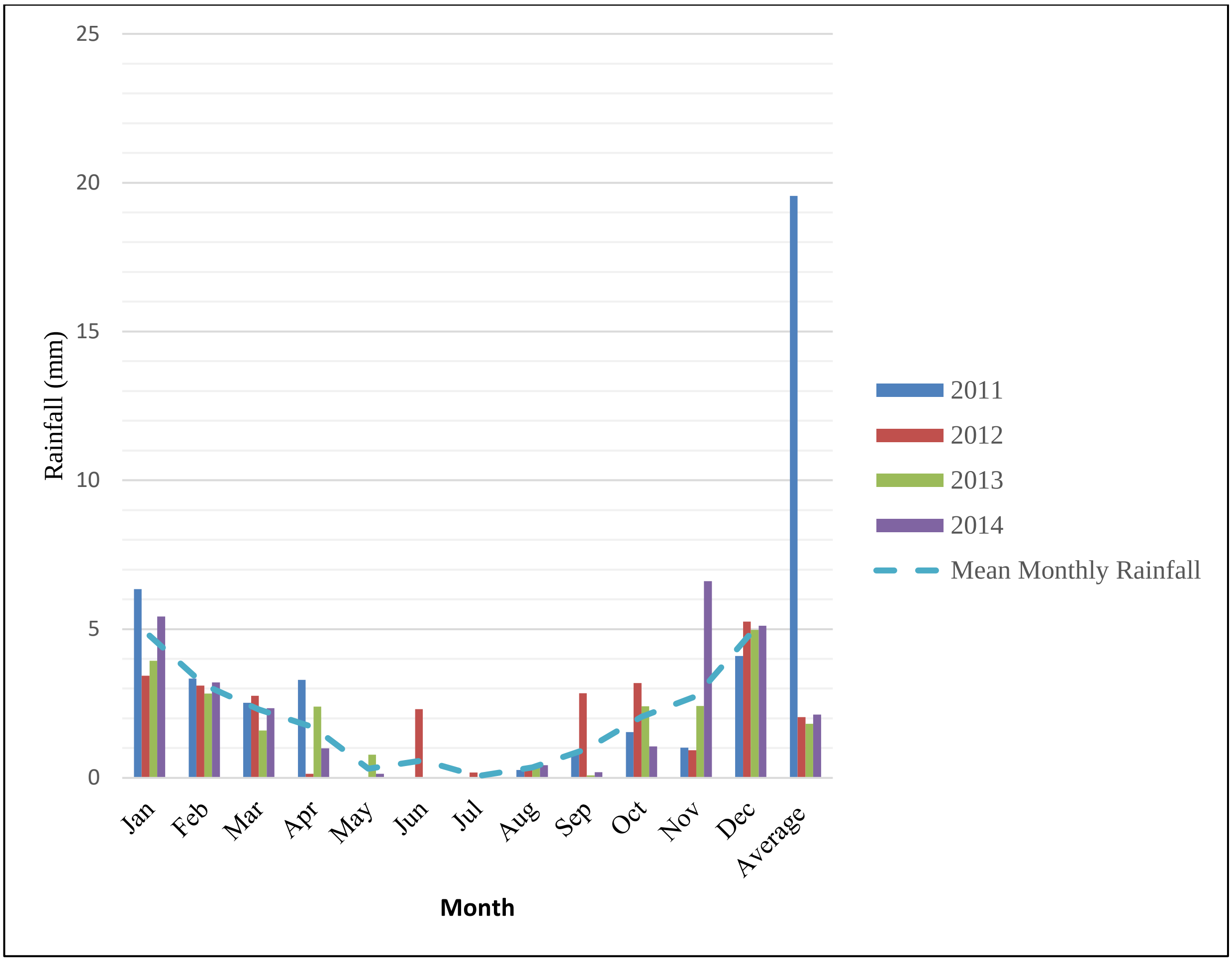



Figure 1:5. Average month rainfall (2011 -2014) at Clarens Golden Gate Agricultural Weather Station

## 1.9 Outline of Chapters

The dissertation was organized in four (4) chapters.

Chapter 1 provided background information about the consequences and effect of fires on ecosystem; drivers of wildfire; role of remote sensing in wildfire risk assessment and problem statements of the current wildfire risk assessment. This chapter also covered the study aim, objectives and the structure of the research report. Chapter 2 presented the literature review on remote sensing data and techniques used for monitoring fire risk conditions and its implications for fire risk assessment and mapping in protected areas. Chapter 3 presents the development of the scheme for estimating Fuel Potential Index using remote sensing-based variables and GIS for the mountainous GGHNP. Finally, Chapter 4 summarizes the research outcomes and recommendations for further improvements based on the results of chapter two (2) and three (3).

# Chapter 2

# Review of the Use of Remote Sensing for Monitoring Wildfire Risk Conditions to Support Fire Risk Assessment in Protected Areas

This chapter is based on:

Molaudzi, D.O and Adelabu, S. "Remote Sensing for Monitoring Wildfire Risk Conditions in Protected Areas" 11th International Conference of Africa Association of Remote Sensing of the Environment, 24-28 October 2016, Kampala, Uganda

Molaudzi D.O, Adelabu S.A & Mokubung C.L, "Review of the use of Remote Sensing for Monitoring Wildfire Risk Conditions in Protected Areas to support fire risk assessment" South African Journal of Geomatics (In review)

## ABSTRACT

*Fire risk assessment is one of the most components of the management of fire that offers the framework for monitoring fire risk conditions. Whilst monitoring fire risk conditions commonly revolved around field data, Remote Sensing (RS) play key role in monitoring and quantifying fire risk indicators. This study presents a review of remote sensing data and techniques for fire risk monitoring and assessment with a particular emphasis on its implications for wildfire risk mapping in protected areas. Firstly, we concentrate on RS derived variables employed to quantify both the intrinsic and extrinsic factors that influence vegetation flammability. Thereafter, an evaluation of the prominent RS platforms such as Broadband, Hyperspectral and Active sensors that have been utilized for wildfire risk assessment Furthermore, we demonstrate the effectiveness in obtaining information that have operational use or immediate potentials for operational application in PA. RS techniques that involve extraction of landscape information from imagery were summarised. A review has concluded that in practices, a fire risk assessment that consider all factors that influence fire ignition and propagation is impossible to establish, however it is imperative to incorporate indicators or variables of very high heterogeneous.*



**Keywords: Protected Areas, Fire Risk conditions; Remote Sensing, Wildfire risk assessment**

## 2.1 Introduction

Approximately 133,000 Protected Areas (PA) worldwide covering over 12% of the land surface of terrestrials biomes emerged as the cornerstone of efforts towards conservation (Nagendra *et al.*, 2013). PA is a clearly defined geographical space, recognized, dedicated and managed through legal or other effective means to achieve the long-term conversation of nature with associated services and cultural values (International Union for Conservation of Nature (IUCN), 2015). Fire is considered as a major factor of environmental transformation of ecosystem (Food and Agricultural Organisation, 2007). On the other hand, fire is recognized as an important ecological process used as the management tool for maintaining health ecosystem particularly in PA. However, fires in PA are paradoxical (Pereira *et al.*, 2012), in that if properly planned, desired outcomes such as regulating fuel accumulations, regeneration of vegetation by removing fungi and microorganisms, diseases and insect control, receiving more energy through exposure to solar radiation, mineral soil exposure and nutrients release (Bond *et al.*, 2005, Pausas and Paula, 2012) are achieved. In contrast, unwanted or uncontrolled fires can be destructive or result in ecological disturbance causing bush encroachment, invasion by alien plants, reduction in water yield and loss of biodiversity (Brown and Smith, 2002, Jhariya and Raj, 2014). It is always a challenge to reconcile the fire management goals that relate to safety on one hand to the maintenance of ecosystem health as acknowledged by Van Wilgen *et al.* (2011). Because approaches to fire management in PA have focused on encouraging particular fire patterns in the absence of sound monitoring and assessing fire risk conditions (Mbow *et al.*, 2004). Hence, it is imperative to develop an effective and efficient fire management plan to reduce these losses and optimize the benefits from fires. Towards the achievement of this goal, fire risk assessment has been commended as one of the major components of integrated fire prevention and management (Chuvieco *et al.*, 2004a, Leblon *et al.*, 2012, Yebra *et al.*, 2008).

Different systems or techniques have been used to monitor and assess fire risk conditions in the past. For instance, conventional methods such as (i) field reconnaissance (traversing the landscape on the ground and recording the extent of similar fuel conditions in notebooks or on paper maps); (ii) directly mapped fuel from aerial photo interpretation and (iii) ecological modelling approach which uses environmental gradient to create fuel maps for monitoring vegetation conditions have been applied for fire risk assessment (Arroyo *et al.*, 2008, Keane *et al.*, 2001). Field sampling involving oven drying methods such as gravimetric sampling (involves comparing the difference in weight of sample from the field and its oven drying) (Aguado *et al.*, 2007) and analogue sampling methods (involves the repeated weighing of a sample exposed to field conditions) such as calibration of a sticks known as hazard sticks (Yebra *et al.*, 2013) were employed to measure fuel moisture content. In addition, Fuel moisture content (FMC) has been indirectly measured using meteorological variables through the analysis of atmospheric characteristics from which fuel water status is estimated (Yebra *et al.*, 2008). Although these conventional methods are considered to be reliable, accurate and useful for calibration and final product accuracy assessment of derived from remote sense data (Arroyo *et al.*, 2008), they however suffer from numerous drawbacks. For example, field measurements are primary based on point-source data. In general, to forecast fire danger rating over a large geographic regions point data must be interpolated (Leblon *et al.*, 2012) which would be quite expensive and laborious in terms of data collection and its processing (Chowdhury and Hassan, 2015). Therefore, Leblon (2005) argued that the accuracy of ratings may be limited by the density of point data and interpolation methods that generally does not account for fine-scale variations in environmental conditions.

In the past three decades, passive and active remote sensing systems have been employed to address the spatial and temporal interpolation limitations associated with conventional methods with obvious advantage of spatial and regular temporal coverage (Dalponte *et al.*, 2009). With the consideration of the characteristics of various remote sensing systems developed over the past decades, the significant mandate of PA and the impacts of fire as well as heterogeneity of environmental factors that influence vegetation flammability need to be considered. Questions such as how to ensure the long-term sustainability of the PA with complex landscape where diverse conflicts of interest meet, i.e. nature conservation and tourism (Aretano *et al.*, 2015). How to effectively apply fire as ecological process and develop sound fire management strategy and how to monitor fire risk conditions for fire risk assessment based on the remote sensing technology has become a critical question within PA. Therefore, summaries and comparisons of different remote sensing approaches are urgently required and indispensable for PA management to better understand the mechanisms of interactions between vegetation characteristics and its environmental conditions. Thus, the objective of this manuscript therefore is to review different remote sensing data and techniques that have been used for predicting and monitoring fire risk conditions and its implication for fire risk assessment and mapping in PA.

## 2.2 Remote Sensing in Monitoring Vegetation Conditions for Fire Risk Mapping.

In wildfire risk assessment, RS assists in elaboration of fuel or biomass maps in order to create a permanent and static database and to determine the meteorological conditions and vegetation state in real time and in dynamic way in order to provide the risk indexes (Calle and Casanova, 2008). Several studies have demonstrated the existence of relationship between fire and vegetation characteristics (Lozano *et al.*, 2007, Schneider *et al.*, 2008) as well as the relationship between remote sensing and these variables or indicators (Arroyo *et al.*, 2008). However, in order to understand the usefulness of remote sensing in monitoring and mapping wildfire risk conditions, it is crucial to understand the relationship between environmental conditions and fire occurrence following protocols as suggested by Chowdhury and Hassan (2015). In doing so, more information on remotely sensed data used to quantity vegetation flammability was discussed.

### 2.2.1 Vegetation flammability remote sensing derived indices

Generally, remote sensed based vegetation and water indices have been used to assess the extent of vegetation flammability conditions and to understand the fire risk conditions. In simplicity, Chowdhury and Hassan (2015) on the basis of environmental conditions broadly categorised these indices into (i) vegetation greenness, (ii) meteorological variables; (iii) surface wetness conditions and (iv) vegetation wetness conditions.

#### *2.2.1.1 Vegetation greenness*

Vegetation greenness-related indices have been immensely used for obtaining information relative to the photosynthetic state of the vegetation and is based on the spectral signature of vegetation greenness expressed in Red (R) and Near Infrared (NIR) portions of the spectrum (Table 1). The internal structure of healthy leaves act as excellent diffuse reflectors of near-Infrared reflectance wavelengths and therefore measuring and monitoring near–infrared reflectance (NIR) is used to determine the healthiness of the vegetation (Barroso and Monteiro, 2010). The healthy vegetation shows a very low reflectivity in the Visible Band of the electromagnetic spectrum (0.4 -0.7 micrometer), less than 20% and its local maximum belong to colour green (0.55 micrometer). While unhealthy vegetation lack of chlorophyll in their leaves makes the spectral curve of reflectivity move significantly towards the red colour (Calle and Casanova, 2008).

Normalized Difference Vegetation Index (NDVI) also known as "continuity Index is calculated as function of surface reflectance of red (0.6 – 0.70 µm) and NIR (0.70 – 0.90 µm) (Huete *et al.*, 2002). No doubt, that NDVI is one of the immensely utilized and well-known VI in measuring both morphological and physiological characteristics of the vegetation conditions for estimation and monitoring fire risk conditions for fire risk assessment and mapping with PA. For example, NDVI have been used to distinguish shrub height in order to distinguish shrub for description of fuel conditions (Riaño *et al.*, 2007), to evaluate vegetation cover or canopy cover (Falkowski *et al.*, 2004); Leaf Area Index (LAI)(Yebra *et al.*, 2008); biomass (Saatchi *et al.*, 2007, Sannier *et al.*, 2002, Verbesselt *et al.*, 2006b); phenology (Van Wagtendonk *et al.*, 2003), and fraction of Absorbed Photosynthetic Active Radiation ( fAPAR); fractional of vegetation cover (fPAR) (Jia *et al.*, 2006b).

Other indices based on R & NIR exhibit strong relationship with vegetation or fuel conditions than NDVI in the both protected and unprotected areas. For example, Soil Adjusted Vegetation Index (SAVI) that take into account the influence of bare, unsaturated soil backgrounds in order to minimise soil noise (Huete, 1988, Moreau *et al.*, 2003). While Enhance Vegetation Index (EVI) is an example of optimized spectral band combinations that aim to minimize VI biases from canopy background and aerosol variations and outperformed NDVI over high biomass area since it does not saturate easily and it is recommended for tropical dense vegetation (Huete *et al.*, 2002, Huete, 2012). Visible Atmospherically Resistant Index (VARI) was developed for estimating green vegetation fraction since it minimizes the sensitivity to atmospheric effects (Stow *et al.*, 2005). Since NDVI is also known to be impacted by the surface bi-directional reflectance distribution function depending on the structure of the vegetation (Gao *et al.*, 2002), Newnham *et al.* (2011) used Relative Greenness (RGI) calculated from minimum and maximize of NDVI to assess the grassland curing (the senescence of plant material caused by seasonal weather pattern, species-specific phenological cycles and plant succession). The results showed that RG explained a greater proportion of the variance and provided a more accurate estimate of the degree of curing than linear regression against NDVI. The study conducted by Zhang *et al.* (2005) at Grassland National Parks commended the use of Global Environmental Monitoring Index (GEMI). GEMI, one of the hybrid vegetation indices for extraction of biomass data because is good for vegetation canopy of low cover. On the hand, Bisquert *et al.* (2014) established that GEMI and EVI were the best indices to characterized the state of vegetation at their protected area of Galicia and Asturias in Spain.

Table 2.1. Selected vegetation greenness indices in monitoring fire risk conditions in the literature

| Indices | Formula | Reference |
|---|---|---|
| SR | $SR = NIR/R$ | (Falkowski *et al.*, 2004) |
| NDVI | $NDVI = (NIR - R)/(NIR + R)$ | (Rollins *et al.*, 2004); (Bisquert *et al.*, 2014); (Wang *et al.*, 2013b) |
| SAVI | $SAVI = (NIR - R)/(NIR + R + L) * (1 + L)$ | (Verbesselt *et al.*, 2006b) (Huete *et al.*, 2002) |
| VARI | $VARI = Green - R/ Green + R + Blue$ | (Gitelson *et al.*, 2002) (Schneider *et al.*, 2008); (Stow *et al.*, 2005); |
| GEMI | $GEMI = ŋ (1 - 0.25ŋ) _ [(R - 0.125)]/1 - R$ Where Ŋ = $2(NIR^2 - R^2) + 1.5R_2 + 0.5NIR_2 / R + NIR + 0.5$ | (Pinty and Verstraete, 1992); (Bisquert *et al.*, 2014) |
| RGI | $RGI = NDVIi - NDVImin / NDVImax - NDVImin$ | (Schneider *et al.*, 2008);(Riaño *et al.*, 2002);(Oldford *et al.*, 2006);(Newnham *et al.*, 2011) |
| EVI | $EVI = 2.5 [(NIR - R)/ (NIR + 6 R - 7.5 BLUE + 1)]$ | (Huete *et al.*, 1984); (2002); (Mildrexler *et al.*, 2007); (Bisquert *et al.*, 2014) |

#### *2.3.1.2 Meteorological index*

Remote Sensing meteorological variables such as Surface Temperature ($T_s$), Air Temperature ($T_a$) and Relative Humidity (RH) are used as indicators in monitoring and analysis of fire risk conditions. Keetch-Byram Drought Index (KBDI) is a fire/drought index that has been used to estimate fire risk conditions from meteorological data such as daily maximum temperature, daily total precipitation and minimum annual precipitation (Keetch and Byram, 1968). KBDI is strongly related to vegetation water content since most of the vegetation moisture stress are caused by soil moisture deficiencies (Aguado *et al.*, 2003) and it has been recommended for operational use in South Africa (Dimitrakopoulos and Bemmerzouk, 2003). Its utility has been effectively demonstrated on shrub species or herbaceous fuel moisture content (Riaño *et al.*, 2005).

### *2.3.1.3 Surface Wetness Conditions*

Surface Wetness Conditions have been monitored based on the concept of evapotranspiration (ET). ET is described as the loss of water from the Earth's surface to the atmosphere by the combined processes of evaporation from the open water bodies, bare soil and plant surfaces, etc. and transpiration from vegetation or any other moisture containing living surface (Li *et al.*, 2009). RS-based ET estimation methods can be broadly categorised into the following groups based on the following principles (i) water balance,(ii)surface energy balance, (iii) vegetation indices and (iv)hybrid approaches based on vegetation indices and $T_s$ (AghaKouchak *et al.*, 2015). In fire risk assessment, hybrid approaches had been widely applied whereby Surface Temperature ($T_{S)}$ has been incorporated with the vegetation greenness variables to indirectly estimate the surface wetness condition as the indicator for wildfire risk. For example the ratio of NDVI/$T_s$ (Aguado *et al.*, 2003, Prosper-Laget *et al.*, 1995); and EVI/Ts (Mildrexler *et al.*, 2007). The incorporation of NDVI and $T_s$ assists in justification for the influence on the ground cover rate over the composite $T_s$ measured by the sensors (Leblon *et al.*, 2012). This resultant to the various indices such as Stress Index (SI) (Vidal *et al.*, 1994), Water Deficient Index (WDI) (Moran *et al.*, 1994, Vidal and Devaux-Ros, 1995); Temperature –Vegetation Wetness Index (TVWI) (Akther and Hassan, 2011).

WDI developed by Moran *et al.* (1994) estimated by the ratio of LE/LEp by using land surface temperature and ambient $T_a$ and has been used for partially vegetated covers. $LE_p$ is the latent heat flux for potential evapotranspiration rate (Rahimzadeh-Bajgiran *et al.*, 2012) and have a potential for evaluating evaporation rate and relative field water deficient for both full cover and partially vegetated sites (Verbesselt *et al.*, 2002). TVWI was developed by Sandholt *et al.* (2002) as a simplification of WDI by interpreting the relationship between LST and NDVI in terms of soil moisture. It is important for the PA managers to note that these evapotranspiration-concept indices are acquired through thermal inertia approach and have two important limitations as described by (Calle and Casanova, 2008). Firstly, indices only yield to satisfactory results in soils with little vegetation cover since the latter reduces the temperature differences between day and nights. Secondly, in order to determine the moisture in a concrete point it is necessary to have the day and night temperature in a cloud –free images. However, globally thermal inertia and moisture are empirical parameters which provide a reasonable solution to the energetic balance equation (Calle and Casanova, 2008).

### *2.3.1.4 Vegetation Cover Moisture*

In general, quantification of vegetation/fuel cover moisture has been conducted through the measure of FMC as defined above or the Equivalent Water Thickness (EWT) defined as ratio between the quantity of water and the leaf area (Leblon *et al.*, 2012) and Relative Water Content (RWC) compare the water content of a leaf with the maximum water content at full turgor (Ceccato *et al.*, 2002, Wang *et al.*, 2013b). It is regarded as extremely essential vegetation condition parameter since it has inverse relation with ignition probability owing to the fact that the energy necessary to start a fire is used up in the process of evaporation before the fire starts to burn (Dimitrakopoulos and Bemmerzouk, 2003). Moreover, fuel cover moisture dilutes volatiles and excludes oxygen from combustion zone, however, the water content also affects fire propagation as the source of the flames as it reduced with humid materials and therefore reduce vegetation flammability (Chuvieco *et al.*, 2009). Most studies have directly measured vegetation water content by utilizing water absorption channels in the SWIR and contrast it with NIR channels to account for the variations in reflectance due to leaf internal structure (Dalponte *et al.*, 2009) (Table 2.2.). However, the sensitivity of these indices to the fuel moisture content or vegetation water content varies and similarly fire risk index yield to dissimilar results when applied to different biomes or geographic and these creates a confusion concerning their efficiency on which the PA managers should take into consideration. Therefore, the best index account for the changes in vegetation studies must be determined for each species or regions. With the acknowledgement of limitations related to VI, the researchers have developed and improved techniques by using hyperspectral and hyper-temporal remote sensing derived indices as well by integrating differences indices. For example, Accumulative Relative Normalized Difference Vegetation Index (ARNDVI) and integral Ratio Vegetation Index (iRVI) for VWC and biomass respectively were used to improve fire risk assessment in savannah ecosystem in Kruger National Park of South Africa (Verbesselt *et al.*, 2006b). Hence, it is vital important for PA to consider the ratio indices for better operational fire danger estimation.

#### *2.3.1.5 Other variables*

Topography is a very important extrinsic, physiographic variable under static risk which is related to wind behaviour and then affects the fire proneness (Jaiswal *et al.*, 2002). It affects the fire risk condition through configuration, exposure and slope (Calle and Casanova, 2008). RS imagery from High spatial resolution airborne laser altimetry tool has the capacity to measure surface topography commonly used to develop Digital Elevation Models (DEM) or Digital Terrain Models (DTM). DTM provide the base elevation which is subtracted from digital surface model to estimate vegetation heights and fuel loading (Morsdorf *et al.*, 2008). Moreover, DTM can be used as topographic inputs or base elevation map subtracted from canopy and vegetation height to access fuel (Burns, 2012). Other variables or parameters, which are very important in fire ignition and suppression, are related to human-socio factor, which includes factors such as proximity to roads, settlement, rivers or drainage, recreational activities in the natural areas (Chuvieco *et al.*, 2010).

Table 2.2. Selected vegetation wetness condition indices derived as a function NIR and shortwave infrared (SWIR) to determine the fuel moisture content for fire risk

| **Indices** | **Algorithm** | **References** |
|---|---|---|
| Normalized Difference Water Index | $"NDWI = " (\rho NIR - \rho SWIR)/(\rho NIR + \rho SWIR)$ | (Gao, 1996); (Verbesselt *et al.*, 2006a) |
| Global Vegetation Moisture Index | $GVMI = [(\rho NIR + 0.1) - (\rho swir + 0.2)]/[(\rho NIR + 0.1) + (\rho swir + 0.2)]$ | (Wang *et al.*, 2013b); (Ceccato *et al.*, 2002) |
| Normalized Differences Infrared Index | $NDII = \rho NIR - \rho SWIR/\rho NIR + \rho SWIR$ | (Hunt and Rock, 1989);(Chuvieco *et al.*, 2002) |
| Moisture Stress Index (MSI) | $MSI = \rho SWIR/\rho NIR$ | (Sow *et al.*, 2013) |
| Simple Relation Water Index (SRWI) | $SRWI = \rho NIR/pSWIR$ | (Gao, 1996); (Sow *et al.*, 2013) |
| Normalized Multi Drought Index (NMDI) | $NMDI = \frac{float(band2)-(float(band\ 6)-(band\ 7))}{float(band\ 2)+(float(band\ 6)-(band\ 7))}$ | (Wang et al., 2013), |

## 2.3. Remote sensing platforms for monitoring, assessment and mapping wildfire risk

Fundamentally, the choice of remote sensing data will depend on the amount of information or variables that is available to create a fire risk index or model to suffice degree of accuracy and to monitor changes (Kennedy et al., 2009). Furthermore Nagendra *et al.* (2013) highlighted three critical aspects that should be considered in the selection of datasets, i.e. (i) Scale (spatial and temporal), (ii) the adequacy or quality of spatial datasets and (iii) dataset sources. Different RS instruments and platforms have been utilized in the past decades for acquiring imagery to extract indicators for monitoring fire risk conditions for wildlife risk mapping with differences success. Thus, a review of the prominent remote sensing platforms that have been utilized for obtaining information that have operational uses or immediate potentials for operational application in PA management are explored in the following section.

### 2.3.1. Broadband sensors

Remote sensing broadband sensors imageries have been found to effectively monitor vegetation conditions for fuel or biomass mapping and fuel moisture content in wildfire risk assessment for PA. Landsat and other coarse, medium to high spatial resolution sensors have relative good spatial and spectral resolution essential for the fuel mapping. The 30m spatial resolution of Landsat sensors allows spatial detail to be captured at a scale appropriate for monitoring vegetation structure and composition (Willis, 2015) and good spectral resolution of seven bands. Erten *et al.* (2004) used

Landsat TM images taken before and after the forest fire in Gallipoli Peninsula Historical National Park in Spain to map burned area and to estimate vegetation moisture context in conjunction with topographic maps, forest type map, vegetation map, elevation, slope, aspect, topographic map and climate data (average, wind, rainfall data and temperature to determine fire risk areas. The authors concluded that remote sensing is a useful tool to determine fire risk area and could support fire management activities. Banu *et al.* (2014) employed Landsat 8 imagery to estimate the vegetation moisture in combination with other variables for the cartographic wildfire risk areas in National Park Domogled- Cerna Valley in Romania. Because of its revisiting time of 16 days, the operativeness for estimation of the FMC in real time is ruled out (Calle and Casanova, 2008) and the constraints to cover a cloud-free landscape in a large area, it is difficult to reveal key characteristics of the plant where vegetation is highly dense or saturated (Mbow *et al.*, 2004).

As an alternative, Advanced Very High Resolution Radiometer (AVHRR) sensors of National Oceanographic and Atmospheric Administration (NOAA) with a daily temporal resolution have demonstrated to be effective for mapping fire risk (in particular dynamic fire risk map) through the study of water stress. Sannier *et al.* (2002) used NOAA- AVHRR to estimate the biomass for wildfire risk assessment in Etosha National Park. The study had demonstrated the suitability of AVHRR for measuring biomass of grassland in the Park. Maselli *et al.* (2003) used past-fire occurrence data and NOAA-AVHRR NDVI data of 16 years (1985-2000) to estimate fire risk in Tuscany (Central Italy . AVHRR has an image archive with long history, it is useful to study long-term changes of vegetation however its utility has been restricted because its often introduce substantial errors at the various stage of processing and analyzing (Xie *et al.*, 2008).

Another sensor that has been applied in wildfire risk mapping is Système Pour I'Observation de la Terre (SPOT) managed by French Space Agency (CNES). Verbesselt et al. (2006a) used SPOT VEGETATION time-series to monitor the vegetation biomass and water content to improve fire risk assessment in the savannah ecosystem of Kruger National Park in South Africa. This study illustrated the importance for the combination of both vegetation biomass and vegetation water content for fire risk assessment. The study concluded that monitoring of vegetation biomass and water content with SPOT VGT provided a more suitable tool for fire management and suppression compared to satellite-based fire risk assessment methods only related to vegetation water content.

Fire risk assessment and mapping have been extensively investigated using Moderate Resolution Imaging Spectro-radiometer (MODIS). For example, Yebra et al. (2008) estimated FMC of Mediterranean vegetation species using a 5-year time (2001 -2005) of Terra MODIS for fire risk assessment in the Cabañeros National Park (Central Spain) offering reasonable result with better performance on grassland (91% & 89%) than shrublands (73% and 84 %). Dlamini (2011) used MODIS Terra and Aqua satellites' active and burnt area data for the period of between April 2000 to December 2008 and January 2001 and December 2001 respectively, to analyse and process the biophysical and socio-economic variables to generate a fire risk map of the Kingdom of Swaziland. Accuracy assessment and comparison of the fire risk maps resulted in 93.14% and 96.64% accurate respectively, showing adequate agreement between risk maps and the existing data. Although the model is valid for generalized national planning and assessment purposes the author suggested that more work is needed to improve data collection and integration for practical application in near real-time fire risk analysis. Furthermore, the utility of MODIS data was found to be useful for estimating herbaceous water content and for monitoring the drying process of herbaceous vegetation and in the management of savannah fire by the study conducted by Sow *et al.* (2013) at Senekal. In comparison with other broadbands sensors, MODIS data are available at a significantly higher temporal resolution (daily) with the spectral bands available in Landsat data. However, MODIS imagery has limitations for monitoring land cover changes (Gillespie *et al.*, 2014) and for validating fire susceptibility indices because of possible over or underestimation of the model performance since some large fires have several fires detections which are likely to have similar environmental conditions and spatial and temporally correlation (Schneider *et al.*, 2008).

Data from Very High Resolution (VHR) multispectral remote sensing image such as Quickbird was employed to map the forest fuel in central Spain and reported an overall accuracy of 85% (Arroyo *et al.*, 2006a). The study illustrated that VHR data can be used to create fuel classification that are potentially useful in the prediction of fire behaviour and effects. Similarly, Santi *et al.* (2014) used QuickBird data for mapping fine and coarse biomass/fuel in Florence, Tuscany by determining the relationship of NDVI and fine and coarse biomass. Giakoumakis *et al.* (2002) used both Landsat TM and IKONOS imageries to develop fuel type mapping. IKONOS was found to be useful than Landsat TM for the forest density measurement. However, because of its poor spectral information unnecessary data were included in the results as unclassified (noise). The primary value of VHR imagery for fuel mapping therefore lies not only its ability to produce high resolution maps but also in its potential to improve fuel map accuracy with its capability to detect submetric fuel components (Arroyo *et al.*, 2006b). The application of VHR is limited to study special topics in relatively small area (local scale) due to its high cost and rigid technical parameters (Xie *et al.*, 2008). Although not for fire risk assessment, the utility of WorldView 2 images were recommended for mapping tree species and canopy gaps in one of the protected subtropical forest in South Africa (Cho *et al.*, 2015).

Meteosat Second Generation (MSG), the new generation of geostationary meteorological satellite developed by the European Space Agency (ESA) in close corporation with the European Organisation for the Exploitation of Meteorological Satellites (EUMESAT), possesses a high temporal resolution (a near earth image every 15 min) together with a spatial resolution (3 km at sub-satellite point) appropriate to regional to continental scales. In addition, the optical imaging radiometer on-board MSG (Spinning Enhanced Visible and Infrared Imager (SEVIRI) presents spectral capabilities that are very similar to the TIR bands around 10.8 and 12.0 μm of the NOAA- AVHRR series (Peres and DaCamara, 2004). These temporal, spatial and spectral characteristics make MSG-SEVIRI suitable for retrieval of environmental parameter that change rapidly in time. Nieto *et al.* (2010) used MSG-SEVIRI data to estimate dead fuel content in the Iberian Peninsula of Spain. The accuracy assessment showed a negative bias comparison between equivalent moisture content (EMC) of the vegetation derived from $T_a$ and vapour pressure, and surface meteorological data. The remote sensed tends to underestimate the EMC from the ground. The authors recommended the improvements in $T_a$ and vapour pressure would lead to a better agreement between the observed and the predicted values and alternative method for estimation NDVI max that produced unbiased estimation of $T_a$.

### 2.3.2 Hyperspectral remote sensing

Advancement in remote sensing and imaging spectrometry led to the development of hyperspectral imagery which has demonstrated to be useful for the spectral and spatial discrimination of fire-related vegetation attributes such as green canopy closure, vegetation moistures, ratio dead to live plant materials and distribution of bare ground (Wang *et al.*, 2010). Hyperspectral imagery also known as Imaging Spectrometers (IS) are instruments that have the ability to collect ample spectral information across a continuous spectrum general with 100 or contiguous spectral bands across the visible (VIS), NIR and SWIR regions of the electromagnetic spectrum, offering unprecedented detailed spectral reflectance data from land surface features. Because of its fine spectral information facilitates hyperspectral sensors have been used for remote sensing mapping of biophysical and chemical information that is directly related to the quality of wildfire fuel including fuel type, fuel moisture, green biomass and fuel conditions (Yoon and Kim, 2003). Kötz *et al.* (2004) demonstrated the potential for utility of imageries from hyperspectral remote sensing in assessing and mapping wildfire risk assessment. Jia *et al.* (2006a) used AVIRIS data to map major forest components and fuel types by discriminating the fractional covers of photosynthetic Vegetation (PV), non-photosynthetic vegetation (nPV) and bare soil with 73,5%, 40,3% and 77,6% for PV, NPV and soil respectively. These make hyperspectral remote sensing an excellent indicator not only for fuel fractional cover but also for fuel condition after fire by greatly improving regional fire risk assessment.

Similarly, Dennison *et al.* (2006) illustrated the ability of hyperspectral data AVIRIS to retrieve both fire temperature and background land cover for fire spread model in wildfire risk assessment with the conclusion that fire and fuel information extracted from hyperspectral data provide the basis for eventual real-time complex fire spread model. However, the limitations of AVIRIS are that it is only available in small areas upon request and that data processing requires special expertise and software (Jia *et al.,* 2006a). Additionally, the capability of Airborne Imaging Spectrometer data (DAIS7915 and ROSIS) to estimate structure and foliage water content of a coniferous canopy for fire risk assessment and fire impact management at Ofenpass Valley in Swiss National Park with accuracy assessment of 71,6% and 78,2% for foliage water content and dry matter respectively (Kötz *et al.*, 2004). Yoon and Kim (2003) applied Hyperion hyperspectral remote sensing data acquired to evaluate its potential of mapping fuel properties such fuel moisture, fuel greenness, live biomass and fuel types. Although the Hyperion imagery included a lot of sensor noise and poor performance in liquid water band, the overall results showed that Hyperion imagery is useful for wildfire fuel mapping. The usefulness of hyperspectral data to recognize and map fuel type was illustrated when the highest accuracy level of 90% was achieved when comparing the MIVIS based results with ground truth data of Pollino National Park in the south of Italy (Lasaponara *et al.*, 2006).

Thenkabail *et al.* (2004) compared the ability of Hyperion data with broadband sensors, hyper spatial IKONOS, Advanced LandImager (ALI) and ETM+ for southern Cameroon. The study established that even the most broadband sensors such ETM+, IKONOS and ALI had serious limitations in modelling biomass and in classify Land Use Land Classification (LULC) classes. The study showed the broadbands model that explained 13 -60% of the variability in biomass and LULC classification of 42% and 51 % with ALI sensor outperforming IKONOS and ETM+ sensors. When compared to other broadband sensors Hyperion produced models that explained 36 -83% more of the variability in rainforest biomass and LULC overall accuracy classification of 96% was achieved through Hyperion wavelengths. Recently, Mallinis *et al.* (2014) evaluate and compare the spectral and spatial information in Hyperion with QuickBird and Landsat TM image to discriminate and map Mediterranean fuel types. The results revealed that the overall accuracy of the QuickBird based fuel type mapping was high than 74% with quantity disagreement of 9% and allocation disagreement of 17%. The overall accuracy of classifications from Hyperion and Land TM fuel type maps were approximately 70% with 16% allocation disagreement and suggested that high spatial resolution might be more decisive than high spectral resolution in fuel type mapping of Mediterranean region. Although Hyperion has large number of spectral bands that should improve mapping, its operational use is limited by higher data cost, considerable more completed pre-procession phase due to data volume and inherent noise, in contrast to Landsat TM imagery which is easier to process, and covers a large area (Mallinis *et al.*, 2014). Implicitly assumptions of greater utility of High resolution satellite imagery are widespread but its credibility has been questioned depending not only on the classification content but on image acquisition parameters and scene configuration (Carter *et al.*, 2009). Based on the evaluation of classification results in terms of cost and technical characteristics the author suggested that the use of hyperspectral datasets is suitable for use in wildfire management although they are still unavailable and costly for most developing countries.

### 2.3.3 Active sensors

The emergence of active sensors such as Light detection and Ranging (Lidar) and RADAR sensors has resulted in increased emphasis on fuel treatment across wide range of spatial scale. Active sensors had been widely used to estimate various components of forest structures such as crown and stem biomass, foliage water content, crown bulk density and forest height that can be directly incorporated into fire spread and fire risk assessment (Saatchi *et al.*, 2007). Furthermore, it has be used as an effective solution for overcoming the difficulties encountered when mapping fuel using data derived from passive optical sensors (Arroyo *et al.*, 2008). It is employed to estimate fuel height which is critical both in fuel loads assessment and fuel discrimination and it provide information of surface fuels when they covered by forested canopy (Keane et al., 2001). Several studies have demonstrated the successful use of Lidar system in measuring vegetation characteristics. For instance, Morsdorf *et al.* (2008) employed Airborne laser scanner (ALS) to measure the location and geometry of individual trees and vegetation cover to quantify fire risk of Swiss National Park in Switzerland. Gonzalez-Olabarria *et al.* (2012) illustrated the operational application of Lidar derived data for fire risk assessment at the landscape level for fire management and planning. Due to its efficiency and ability to record elevation information below vegetation cover, Lidar has been effectively used to develop Digital Elevation Models (DEM) or Digital Terrain Models (DTM) (Burns, 2012). However, its affordability would be ultimately be limited by logistics costs and challenges associated with the deploying of such airborne sensor system in an African landscape (Naidoo *et al.*, 2012).

Similar to Lidar, active microwave sensors with the potential to complement optically measured characteristics of fuel. The widely used satellite microwave sensors such as European Remote Sensing Satellite Synthetic Aperture Radar (ERS-SAR) and RADARSAT have been beneficial in wildfire risk analysis. Leblon *et al.* (2002) demonstrated the efficacy of using imaging radar system to assess canopy and forest fuel moisture content through analysing the potential use of ERS-1 SAR backscatter for retrieving Fire Weather Index (FWI) data and FMC. The results revealed significant relationships between backscatter and the FWI, and between rate of change in backscatter coefficient and in the LFMC, and this indicate the usefulness of ERS-1 images in monitoring fuel moisture. The capability of RADAR system for monitoring forest fuel and as potential tool for forest fire risk assessment was illustrated by (Saatchi *et al.*, 2007) through the use of Airborne SAR imagery to estimate the distribution of forest biomass and canopy fuel loads in Yellow Stone National Park. The authors found good agreement between radar- generated fuel parameters and in-situ measurement with $r^2$ value of 0.85 (canopy fuel weight), 0.84 (canopy bulk density) and 0.78 (foliage biomass). While some studies including García *et al.* (2011) combined active and multispectral sensors for improving the accuracy of fuel mapping taking advantage of the information provided by Lidar data on vertical structure of the fuels and the capability of multispectral sensors to capture horizontal distribution of the fuels. SAR usually provide higher resolution images however has inherent of speckles which looks as a grainy texture due to random construction and destructive interference from multiple scattering (Chowdhury and Hassan, 2015). Other notable limitations include for instance right angle surface causes double bounce reflection, volume scattering may occur when radar beam penetrates the top most surface and the brightness of the image increase due to high moisture content of the target surface (Moreira et al., 2013). According to Levin and Heimowitz (2012) the radar operates under commercial mode and revisits time period is quite long (ERS1/2) repeat cycle is around 35 days compared to RADARsat -1/2 almost 24 days coverage which limits capturing the temporal dynamic of moisture conditions.

## 2.4. Remote sensing techniques for wildfire risk mapping

Regardless of the variety of uses for remote sensing images, the first goal is to extract landscape information from the satellite images. Image classification is defined as the process of extracting different classes or themes from raw remotely-sensed data (Xie *et al.*, 2008) is known to be a powerful technique to do so since mid-1800, when humans first identified different types of land-use and land-cover in aerial photography (Wang *et al.*, 2010). However, pre-processing image prior to information extraction in order to eliminate data registration errors and to increase interpretability of image is essential. Image pre-processing involves series of operation including but not limited to bad lines replacement, geometric and radiometric corrections, image enhancement & masking as well as geo-referencing. Techniques for extracting data from pre-processed images are grouped into two types: traditional and advanced methods.

Traditional methods include supervised and unsupervised classifications. In an unsupervised classification methods are purely relying on spectrally pixel-based statistics and incorporate no prior knowledge of the characteristics of the themes being studied (Xie *et al.*, 2008). Two most frequently applied methods are K-means (Bian *et al.*, 2013) and ISODATA (Puri *et al.*, 2011). In contrast, a supervised classification is an established classification from a training dataset, which contains the predictor variables measured in each sampling unit and assigning prior classes to sampling units being studies (Xie *et al.,* 2008). Maximum Likelihood classification is regarded as a classic and most widely used supervised classification method (Mbow *et al.*, 2004, Rahimzadeh-Bajgiran *et al.*, 2012, Verbesselt *et al.*, 2007). A parametric classifier that presuppose that training data values for each class in each spectral band are normally distributed (Schneider *et al.*, 2008). Pixel-based classification is associated with salt-pepper artefacts limitation (Arroyo *et al.*, 2006b). As a solution to derive on classification that is, more accurate, different approaches emerged and made significant contributions to the wildfire risk mapping.

While advanced methods also known as improved classifiers are generally based on traditional methods however focus on and expand on specific techniques or spectral features that can lead to better classification results. For example, with an increase of high-spatial resolution satellite data, pixel-based classification algorithms tend not to be ideal to extract information desired from the data exhibiting high frequency components with high contrast and horizontal layover of objects (Wang *et al.*, 2010). Therefore, objected-oriented classification algorithms have been developed as a solution to this limitation. In object-based approach, pixels are aggregated before and not after classification. The classification is performed on groups of pixels (objects) identified according to predetermined rules and objects can be on the basis of spectral values, spectral variability, size, shape or in relation to neighbouring objects as well on hierarchical, with the arrangement of objects on one level informing the creation of higher –order objects (Arroyo *et al.*, 2006b).

Due to the sub-pixel issue associated with medium to coarse spatial resolution of operation satellite system like Landsat, a number of image analysis accommodating mixing problems exits (Gitas *et al.*, 2012). Spectral Mixing Analysis (SMA) has being the most common technique utilized in many applications (Riaño *et al.*, 2002, Veraverbeke *et al.*, 2014). SMA addressed this issue by quantifying the sub-pixel fraction of cover of different endmembers, which are assumed to be representing the spectral variability among the dominant terrain features. Support Vector machines (SVMs) are among advanced methods mostly used and highly performing one. SVMs are non-parametric linear classifiers that delineate the optimal separating hyperplane between classes by focusing on pixels that lie at the edge of the class distributions with the rest of the training sample effectively being discarded (Mallinis and Koutsias, 2012). Mallinis *et al.* (2014) used SVM method of classification for comparing the efficacy of Hyperion with Landsat TM and Quickbird imageries. However, the main issue with SVM include difficulty in choosing the best kernel function (Hussain *et al.*, 2013). Although SVM is complex and time consuming method (Hussain *et al.*, 2013), it has the crucial ability to detect low cover fractions, which remains challenge to conventional approaches. Besides typical techniques, Artificial Neural Network (ANN) a non-parametric approach appears to work well with training data sets that are smaller in size than those required for statistical procedures (Mallinis and Koutsias, 2012) has been used in wildfire risk analysis (Alonso-Betanzos *et al.*, 2002) however its functionalities are not common in image processing software (Hussain *et al.*, 2013).

Several studies in monitoring and mapping the wildfire risk combined more than one method or data source in order to address the shortcomings or limitations of another through integrated approaches known as data or image fusion. For instance, MODIS imagery has significant advantage in temporary resolution (daily) but it is very poor in spatial resolution 250,500 -1,000 m for certain applications whereas Landsat TM imagery performed well in spatial resolution (30 m) but with 16-day revisit. Chen *et al.* (2011) used MODIS – Landsat TM NDVI and fraction of photosynthetically active radiation (fPAR) data to assess pre-fire vegetation characteristics and fuel load change of Big Desert in south-eastern Idaho. Riaño *et al.* (2007) combined Lidar and Colour infrared Ortho images of Gestosa in Portugal for shrub height mapping.

Generally, the fusion techniques can be grouped into two classes : (i) colour-related techniques such as colour composites (RGB), intensity –hue – saturation (HIS) and (ii) statistical or numerical methods such as Principal Component Analysis (PCA) and Tasseled Cap Transformation (TCP, band combinations using arithmetic operators and others (Pohl and Van Genderen, 1998). TCP approach was employed on Landsat-ETM derived Wetness and Brightness Indices to assess the risk of intensive fire propagation in a National Park named Niokola Koba, Senegal West Africa (Mbow *et al.*, 2004). Xu *et al.* (2006) used PCA to sort-out the relationship between forest fire potentials and environmental factors to map forest fire risk zones in the Changbai Mountain of Jilin Province, China.

Integration of RS and GIS is becoming apparent technique in the wildfire risk mapping. There is mounting evidence illustrative the utility and operational application of this method of the combination of GIS and RS in wildfire risk assessment on which requires its own review. In summary, the contribution of RS to GIS includes: (1) RS develops thematic layers for GIS, such as surface elevation (Digital Elevation Model [DEM]), land use and land cover mapping, biophysical parameters, feature extraction and landscape change; and (2) RS provides ortho-imagery as base data, which plays key role in positioning, registration and geo-referencing. On the other hand, the contribution of GIS to RS consists of (1) mission planning; (2) ancillary data for geometric and radiometric correction, and image classification; and (3) collection, organization and visualization of reference data (Wang *et al.*, 2010).

## 2.5. Conclusion

The objective of this chapter therefore was to review different remote sensing data and techniques that have been used for predicting and monitoring fire risk conditions and its implication for fire risk assessment and mapping in PA. To effectively and efficiently use of fire as the management tool in PA, it is important to have knowledge on spatial-temporal distribution of fire risk conditions for design of fire prevention, detection, and suppression as well as fire effects assessment strategies. RS is capable of providing fuel type, load, LULC, topography and weather data at spatial and regular temporal coverage at cost-effective with zero destructive way for vegetation studies at remote and inaccessible areas. However, the selection of suitable RS data depends on the following: (i) description and scale of the study area; (ii) the cost of acquiring, processing the RS imagery as well as of the cost and maintenance of hardware and software; (iii) limitations and advantages of each sensor and the data source that has a record especially from reviewed literature (operativeness vs research purposes). These are important factors to be considered for monitoring fire risk conditions for fire assessment and mapping in PA.

The review indicated that numerous fire risk indicators have been introduced, however, in general Vegetation Greenness-related indices (based on chlorophyll absorption) such as NDVI, EVI and SAVI. Vegetation water related indices (based on water absorption) such as NDWI, NDMI and GVMI are the most commonly used indices for quantifying fire risk conditions with NDVI & NDWI at the top of the list. Overall RS remote sensing data, ranging from Broadband, Hyperspectral and active (LiDAR and Radar) have shown great potentials in monitoring fire risk indicators or variables for fire risk assessment at all scale. Based on their stress-free acquisition and accessibility, broadband Multispectral data have been found to be more effective for monitoring fire risk conditions at regional scale. However, mixed pixels and sensor saturation problem have been reported with these data in fire risk assessment for complex environments. Furthermore, the absence of red-edge and narrow bands to target and highlight specific biophysical parameters such as vegetation dry matter content and biomass estimation which are critical for fire risk assessment.

Although large number of spectral bands in Hyperspectral data should provide accurate mapping of fuel types and FMC, its operativeness in fire risk assessment in PA is limited due to higher data cost and more complicated pre-processing phase due to increase data volume and inherent noise. However, data from active sensors such as RADARSAT-3 and Sentinel 3 (that provide data continuity for ERS,) and Advanced Land Observing Satellite (ALOS) PALSAR-2 with different polarizations, resolutions, incident angles and microwave bands can offer great opportunity of introducing “multi-index of multivariate fire risk index” that combine both vegetation water content and surface wetness condition (soil moisture) in fire risk assessment. The Soil Moisture Active Passive (SMAP) is a further promising data source that should be evaluated for fire risk assessment in PA.

Remote sensing approaches to be useful for fire risk assessment in PA the study should be conducted not for research purpose only but also should be useful at the operational level. Moreover, the specific remote sensing tools and products as well the results should be communicated to the general decision-making in non-technical manner. Lack of error values evaluation uncertainty of the outcomes in the majority of the RS studies is a critical issue that often prevent stakeholders to trust RS data and techniques for conservation assessment in PA (Petrou *et al.*, 2015). Therefore, fusion of multisensory and multiresolution data might overcome problems faced by single dataset ad has the potential to improve fire risk assessment and mapping in PA. On that note, a lot of research is still need to be conducted to full understand the potential of multi sensoral or multi-variate fire risk index approach in fire risk assessment especially in PA.

Noticeably, long-term or structural, short-term or dynamic and advanced or FPI have been used extensively for fire risk assessment. However, despite the wide range availability of RS derived variables, the synergy between RS derived methods and operational fire danger forecasting systems have not been fully exploited mainly because of variation in temporal and spatial dimensions of both systems. Furthermore, a note should be taken that in practise a fire risk index that consider all the factors that influence or affect fire behaviour it is impossible to establish but it is necessary to incorporate RS indicators or variables of very high heterogeneous types.

Finally, for remote sensing approaches to be useful for the park or land resource management the study should be conducted not for research purpose only but also should be useful at the operational level. Moreover, the specific remote sensing tools and products as well the results should be communicated to the general decision-making in non-technical manner. Lack of error values evaluation uncertainty of the outcomes in the majority of the RS studies is a critical issue that often prevent stakeholders to trust RS data and techniques for conservation assessment in PA (Petrou *et al.*, 2015).

# Chapter 3

# Estimation of Fire Potential Index using Remote Sensing and GIS over the Mountainous Area of Golden Gate Highlands National Parks

This chapter is based on:

Molaudzi, D.O and Adelabu, S.A. “Development of Fuel Moisture Index for fire danger assessment over mountainous area using remote sensing”, Disaster Management Institute of Southern Africa (DMISA) Conference 2013, 27 -28 September 2017; Eastern Cape, South Africa

Molaudzi, D.O and Adelabu, S. “Estimation of Fire Potential Index using Remote Sensing and GIS over protected mountainous area” (In the preparation)

## ABSTRACT

*Fire is a good servant but a bad master. Effective application of fire requires a proper and effective integrated fire management plan. Fire risk assessment is the critical components of the plan. However, it is very complex. Thus, there is need to understand the complex parameters which are responsible for fire risk. Fire risk index can be useful for estimation of the vegetation susceptibility to fire occurrence. The objective of this chapter was to generate fuel potential index using remote sensing and GIS techniques for fire risk assessment of Golden Gate Highlands National Park. Remote sensed data has been used for creating data layers further FPI Map using GIS techniques. Parameters including Fuel moisture content was computed as a ratio of vegetation water index (Normalize Differences Water Index derive Relative Greenness Index* $RGI_{NDWI}$*) to a vegetation dry-matter index (Normalised Multi-Band Drought Indices). Potential Surface Temperature computed from Land Surface Temperature and Elevation. The results revealed that 34%, 42%,13%, 8% and 4% area of GGHNP are categorized under insignificant, low, medium, high and extreme high respectively. Largest area coverage of high to extreme fire danger classes was observed during 2013 (17%), followed by 2014 (16%), 2012 (8%) and 2011(6%). Whereas in monthly basis was observed in September (17%) followed by August (11%) and July (6%). The model revealed an overall accuracy of 89% ranging from 33%-100% indicating that maximum of fires fell under low to extreme high fire danger classes. GWR analysis show a sound agreement between FPI and the fire danger with overall* $R^2$ *of 0,69 ranging from 0,17 to 0,98. The goodness of fit of the model suggested that MODIS products and derived indices have a great potential to predict fire danger in GGHNP. These results indicate that this index might be useful for monitoring spatiotemporal distribution of susceptibility of vegetation to fire. It is imperative to consider that the derived fire potential or danger maps do not completely explain fire occurrence since high FPI values are necessary condition for, but not a cause of fires because fire only occurs when ignition agents is present.*



**Key words GGHNP, Fire Risk Assessment, Fire Potential Index, Remote Sensing**

## 3.1 Introduction

Historically, fire was regarded as a detrimental force and evil to be avoided, until many of fire ecologists begin to realise that fire is not that bad but a beneficial phenomenon that should be tolerated and understood (Van Wilgen, 2009). Fire is regarded as an important ecological agents, an organising factor of ecosystem sustainability (Pereira *et al.*, 2012). Some ecosystems like grassland require fires for its stability. Because without the existence of fire, ecosystem such as grassland would be substituted by forest (Bond *et al.*, 2005, Van Wilgen, 2009). Generally, the purpose of application of fire in the protected or non-protected area is to meet the specific ecosystem services (ES). The most significant role that the fire plays in the supply of ES is its use in maintaining fire-dependent vegetation structure, since the change in fire regime is likely to change vegetation structure and therefore alter the supply of services (Schmerbeck and Fiener, 2015).

Fire regimes defined by Forsyth *et al.* (2010) “as the history of fire in particular vegetation type or area including the frequency, intensity, season of burning” shape the functionality, structure and composition of ecosystem. Fire can be a good tool or a bad visitor. Stemming from this conundrum, fires have to be managed with the aim of preventing negative consequences and maximizing the benefit. Integrated fire management approach which include integration of fire prevention and fire suppression strategies for addressing this fire paradox has been commended (Silva *et al.*, 2010). However, from ecological point of view, fire suppression *per-sê* has been discouraged as a fire management strategy because it is creating flammable landscape (Bowman *et al.*, 2009).

Fire risk conditions have for considerable time been used for fire prevention (Sebastián-López *et al.*, 2002). Since fire risk conditions are dynamic and static both in spatial and temporal dimensions, therefore, it is a complex notion to measure (Chuvieco *et al.*, 2010). Furthermore, fire risk conditions are highly influenced by both biotic and abiotic factors (Fischer *et al.*, 2015). Quantification of biotic conditions or indicators aimed at studying the morphological (i.e. fuel load, composition, height and density) and physiological (i.e. moisture status and chemical properties) characteristics of vegetation (Flasse *et al.*, 2004, Xiao-rui *et al.*, 2005). While abiotic indicators are related to external conditions such as topography and meteorological factors (Calle and Casanova, 2008). Knowledge of the vegetation characteristics and its environmental conditions have shown to be critical, since they constitute primary components of fire risk (Chuvieco *et al.*, 2004b).

Several studies have demonstrated the relationship between fire occurrence and vegetation conditions (Lozano *et al.*, 2007, Sow *et al.*, 2013). In particular vegetation water content as a key factor and the most critical indicator affecting fire interaction with fuel (Chuvieco *et al.*, 2002). The most widely used parameter to characterized vegetation water content for fire risk assessment is Fuel Moisture Content (FMC) (Alonso *et al.*, 1996, Ceccato *et al.*, 2002, Chuvieco *et al.*, 2003, Chuvieco *et al.*, 2002, Roberts *et al.*, 2006, Verbesselt *et al.*, 2002, Wang *et al.*, 2013b, Yebra *et al.*, 2008, Zarco-Tejada *et al.*, 2003). Fuel Moisture Content is defined as the ratio of the water quantity in vegetation and the dry weight for both the dead and live vegetation (Chuvieco *et al.*, 2002, Verbesselt *et al.*, 2007, Yebra *et al.*, 2013).

Other variables including fuel load (the amount of biomass per unit area or fuel density (the weight per unit volume of fuel), fuel type, meteorological parameters such Surface Temperature ($T_s$), Air Temperature ($T_a$), and precipitation as well as topography have been widely used as direct or indirect fire risk indicators. These variables are measured and integrating into an index, in thus, several indices have been developed for fire risk assessment based either on the temporal scale by European Union's Joint Research Centre (Adab *et al.*, 2011) or variables data sources (Gabban *et al.*, 2008).

On temporal-scale basis, fire risk indices can be categorized into long-term or structural indices, short-term or dynamic indices or integrated indices (San-Miguel-Ayanz *et al.*, 2003). Adab *et al.* (2013) constructed long-term or structural indices that consider static ( do not change over the short period of time and considered stable (for a given period not smaller than a year) variables including vegetation type, land cover, land use, slope, aspect, distance to roads and vicinity to settlement areas, climatic variables and soils. This index often adopted to identify fire danger that can be identified before the fire season (Carrao *et al.*, 2003) in order to identify areas where static or extrinsic factors influence vegetation flammability. (ii) Short-term or Dynamic Index created from the variables that change moderate continuously due to vegetation or weather conditions. This index detect the susceptibility of vegetation during fire season and to identify areas where intrinsic factors may be more favourable to fire (Dasgupta *et al.*, 2006). Hence it uses variables that change in short period of time (Adab *et al.*, 2013).

Based on the variable data-source, meteorological indices derived from meteorological variables, for instance, most of indices if not all used to compute National Fire Danger Rating Systems (Chowdhury and Hassan, 2015). Remote sensing derived indices make use of remote sensing data to estimate vegetation conditions in relation to photosynthetic activity or environmental conditions (Mbow *et al.*, 2004). Finally, integrated or advanced indices are those that agglomerates several of the variables that are independently taken into account by long-term and dynamic indices and make use of both meteorological and remote sensed derived data, also known as Fire Potential Index (San-Miguel-Ayanz *et al.*, 2003).

FPI estimates vegetation susceptibility to ignition, however does not take into account the probability of ignition source(Burgan *et al.*, 1998). FPI is a fire risk index that is highly specific for fuel type, weather condition and vegetation status (Huesca *et al.*, 2014). United States Geological Survey (USGS) (2016) describe FPI as a moisture-based vegetation flammability indicator for fire risk assessment. In comprehending fire risk assessment and increasing the robustness of the indexes, most of the researchers developed FPI as the combination of both meteorological and remote sensing data. On which meteorological indexes take into account the characteristics of the climate which is related to dead fuel conditions while RS provide data about live vegetation (Martínez *et al.*, 2007). For example: (i) Burgan *et al.* (1998) pioneered FPI and used NOAA AVHRR images to calculate NDVI to develop Relative Greenness Index Map and fuel type map in conjunction with meteorological station- based Relative Humidity and Air Temperature for 10-hour dead fuel moisture in the United State of America and exhibit a strong relationship with fire frequency $R^2$=0.72. (ii) Sebastián-López *et al.* (2002) employed the same method for the assessment of forest fire risk at the European scale. The results showed that the model identifies well those areas at risk of fire. The FPI values increases when the fire density values increases. (iii) Applying the similar approach, Huesca-Martínez *et al.* (2007) investigated the suitability of NDWI derived from MODIS in comparison with NDVI to assess fire potential in three different bio-climatic region of Navarra Automatic Community in Europe for the period of February 2000 – 2005. The researchers showed the usefulness of MODIS SWIR band for characterizing fire potential dynamics at a regional scale. $FPI_{NDVI}$ outperformed by $FPI_{NDWI}$ in Atlantic bioclimatic region indicating that NDWI is useful vegetation index for estimation fire potential in the region.

Although point-based measurements are reliable, the spatial dynamics of the fire danger is calculated using geographic information (GIS)-based interpolation techniques. However, these techniques may produce different map outputs using the same input datasets (Chowdhury and Hassan, 2013). In order to eliminate these uncertainties, remote sensing based data have a greater advantages over point-based data as it acquires the spatial variability and able to capture information over remote areas (Wang *et al.*, 2013b). In this context, Huesca *et al.* (2014) used MODIS derived NDWI as proxy for fire risk to model FPI. Results showed 93.18% accuracy and demonstrated the spatio-temporal dimension that RS data provide combined with statistical time series analysis make it possible to develop robust applications for environmental monitoring and forecasting. (v) Babu -Suresh *et al.* (2015) integrated MODIS derived parameters Potential Surface Temperature, Relative Greenness Index and Moisture Stress Index to develop FPI for fire risk estimation over mountainous area of Uttarakand state (India) with overall accuracy of 87.36%.

Most of the afore-mentioned fuel moisture based remote sensing have focused on live fuels but is less commonly used to estimate dead fuel moisture content (DFMC) because is primary affected by soil moisture near dead fuel surface (Dimitrakopoulos *et al.*, 2010). However, vegetation indices could be used indirectly to estimate dead leaves covering vegetation floor (Adab *et al.*, 2016). Due to uncertainties arise in estimating vegetation water content using NIR – SWIR indices since they cannot completely remove background soil effects (Gao, 1996). Therefore, a new index called Normalized Multi-Band Drought Index (NMDI) was introduced by combining multiple, rather than one SWIR band with a NIR band may provide a solution to separate vegetation and soil moisture variables by amplifying one signal and minimizing the other (Wang and Qu, 2007). Estimation of moisture content (LFMC) and DFMC is critically limited because of disparity in scale of between ground measurement and lower spatial resolutions hence using high resolution remote sensing imagery is a critical step to obtain accurate fire occurrence from MODIS data. The main aim of this chapter was to investigate the potential of remote sensing data in determining the susceptibility of vegetation to fire by developing a FPI for mountainous GGHNP. Firstly, the methods applied to generate remotely sensed risk variables or indicators in a spatial consistent way (geographical data layers) has been discussed followed by addressing the data integrating techniques into a synthetic FPI. Finally, statistical analysis was conducted to assess the effectiveness of the FPI model in fire danger rating.

GGHNP is a mountainous protected areas lies between 1892m and 2829m above sea level, in the foothill of Maloti Mountains in the Rooiberg ranges, north-eastern of the Free State Province in South Africa (Rademeyer and van Zyl, 2014, South African National Parks, 2013). Due to its topography, it is proclaimed as one of the mountainous protected area. Similarly, to other mountainous protected areas throughout globe, GGHNP is of international significances because of its spectacular scenery, quality conservation of natural and cultural resources while improving livelihood in the region. It is regarded as the learning and demonstration site with excellent education, research and awareness opportunities (South African National Parks, 2013). The park forms the part of the most important water catchment in Southern Africa (Drakensberg Catchment Complex) with the patches of high altitude wetlands. The question on how best to manage or use fire as the management tool in mountainous environments is thus an important one that has a bearing on wider range of issues (i.e. biodiversity, cultural and water-resources) than just to protect life and property. Protected area managers often use fire as intervention to influence vegetation structure and composition by manipulating the timing and frequency of fire(Van Wilgen *et al.*, 2011). Although the ecological understanding of the role of fire has advanced significantly over the past decades (Van Wilgen *et al.*, 2012), lack or limitation of information on fuel or vegetation status and fire risk conditions monitoring prior to application of fire as the management tool leads to a significant deterioration in natural vegetation and socio-economic loss. According to Govender (2011), on an average GGHNP lost 6809ha of vegetation to fire that account for 20% of the area . Therefore, fire related researches will be of significance for effective planning and implementation of fire management plans in order to realise its primary mandate of conservation and management of biodiversity, landscapes and associated heritage assets.

## 3.2 Methodology

### 3.2.1 Materials

Remote Sensing data from satellite images were used for this study as shown in Table 3.1.

Table 3.1. Dataset for the FPI

| S. NO | Name of dataset | ID Product | Spatial Resolution | Temporal Resolution | Data Source |
|---|---|---|---|---|---|
| 1 | Historical Fire Records | | | | Fire Ecology: SANParks |
| 2 | Surface Reflectance | MOD09GA | 500m | Daily | Reverb Website |
| 3 | Land Surface Temperature | MOD11A1 | 1km | Daily | |
| 4 | Aster Global Digital Elevation Model | ASTGTM | 30m | | |

#### *3.2.1.1. MODIS Products*

MODIS products freely obtained from Reverb (http://reverb.echo.nasa.gov) maintained by the National Aeronautics and Space Administration (NASA) EOSDIS Land Processes Distributed Active Archive Centre (LP DAAC) were used for retrieval of environmental variables that were employed for developing Fire potential Index of the study area using 2011 -2014 fire seasons. MODIS products included:

**(i) MODIS/Terra Surface Reflectance Daily L2G Global 1 km and 500m SIN Grid V006 (MODO9GA)**

MODO9GA Version 6 product provides an estimate of the surface spectral reflectance as it would be measured at the ground level corrected for atmospheric conditions such as gasses, aerosols and Rayleigh scattering. MOD09GA provides Band 1-7 in daily gridded L2G product in the sinusoidal projection and its associated quality assurance information at 500-meter reflectance value and 1km observation. Among seven bands, 500m Surface Reflectance band 2, 6 and 7 were used. These surface reflectance image were used to calculate NDWI and NMDI.

**(ii) MODIS/Terra Land Surface Temperature/Emissivity Daily L3 Global 1km SIN Grid V006 (MOD11A1)**

This product has been selected because of its spatial and temporal resolution (1km and daily) respectively and has data values with minimal cloud influence. The cloud-affected pixels are already masked from the image. MOD11A1 is constructed with the results in the MOD11_L2 products (generated using MODIS sensor radiance product MOD021km, the geolocation product MOD03, atmospheric temperature and water profile product MOD07_L2, the cloud mask product MOD35_L2, quarterly Land cover MOD12Q1, and snow product MOD10-L2) products of a day, through mapping the Scientific Data Sets (SDS) of all pixels in MOD11_L2 products onto grids in the sinusoidal projection and averaging the LST values of overlapping pixels in each grid with overlapping areas as weight (Wan, 2006). It is comprised of daytime and night-time LST, quality assessment, observation time, view angles, clear sky coverage and emissivity in band 31 and band 32 estimated by the classification -based emissivity methods according to the land cover types in the pixel.

#### *3.2.1.2. ASTER-DEM Data Product*

Advanced Spaceborne Thermal Emission Reflection Radiometer (ASTER) Digital Elevation Model (DEM) data at 30 meters freely obtained from USGS EarthExplorer (http://earthexplorer.usg.gov) was used for retrieval of elevation values

#### *3.2.1.3. Historical Fire Data*

Apart from the satellite data, historical wildfire information for the period of 2011 -2014 fire seasons were used for validation and images downloading purposes, provided by Fire Ecology Department, South Africa National Park.

### Data pre-processing

The data pre-processing of input variables that mainly comprised of MODIS-derived products, fire scar/spot data, and STRM-DEM products were executed following several steps as described in the following subsections.

### Step 1:MODIS Data downloading

The following criteria were applied as a guidance for downloading imageries. (i) Months that experienced the highest number of fire events, (ii) Burn day with fire points equal or greater than five (5), (iii). Imagery with a cloud cover of less than or equal to 10%. MODIS Terra satellite product (MOD09GA) Surface Reflectance and MOD11A1 LST imageries were downloaded from LP DAAC using Reverb/ECHO data portal (http://reverb.echo.nasa.gov/reverb) in Hierarchical Data Format (HDF). The study area is covered in h20v11 MODIS tile. In total, 54 granules of both MOD09GA and MOD11A1 were downloaded to generate seven (7) periodical data for each year (fire season) except year 2014 with only 6 periods. Table 3.2 provide the details of the time periods of data downloaded and their respective Julian Date of Year (DoY).

Table 3.2. Julian day and corresponding date of temporal MODIS datasets

| 2011 | | 2012 | | 2013 | | 2014 | |
|---|---|---|---|---|---|---|---|
| **DoY** | **Date** | **DoY** | **Date** | **DoY** | **Date** | **DoY** | **Date** |
| **241** | 29 August 2011 | **212** | 30 July 2012 | **208** | 27 July 2013 | **204** | 23 July 2014 |
| **242** | 30 August 2011 | **213** | 31 July 2012 | **209** | 28 July 2013 | **217** | 05 August 2014 |
| **243** | 31 August 2011 | **242** | 29 August 2012 | **210** | 29 July 2013 | **236** | 24 August 2014 |
| **244** | 01 September 2011 | **243** | 30 August 2012 | **233** | 21 August 2013 | **248** | 05 September 2014 |
| **246** | 03 September 2011 | **244** | 31 August 2012 | **237** | 25 August 2013 | **249** | 06 September 2014 |
| **247** | 04 September 2011 | **245** | 01 September 2012 | **270** | 27 September 2013 | **252** | 09 September 2014 |
| **248** | 05 September 2011 | **246** | 02 September 2012 | **271** | 28 September 2013 | | |

**Step 2: Re-projection of MODIS Data**

Since MODIS data were downloaded in sinusoidal projection system and the images were re-projected into Universal Transverse Mercator (UTM) Zone 35, DATUM: WSG1984 using Data Management Tool _Projection & Transformation_Raster_Project Raster in ArcMap software.

**Step 3: Retrieval of MODIS Surface Reflectance and Land Surface Values**

Science Data Sets for MODIS products were used to further process projected images to generate land surface temperature and surface reflectance values as depicted in Table 3.3. The pixel values were stored in the SDS as scaled integer values (SI) and the real value were calculated according to MODIS Calibration Support Teams (MCSTs) linear calibration algorithm as shown in Equation 1 using a Raster Calculator of ArcMap.

Real Value= Scale factor * (pixel value-offset value) **[1]**

**Processing of fire scar/spot data**

Historical fire data was received from the Fire Ecology & Biogeochemistry Department, South Africa National Parks in polygon shapefile format (polygon) for the period of 2011 -2014. The file comprises of fire related information such ID and BurnDay. However, missing fire information such as fire location with latitudes and longitudes. Longitude and Latitude were added into the layer of attribute information. ArcGIS software, Data Management Tool, was used to Add XY coordinates and to convert polygon shapefile into point shape file and fire points layer for each year, month and day were created.

Table 3.3. Science data sets (SDS) of MODIS Terra Surface Reflectance and Land Surface Temperature

| **Science data sets** | **Units** | **Bit type** | **Fill value** | **Valid Range** | **Scale Factor** |
|---|---|---|---|---|---|
| | | **Surface Reflectance, MOD09GA** | | | |
| 500m surface reflectance Band 2 (841 -876nm); Band 6 (1628-1652nm) Band 7 (2105 -2155nm) | Reflectance | 16 Bit unsigned Integer | -28672 | -100 -16000 | 0.0001 |
| | | **Land Surface Temperature (LST), MOD11A1** | | | |
| Daytime & Night time LST | Kelvin | 16 Bit unsigned Integer | 0 | 7500-65535 | 0.02 |

#### Processing ASTER-DEM data

Aster DEM at 30 meters was downloaded in Geo-Tiff file format, freely available from USGS EarthExplorer (http://earthexplorer.usg.gov) and was clipped to the study area. Elevation layer for the study area was re-projected into UTM Zone 35 and resampled to 1000m to match the spatial resolution of MOD11A1 using ArcMap Software.

### 3.2.2 Methods

According to Chuvieco and Salas (1996), fire danger ratings can be assessed both qualitatively and quantitatively. With qualitative methods, fire danger is determined by a set of evaluation criteria based on expert knowledge and has been criticised due to its subjectivity (Wang *et al.*, 2013b). Quantitative approach generally, creates model to compute the numerical value of fire danger or potential index, which later is divided into different fire danger/potential ratings. To develop an operational fire potential index, this study employed a quantitative method as proposed and improved by (Chuvieco *et al.*, 2014, Chuvieco *et al.*, 2010). Figure 3.1. shows the schematic diagram showing the methodology adopted in the study.

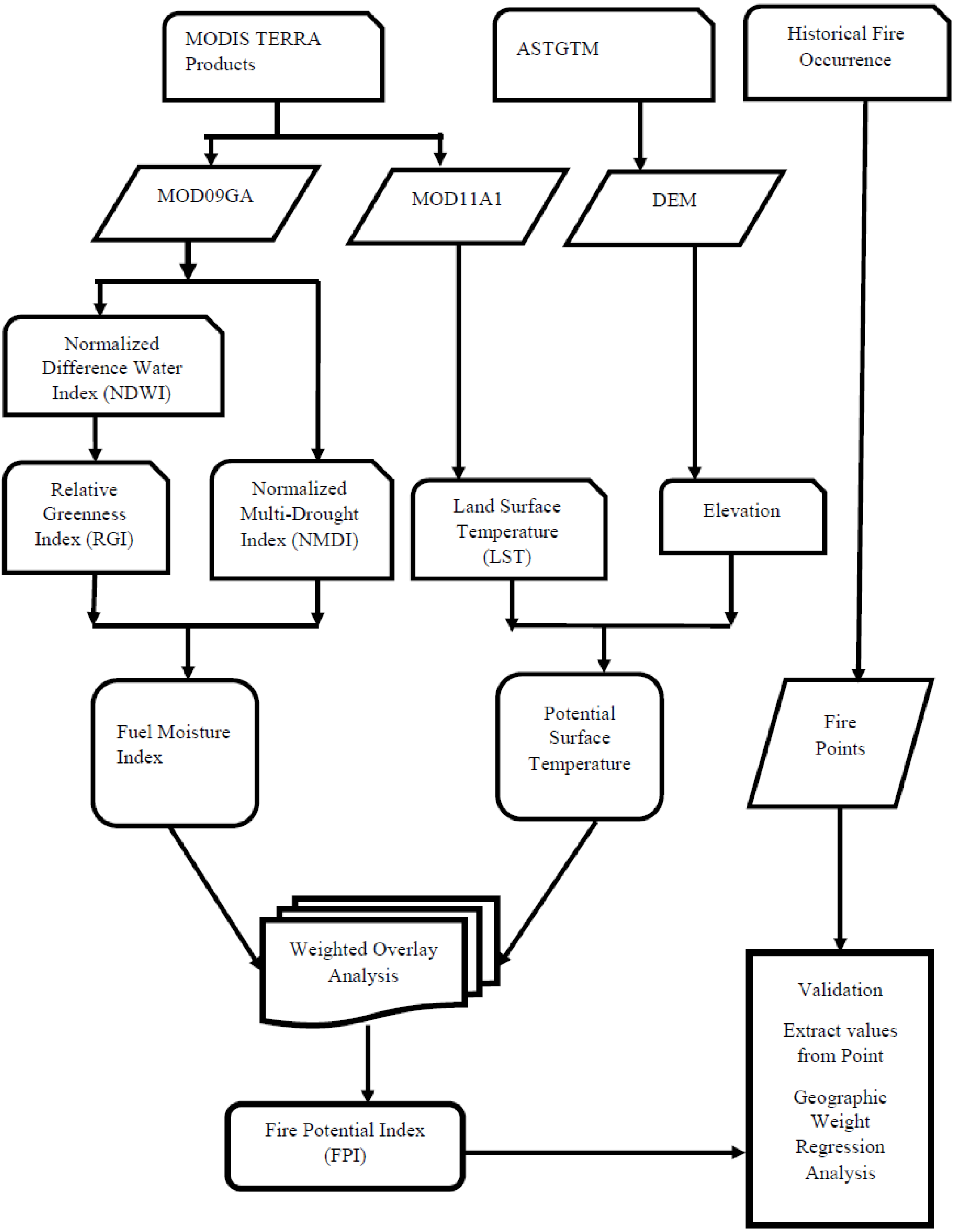



Figure 3:1. Methodology Flow Chart

#### 3.2.2.1 Generation of fire risk factors

Since, FPI is a moisture based fire danger assessment tool, four (4) biophysical variables such Relative Greenness Index derived from NDWI, NMDI, Land Surface Temperature and Elevation were used as input variables for constructions of FPI. Because these factors are not independent of each other, and indeed prolonged heat and absence of rainfall drive vegetation into water stress conditions that lead to an increase of its temperature (Maffei *et al.*, 2013). Moreover, they can be directly derived from remote sensing data.

*(i) Relative Greenness Index (RGI)*

RGI has been used as proxy to estimate the percentage of live vegetation content and as an indicator for live fuel moisture. RGI has been derived from NDVI and NDWI (Burgan and Hartford, 1993, Gao, 1996). NDWI is more sensitive to moisture changes in comparison to RGI derived from NDVI (Suresh Babu *et al.*, 2015). For this study, RGI derived from NDWI has been used to estimate the live fuel moisture in the vegetation. NDWI has been derived from NIR and SWIR bands using the equation

$$\text{NDWI} = \frac{\rho NIR - \rho SWIR}{\rho NIR + \rho SWIR} \qquad \textbf{[2]}$$

In general, NDWI derived from the NIR and SWIR channels responds to changes in both water content (absorption of SWIR radiation) and spongy mesophyll (reflectance of NIR radiation) in vegetation canopies respectively (Gao, 1996). NIR is affected by the internal structure and leaf dry matter content, but not by water. The combination of the NIR and SWIR removes variations induces by leaf internal structure and dry matter content improving the accuracy in retrieving the vegetation water content (Suresh Babu *et al.*, 2015). In general, SWIR reflectance decreases as water content in the vegetation increases. In contrast with NIR with simple relative narrow band region (0.7 -1nm), SWIR is more complicated because SWIR region is relative wide spectral range (1-3nm). For example, SWIR regions of MODIS are band 5, 6 and 7. Ji *et al.* (2011) categorized SWIR region into three (3) variants (i) shorter (1.2 – 1.3nm), (ii) middle (1.55 -1.75nm) and (iii) longer (2.05-2.45nm). For this study, the longer SWIR region has been used. Daily NDWI values were calculated according to expression [3] as proposed by (Chen *et al.*, 2005):

$$\text{NDWI} = \frac{\boldsymbol{float}(\boldsymbol{band}\ \mathbf{2} - \boldsymbol{band}\ \mathbf{7})}{\boldsymbol{float}(\boldsymbol{band}\ \mathbf{2} + \boldsymbol{band}\ \mathbf{7})} \qquad \textbf{[3]}$$

where band 2 and band 7 are the apparent reflectance's observed by a satellite sensor in the NIR & longer SWIR channels respectively. Float was used to prevent byte overflow errors during calculation.

Relative Greenness has been computed by using Equation 4

$$\text{RGI} = \left(\frac{NDWI - NDWI_{min}}{NDWI_{max} - NDWI_{min}}\right) * 100 \qquad \textbf{[4]}$$

where $RGI_{NDWI}$ is the NDWI based relative greenness for a particular pixel, NDWI is the value for a pixel and $NDWI_{min}$ and $NDWI_{max}$ are the minimum and maximum value for that pixel.

*(ii) Normalized Multi-Band Drought Index (NMDI)*

NMDI is relatively new index first described by Wang and Qu (2007) using three spectral bands, band 2 (0.86 nm) as the reference, and instead of using a single liquid water absorption band like NDWI, it uses the difference (slope) between two liquid water absorption bands (band 6: middle and band 7: longer) as the vegetation water sensitive band. For this study, NMDI has been used as an indicator of DFMC. NMDI values were computed using Equation 5.

$$NMDI = \frac{float(band2)-(float(band\ 6)-(band\ 7))}{float(band\ 2)+(float(band\ 6)-(band\ 7))}, \quad \textbf{[5]}$$

where band 2, band 6 and band 7 are the apparent reflectance's observed by a satellite sensor in the NIR, middle & longer SWIR channels respectively.

After computing the live fuel moisture (RGI) and dead fuel moisture from MODIS spectral bands, the composite fuel moisture index was calculated as linear combination of RGI and NMDI using Equation 6. *FMI* is a dimensionless index and should not be considered as a direct measure of fuel moisture content as such, (Sharples, September 2010).

$$FMI = \frac{RGI-NMDI}{NMDI} \quad \textbf{[6]}$$

All calculations were executed using Raster Calculator Tool of ArcMap

(*iii) Potential Surface Temperature*

Potential Surface Temperature ($\Theta_s$), a terrain corrected temperature is described as the temperature that a parcel would acquire if adiabatically brought to a standard reference pressure (Suresh-Babu *et al.*, 2015) Three steps were applied to compute ($\Theta_s$) following procedures of (Hassan *et al.*, 2007, Suresh-Babu *et al.*, 2015). The first step involved was the calculation of Atmospheric Pressure (P) at each of the image pixels referring to their respective point elevations in the acquired DEM of the study area. Atmospheric pressure has been calculated using Raster Calculator of QGIS software applying Equation 7.

$$P = 101.3\left(\frac{293-0.0065Z}{293}\right)^{5.26} \quad \textbf{[7]}$$

where P (in kPa) is the atmospheric pressure and Z (in m) is the elevation above mean sea level. The equation is based on a simplified form of the ideal gas law for neutrally –stratified atmosphere and temperature of $20^{o}C$ at a standard atmosphere (i.e. 101.3 kPa).

Second step was measurement of Land Surface temperature. LST is one of the primary factors leading to fire ignition, a proxy for fuel temperature because LST increase in drier areas due to evapotranspiration (Dasgupta *et al.*, 2006, Wang *et al.*, 2013b). Moreover, LST lead to reduction of fuel moisture content thus making fuel more prone to consumption by fire in the event of ignition. In general, LST retrieval methods have been categorised into Single window algorithm (Jiménez-Muñoz and Sobrino, 2003), split window algorithms and multi-band algorithms provided that Land Surface Emissivity's (LSE) are known a priori. If the LSE are unknown, then the algorithms can be categorised in to three types: stepwise retrieval method, simultaneous retrieval of LSEs and LST with known atmospheric information, and simultaneous retrieval with unknown atmospheric information (Li *et al.*, 2013).

For this study, LST was retrieved directly from MODIS Land Surface product MOD11A1 L3 product using daytime observation. The MODIS LST and emissivity products provide per pixel temperature and emissivity values. Average temperatures are extracted in degree Kelvin with a day/night LST algorithm applied to a pair of MODIS daytime and night observation.

Finally, Potential Surface Temperature ($\Theta_s$) has been calculated using Raster Calculator of ArcMap software applying Equation 8:

$$\theta_s = LST\left(\frac{P_0}{P}\right)^{0.286} \qquad \textbf{[8]}$$

Where $\Theta_s$ is the potential temperature in K, LST is the near surface temperature or land surface temperature in K, $P_o$ is the standard atmospheric pressure at mean sea level usually 101.3 kPa and P is the atmospheric pressure at a surface in kPa;

$\Theta_s$ imageries were re-projected from 1km to 500m for the alignment with FMI imageries.

#### 3.2.2.2 Construction of Fire Potential Index

After the generation of variables (data layers), these variables were integrated for the construction of FPI. Firstly, the original measurement scale of each variable was converted to common danger scale or metric. Several methods have been employed to find common danger scale being variable normalization, qualitative categorisation and probabilistic approaches (Chuvieco *et al.*, 2014, Chuvieco *et al.*, 2010). This study employed variable normalization whereby variables values were normalized to the range of [0-1] based on their maximum and minimum using a Raster normalisation tool from ArcGIS called Geomorphometry & Gradient Metric Toolbox developed by (Evans *et al.*, 2016). Reclass Tool was used to classify each data layer into five classes using manual classification method based on its impact on increasing the fire potential guided by previous researches. These classified groups were assigned numerical rating as shown on Table 3.4.

Based on the previous research, priorities judgement for pairwise comparisons and judgement matrix were established for assigning weights using spreadsheet programme developed by (Goepel, 2013). The calculation of the weight derivation is shown in Figure 3.2. The characteristics roots and vector judgement matrix found that the maximum of characteristics roots is 2.000 and corresponding characteristic vector was 87.4% and 12.50% for FMI and Potential Surface Temperature respectively and then consistency of the judgement matrix was found to be less than 0.10 or 10% (1%). This ratio indicated a good compatibility and a reasonable level of consistency in the pairwise comparison.

Table 3.4. Weighting and ratings assigned to variables and classes for FPI

| Variable | Values | Classes | Fire Rating Category | Numerical Rating | Weights |
|---|---|---|---|---|---|
| Fuel Moisture Index | 0 -0.2 | Very Dry | Very High | 5 | 87% |
| | 0.2 -0.35 | Dry | High | 4 | |
| | 0.35-0.50 | Moist | Medium | 3 | |
| | 0.50 -0.70 | Fresh -like | Low | 2 | |
| | 0.70 – 1 | Fresh | Very Low | 1 | |
| Potential Surface Temperature | 0 -0.2 | Cold | Very Low | 1 | 13% |
| | 0.2 -0.35 | Cool | Low | 2 | |
| | 0.35-0.50 | Warm | Medium | 3 | |
| | 0.50 -0.70 | Hot | High | 4 | |
| | 0.70 – 1 | Very Hot | Very High | 5 | |

Finally, the Fire Potential Index (FPI) was constructed using Weighted Overlay Tools of ArcMap and range of its values was between 1-5. Referring to the fire danger rating system of the Department of Agriculture, Forestry and Fisheries (DAFF, 2013), five classes ranging from low to extremely dangerous, were defined using the value of FPI as shown in Table 3.5.

Table 3.5. FPI values classified into five categories and their descriptions

| FPI value | Fire Danger Class | Rating | Colour-Code |
|---|---|---|---|
| 1 | Low | Insignificant | Blue |
| 2 | Moderate | Low | Green |
| 3 | Dangerous | Moderate | Yellow |
| 4 | Very dangerous | High | Orange |
| 5 | Extreme Dangerous | Extreme High | Red |

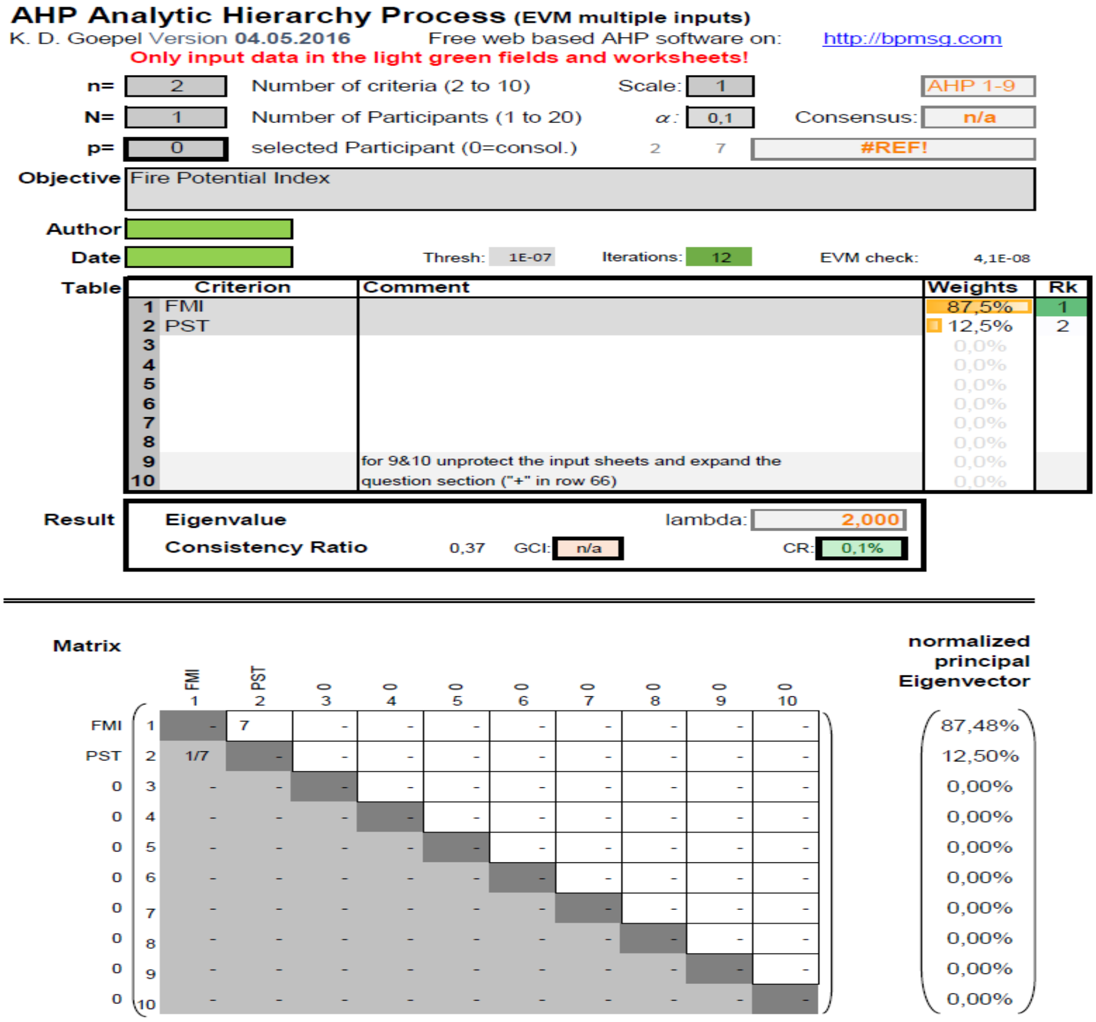



Figure 3:2. Analytic Hierarchy Process of for weighting and ranking parameters

### 3.2.2.3 Validation

Validation is an important process to undertake while creating any kind of index. In order to determine the accuracy of the index's performance, it is necessary to compare index's result to the real world. Fire danger or Potential Indices are typical validated by fire events, meteorological and fuel moisture content (Wang *et al.*, 2013b). Historical fire data from the SANPARKS was used to evaluate the effectiveness of the index. Although is the best way to obtain ground-truth data through field survey to evaluate the effectiveness of the proposed index. It is very difficult, if not possible to conduct it for the study area due to its terrain.

Extract Values to Points Tool was used to determine the accuracy assessment on which FPI pixel cell values were extracted on set of fire points and record the values in the attribute table of an output feature class. In additional, Geographical Weighted Regression (GWR) analysis was used to provide additional measure of index performance. GWR is a local form of linear regression used to model spatially varying relationships, a statistical technique that allows variations in relationships between predictor and outcome variable over space to be measured within a single modelling framework (Fotheringham *et al.*, 2003). The R-squared ($R^2$) was used to measure the model's performance.

## 3.3 Results

### 3.3.1 Historical fire records

In total, 850 fire points were recorded during the fire season of 2011 -2014. During these period, it was observed that 2013 was the most fire occurring year followed by 2014 and 2012. Less fire events were recorded during 2011. Spatial distribution of fire points is shown in Figure 3.3. The highest number of fire events was observed in the month of September that shares 40% of total events for the fire seasons from 2011 to 2014. The monthly distribution of fire points for fire season periods is shown in Figure 3.4.

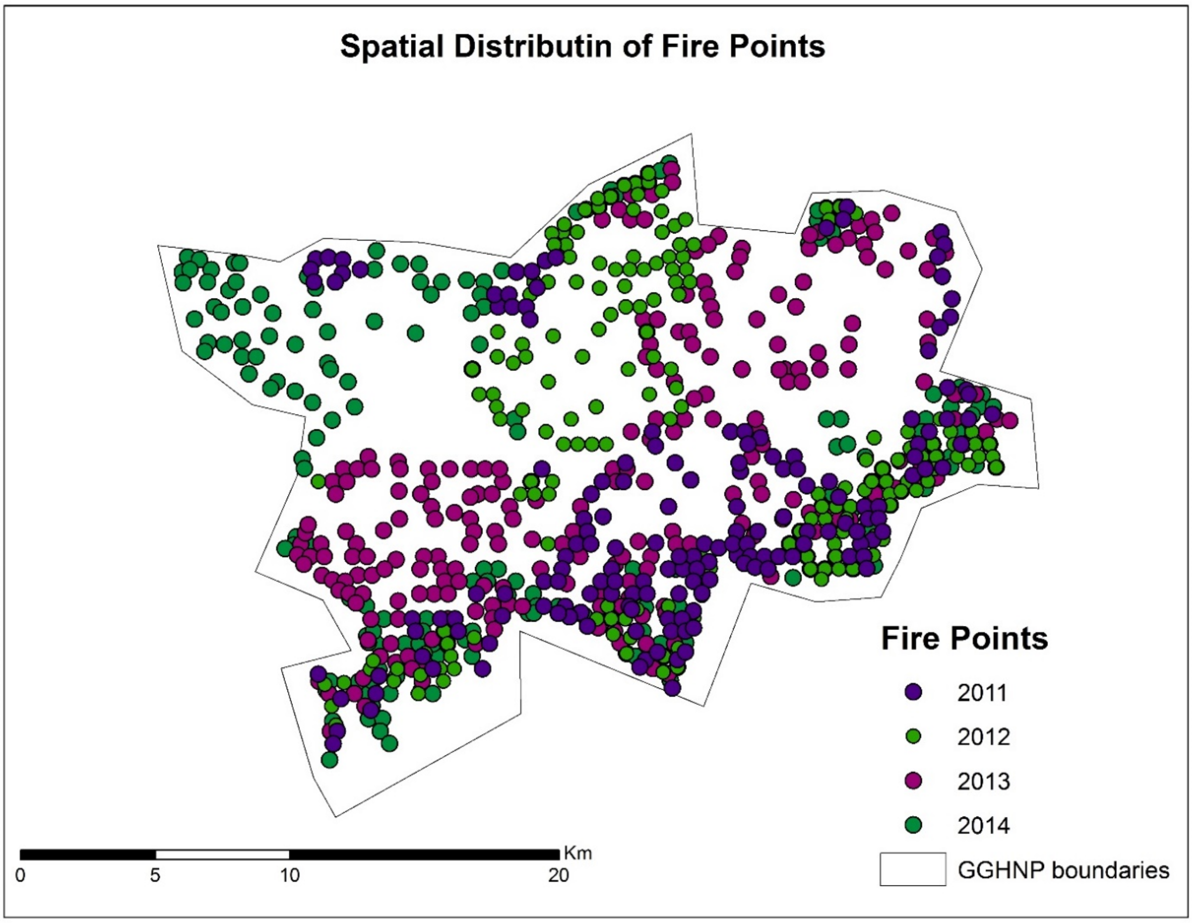



Figure 3:3. Spatial distribution of fire points during 2011 -2014 fire season of the GGHNP

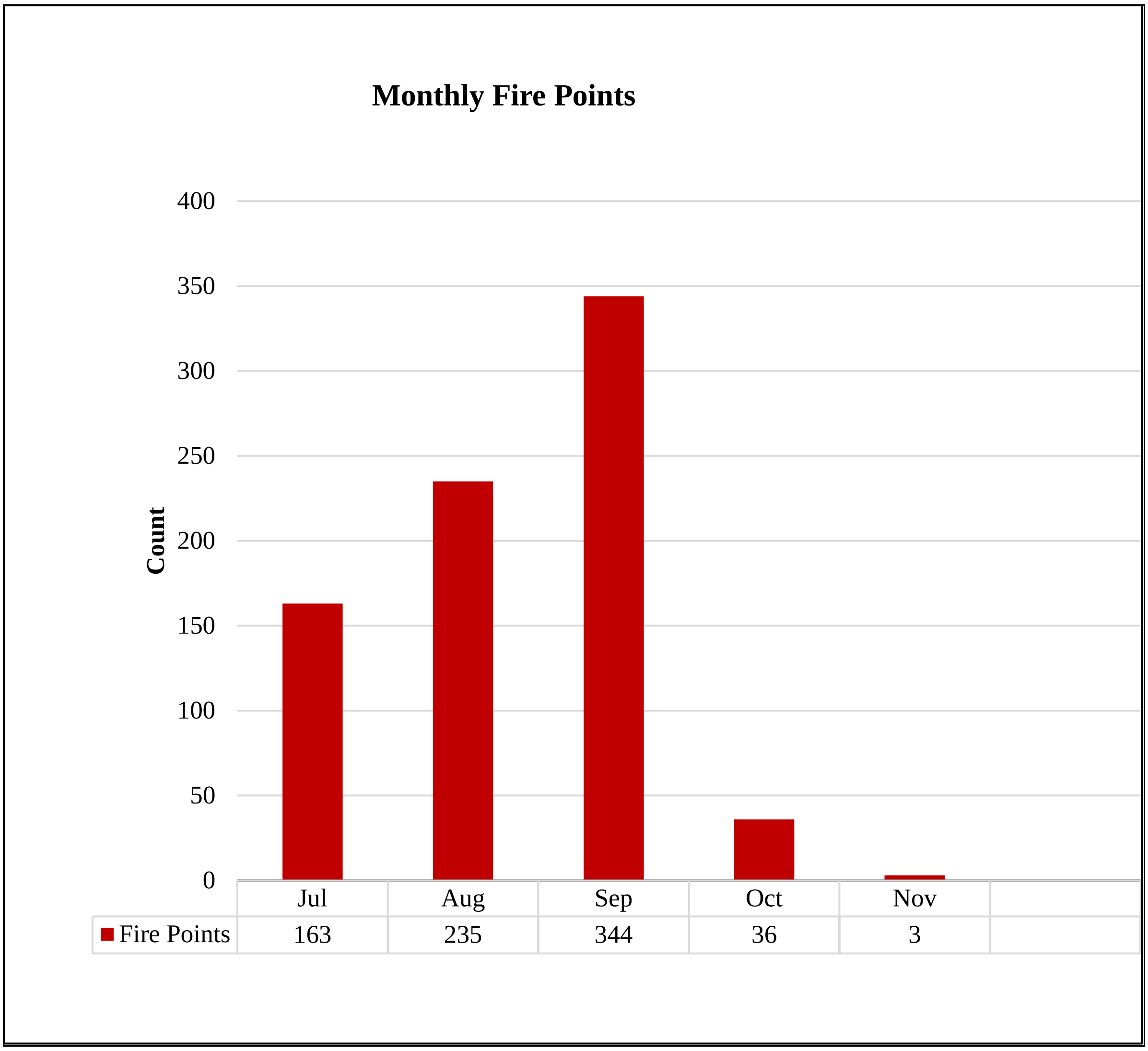
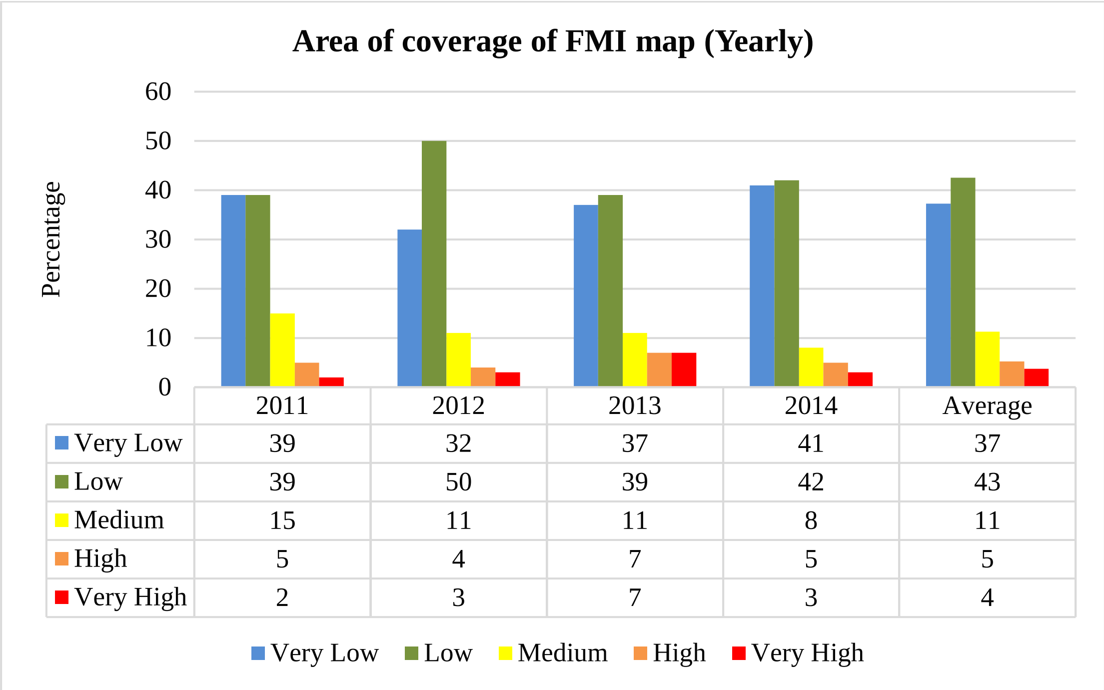



Figure 3:4. Monthly historical fire records for the fire season of 2011 -2014

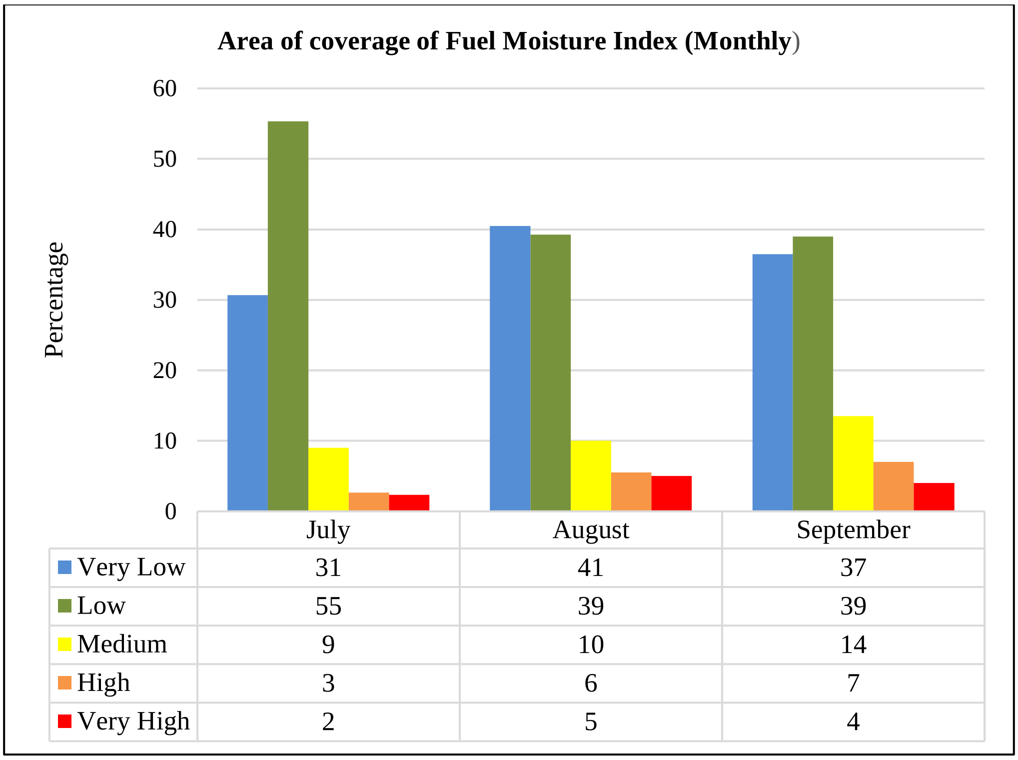
### 3.3.2 Fuel Moisture Index

The maps illustrating the spatial distribution of FMI for the time periods are shown in figure 3.7., 3.8.,3.9., and 3.10 for the year 2011, 2012, 2013 and 2014 respectively. The higher the fuel moisture value the lower the chance of fire occurrence. The results revealed that during time periods, on an average, highest FMI values categorized under very low to low fire danger rating classes constitute 37% and 43% area coverage of study area (Fig 3.5) and the period where these FMI values constitute very low to low fire potential was observed in the year 2014 (Fig 3.5 & Fig 3.10.) and was observed in the month of July (Fig 3.6.). The results showed that lowest FMI values categorized under high to very high fire danger classes were observed in the year 2013 and equally observed during the month of August and September.




| | 2011 | 2012 | 2013 | 2014 | Average |
|---|---|---|---|---|---|
| Very Low | 39 | 32 | 37 | 41 | 37 |
| Low | 39 | 50 | 39 | 42 | 43 |
| Medium | 15 | 11 | 11 | 8 | 11 |
| High | 5 | 4 | 7 | 5 | 5 |
| Very High | 2 | 3 | 7 | 3 | 4 |

Figure 3:5. Mean Annually distribution of area coverage of Fuel Moisture Index for the fire season 2011 -2014




| | July | August | September |
|---|---|---|---|
| Very Low | 31 | 41 | 37 |
| Low | 55 | 39 | 39 |
| Medium | 9 | 10 | 14 |
| High | 3 | 6 | 7 |
| Very High | 2 | 5 | 4 |

Figure 3:6. Mean Monthly distribution of area coverage of Fuel Moisture Index for the fire season 2011 -2014

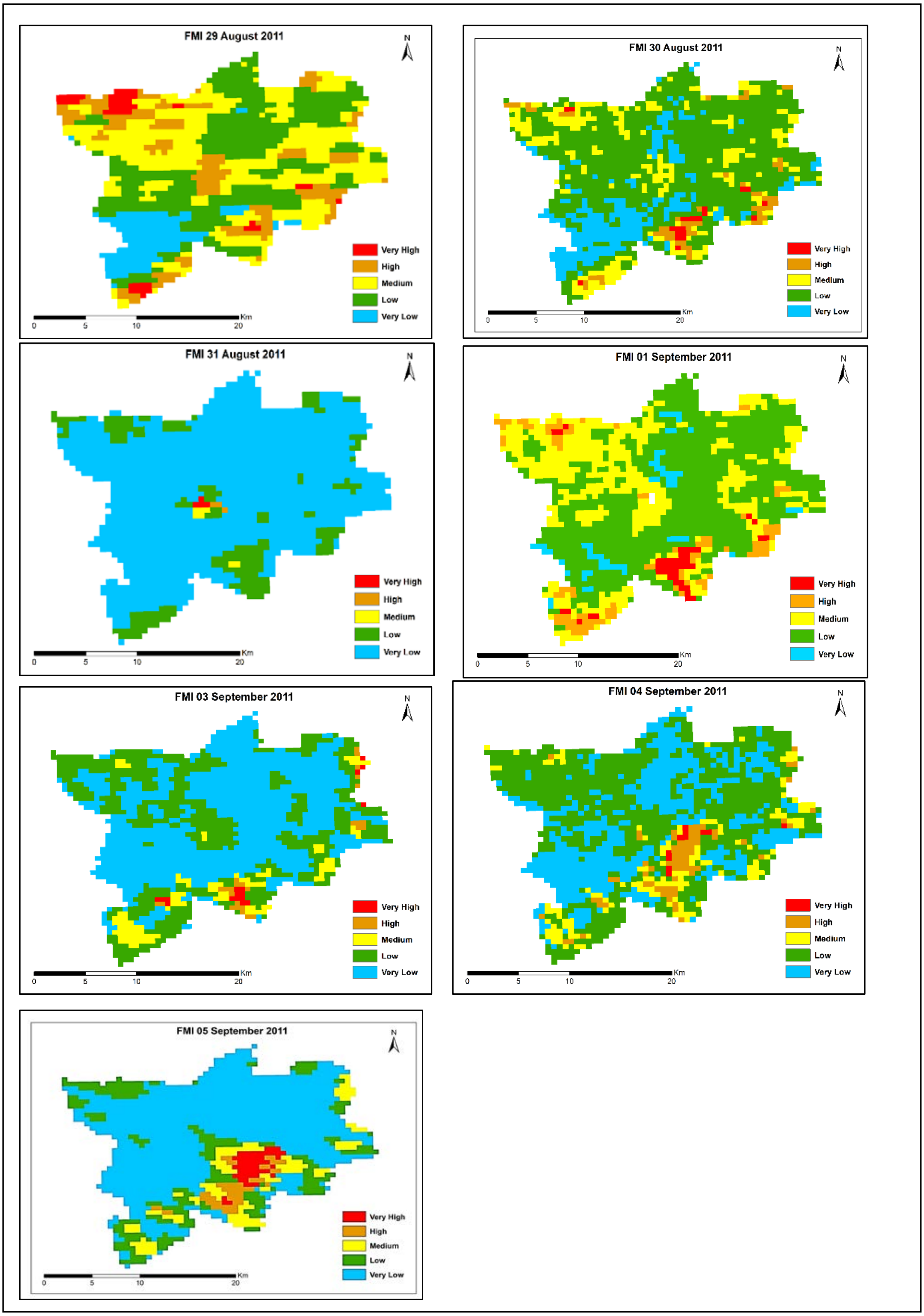



Figure 3:7. FMI map by combining $RGI_{ndwi}$ & NMDI during the year 2011 for GGHNP

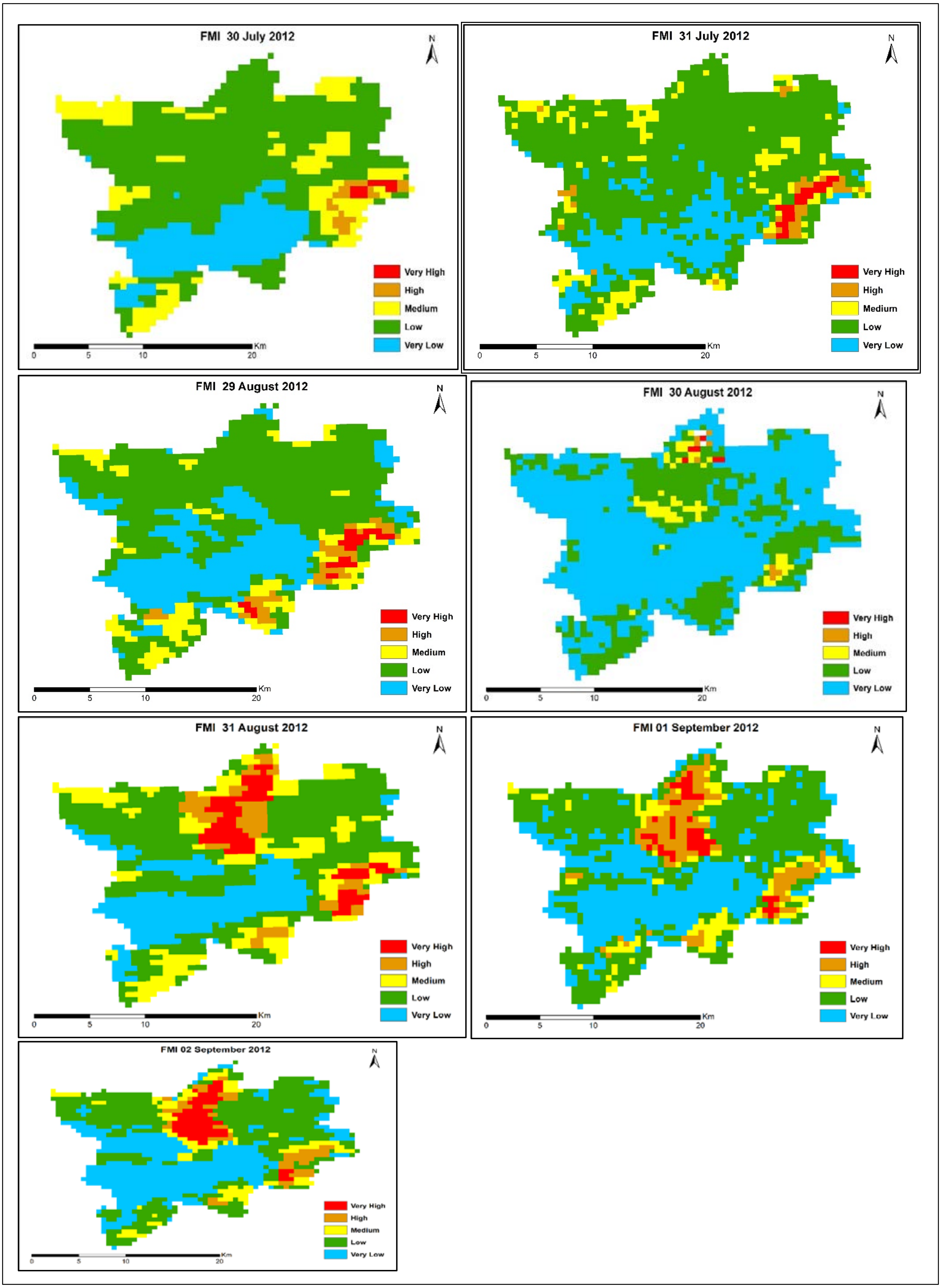



Figure 3:8. FMI map by combining $RGI_{ndwi}$ & NMDI during the year 2012 for GGHNP

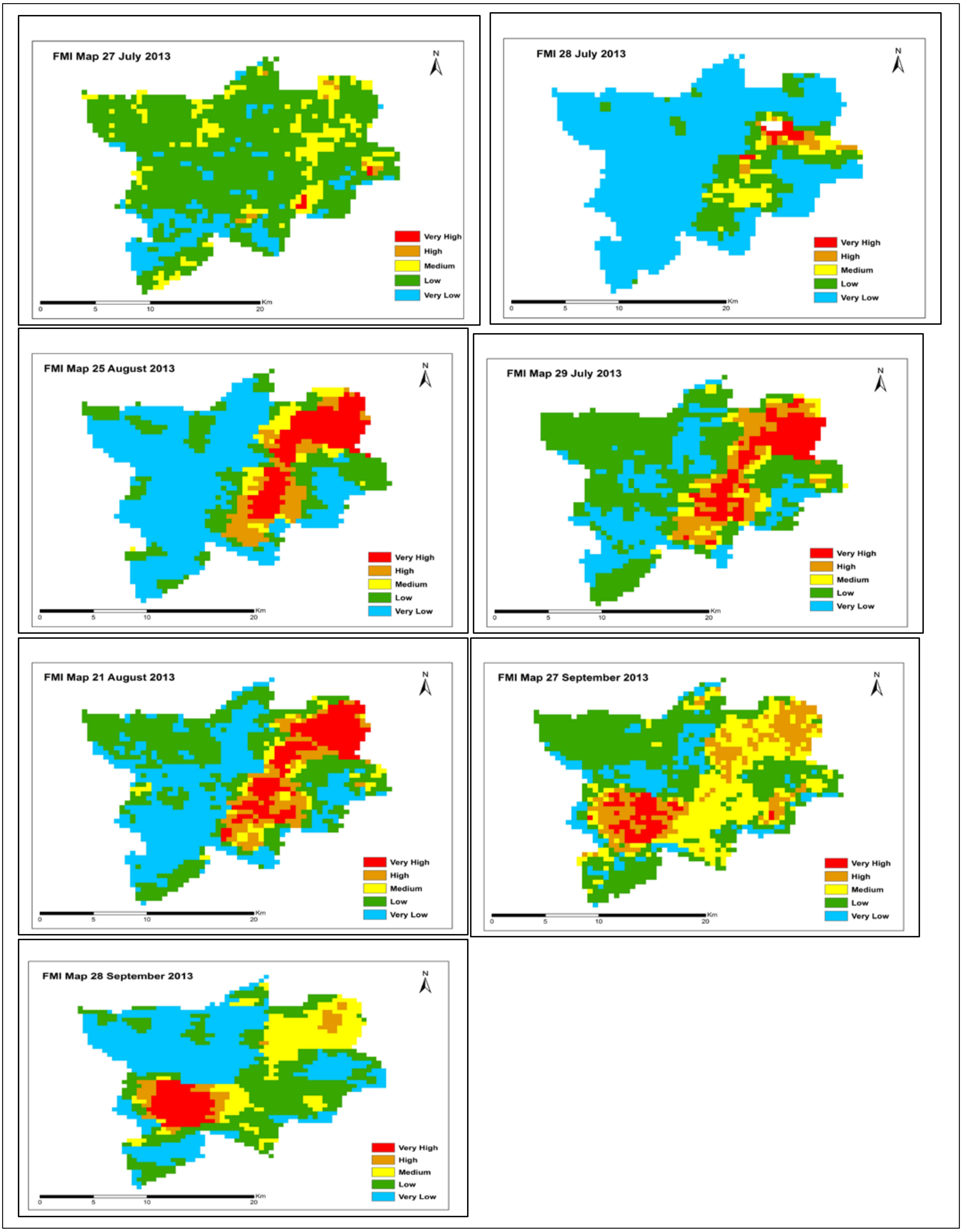



Figure 3:9. FMI map by combining $RGI_{ndwi}$ & NMDI during the year 2013 for GGHNP

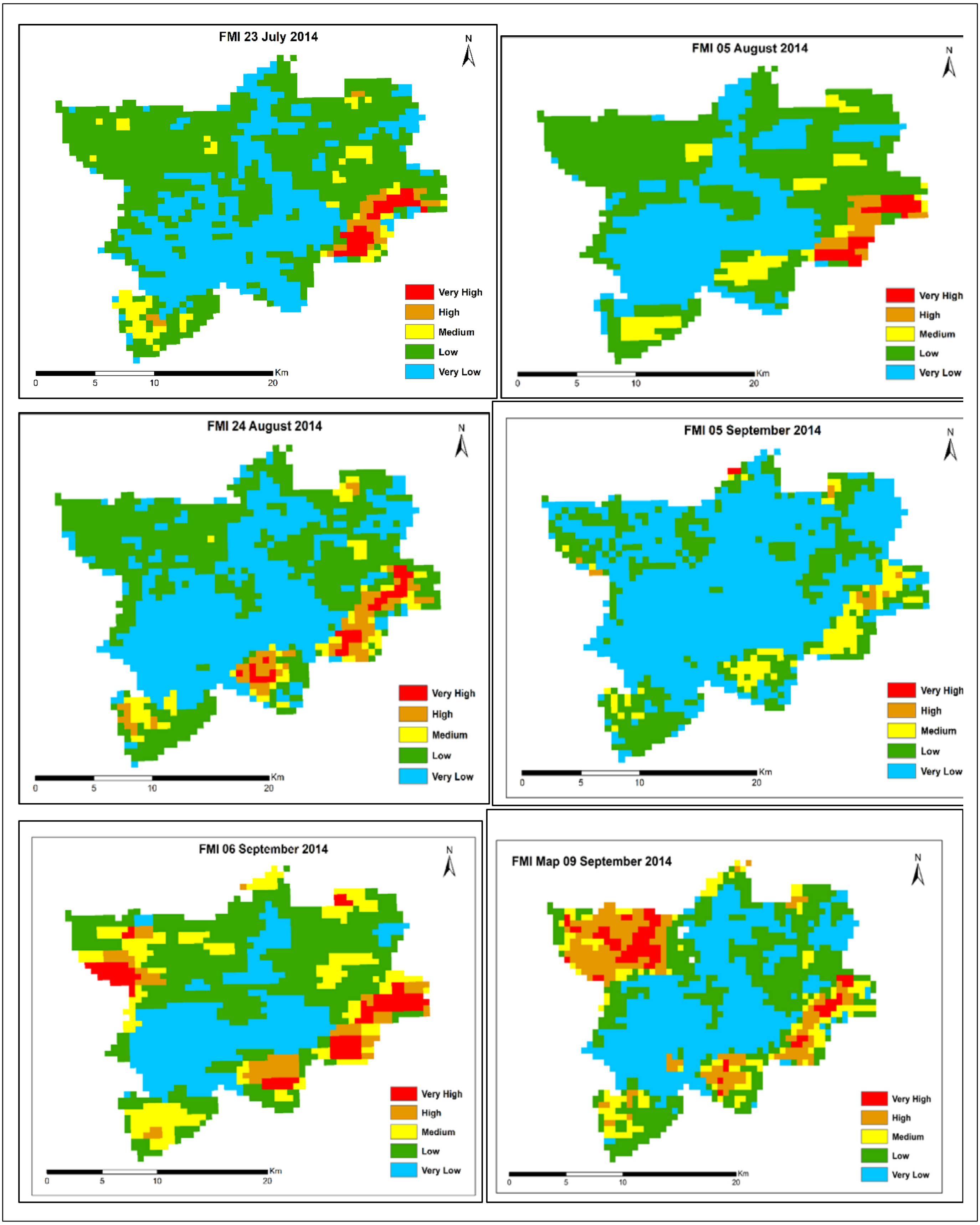



Figure 3:10. FMI map by combining $RGI_{ndwi}$ & NMDI during the year 2014 for GGHNP

### 3.3.3 Potential Surface Temperature

Potential Surface Temperature ($\Theta_s$) was retrieved using LST and elevation. Average ($\Theta_s$) daytime within GGHNP area during 2011 to 2014 fire season was observed between 310K to 325K as shown on Table 3.6. High temperature dries fuels so quickly, and thus increase the probability of fire occurrence. The maps showing spatial distribution of potential surface temperature are shown in Figures 3.13, 3.14, 3.15, 3.16 during the time periods of the year 2011, 2012, 2013 and 2014 respectively. After measuring the potential surface temperature during the fire season from 2011 to 2014, the areas having highest temperature value were categorized under very high danger classes which constituted an average area coverage of 4% (Fig 3.11). Approximately 56% of the area fell in high to medium danger classes and 47% of the area coverage fell under very low to low danger classes as depicted in Figure 3.11. Largest area which fell under very high to medium fire danger classes were observed in 2013 (69%) and during the month of August (66%) (Fig 3.12), followed by 2011 (67%) and 2014(63%) whereas 58% area of coverage was observed in 2012. However, largest area fell under very high fire danger rating was observed in 2011 covering 10% of the study area as shown in Figure 3.11.

Table 3.6. Minimum, maximum and average Potential Surface Temperature value (K) of fire season of 2011 -2014

| **Date** | **Min** | **Max** | **Average** | **Date** | **Min** | **Max** | **Average** |
|---|---|---|---|---|---|---|---|
| 29 August 2011 | 305 | 320 | 315 | 27 July 2013 | 308 | 319 | 313 |
| 30 August 2011 | 315 | 332 | 323 | 28 July 2013 | 306 | 329 | 314 |
| 31 August 2011 | 317 | 326 | 321 | 29 July 2013 | 304 | 317 | 310 |
| 01 September 2011 | 313 | 330 | 320 | 21 August 2013 | 308 | 321 | 316 |
| 03 September 2011 | 314 | 329 | 320 | 25 August 2013 | 309 | 315 | 313 |
| 04 September 2011 | 314 | 328 | 320 | 27 September 2013 | 319 | 332 | 325 |
| 05 September 2011 | 313 | 327 | 318 | 28 September 2013 | 318 | 330 | 323 |
| 30 July 2012 | 307 | 319 | 311 | 23 July 2014 | 309 | 322 | 313 |
| 31 July 2012 | 306 | 322 | 313 | 05 August 2014 | 308 | 318 | 312 |
| 29 August 2012 | 316 | 330 | 319 | 24 August 2014 | 308 | 324 | 315 |
| 30 August 2012 | 315 | 332 | 324 | 05 September 2014 | 314 | 330 | 320 |
| 31 August 2012 | 317 | 326 | 320 | 06 September 2014 | 320 | 330 | 324 |
| 01 September 2012 | 315 | 327 | 320 | 09 September 2014 | 320 | 334 | 325 |
| 02 September 2012 | 314 | 326 | 319 | | | | |

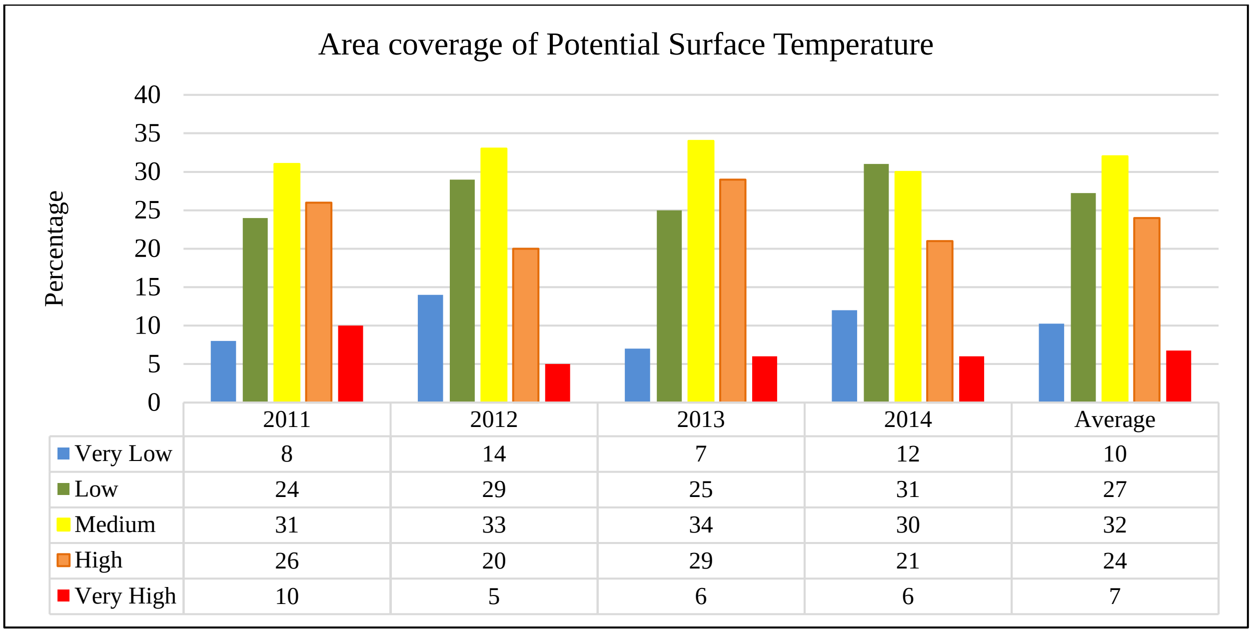



Figure 3:11. Mean Annually distribution of area coverage of Potential Surface Temperature the fire season 2011 -2014

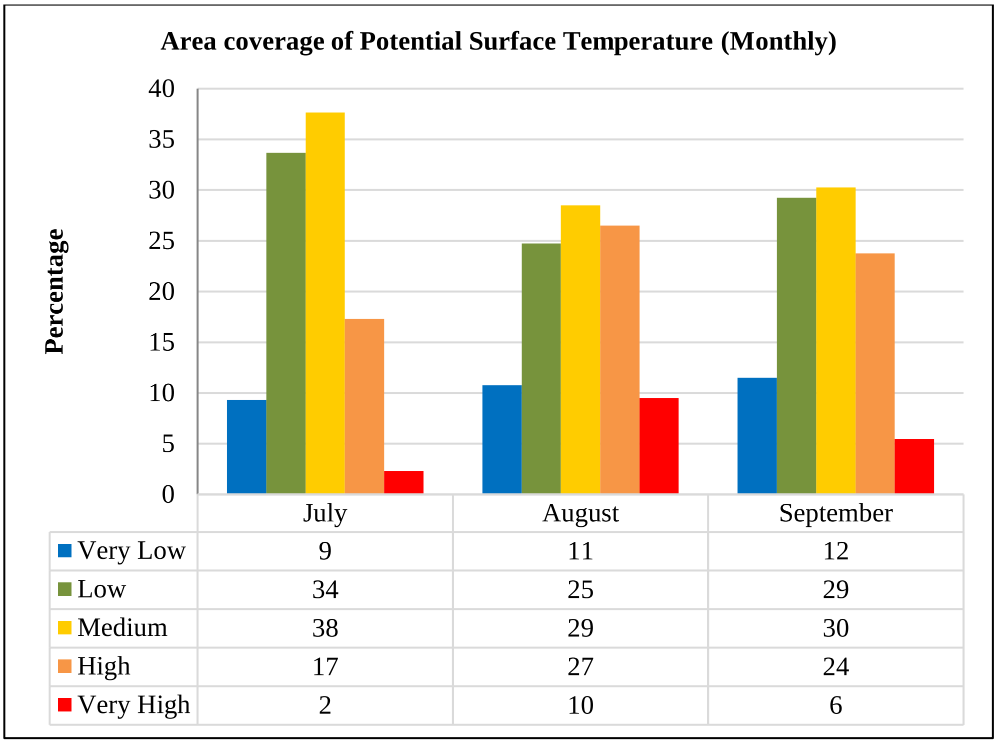



Figure 3:12. Mean Monthly distribution of area coverage of Potential Surface Temperature for the fire season 2011 -2014

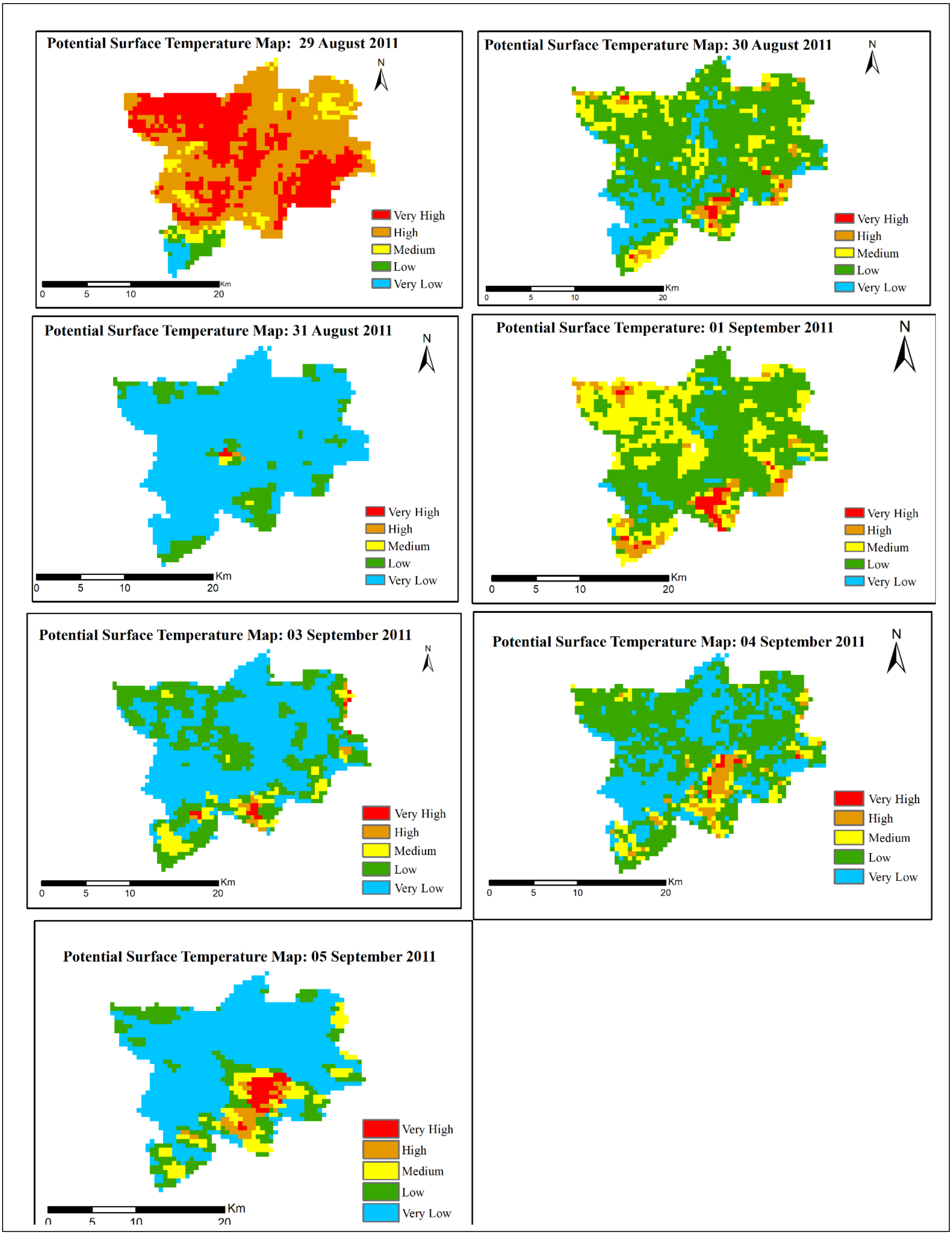



Figure 3:13. Potential Surface Temperature Maps derived from LST and Elevation during the year 2011 for GGHNP

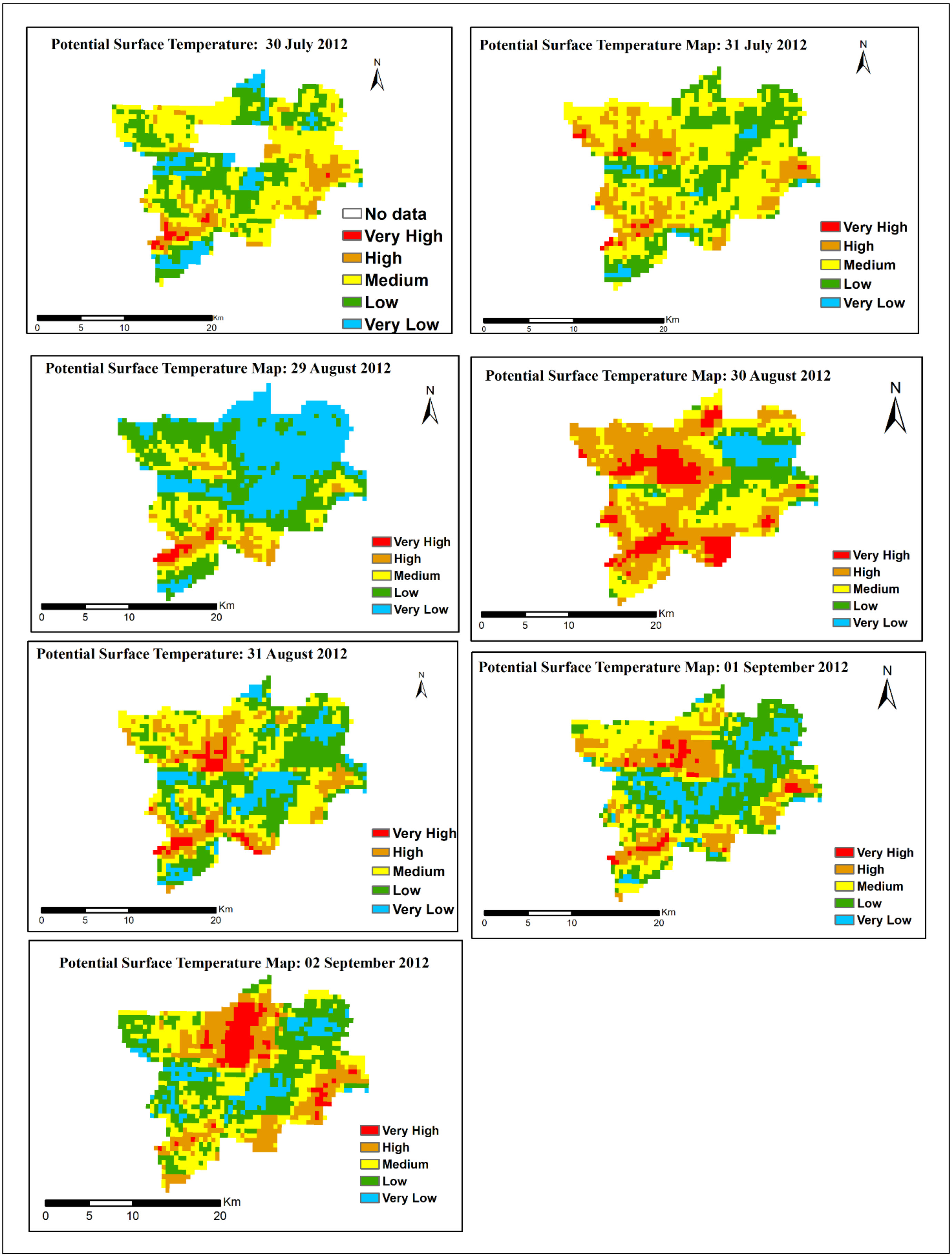



Figure 3:14. Potential Surface Temperature Maps derived from LST and Elevation during the year 2012 for GGHNP

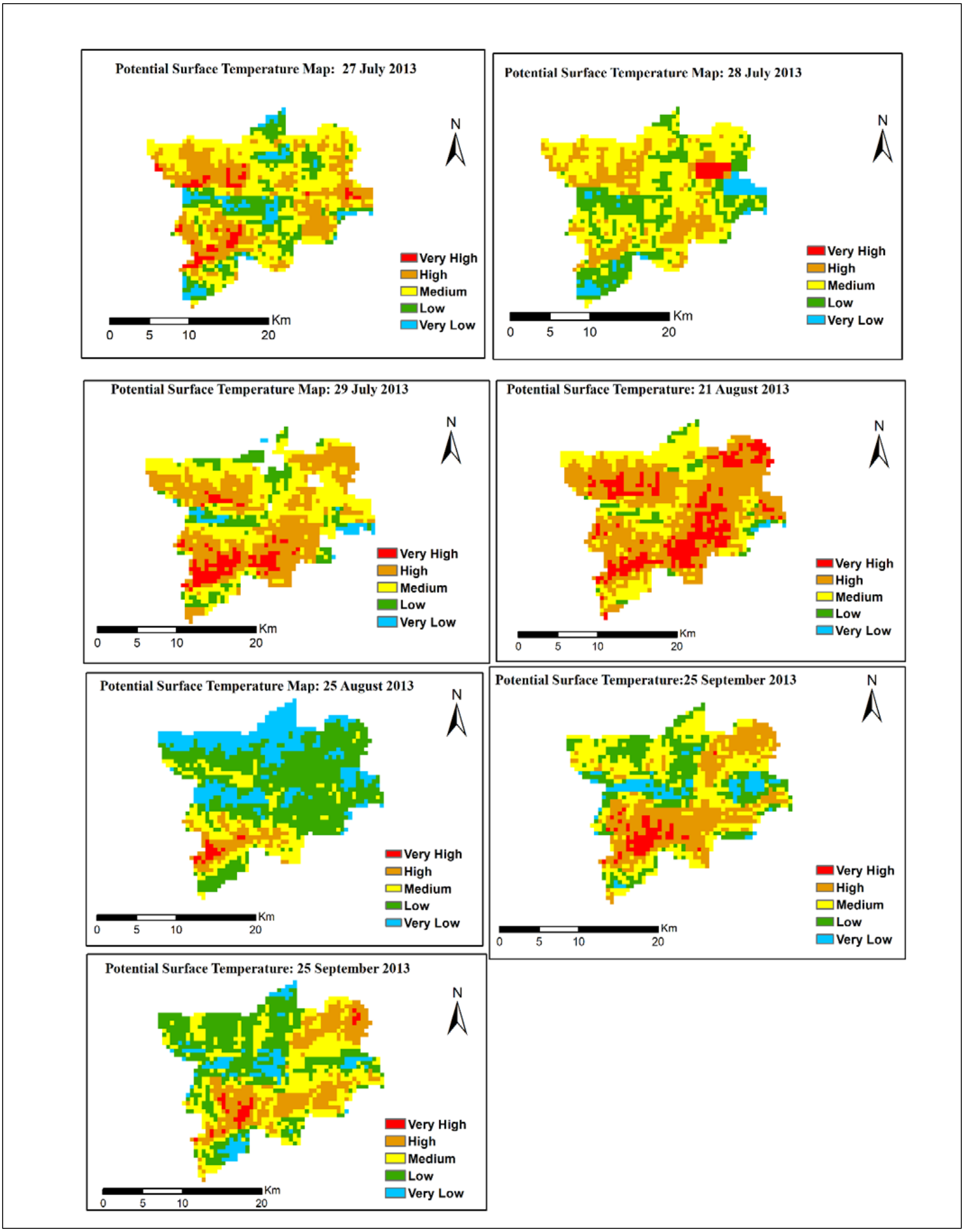



Figure 3:15. Potential Surface Temperature Maps derived from LST and Elevation during the study period of 2013 for GGHNP

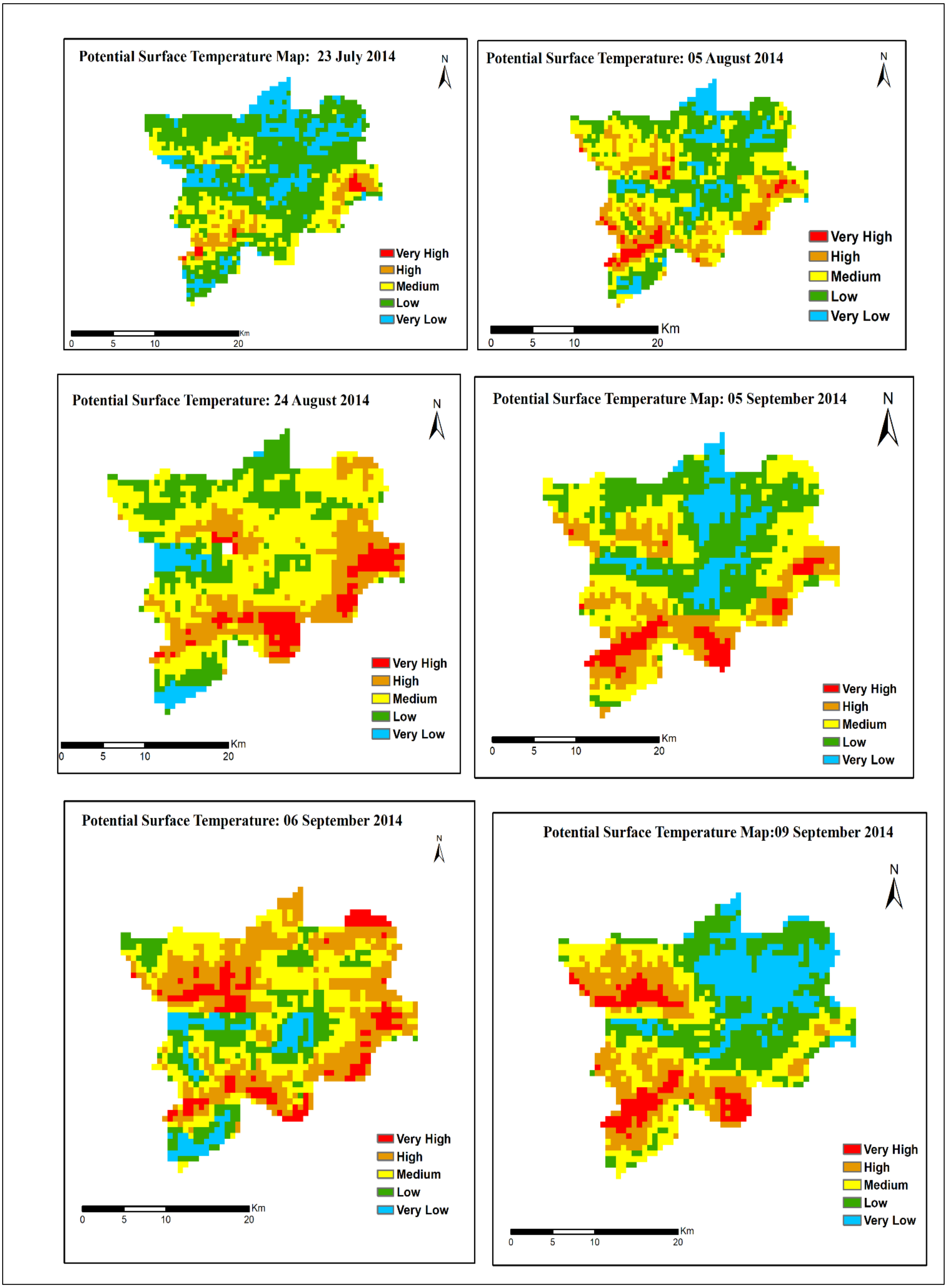
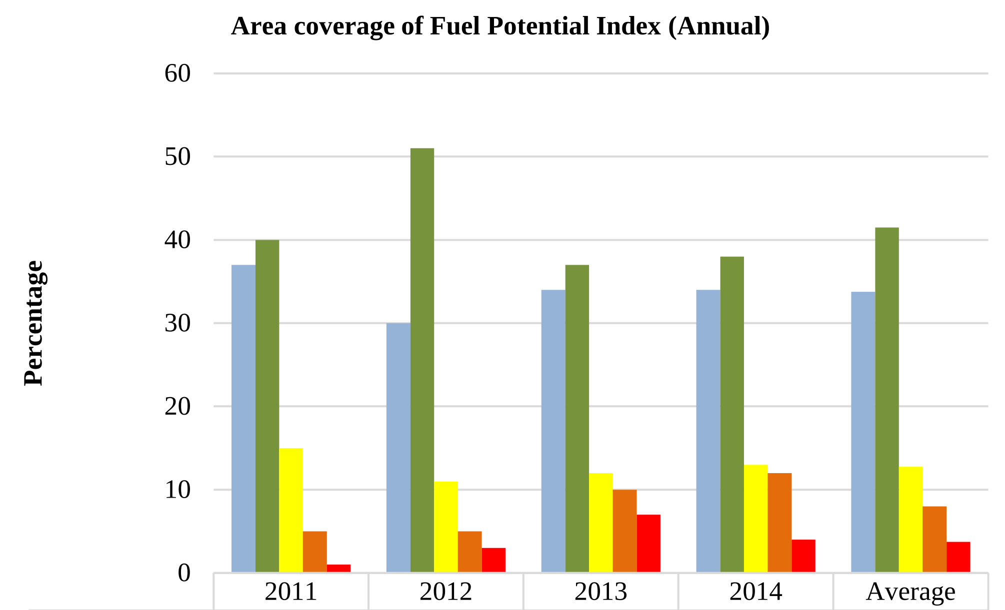



Figure 3:16. Potential Surface Temperature Maps derived from LST and Elevation during the year 2014 for GGHNP

### 3.3.4 Fire Potential Index

FPI values were classified into five fire danger categories, viz, Insignificant (blue), Low (green), Medium (yellow), High (orange) and Extreme High (Red). Figure 3.17 showed the different level of danger classes and corresponding yearly average area of coverage while Figure 3.18 illustrated the monthly average. As shown in Figure 3.11 the maximum area fell under low fire danger class which constitutes 42% followed by medium class with 13% and insignificant fire danger which constitutes 13%. Approximately 12% of the area fell under high to extreme high fire danger classes 8% and 4% respectively. Largest area coverage of high to extreme fire danger classes was observed during 2013 (17%), followed by 2014 (16%) and 2012 (8%) whereas only 6% was observed during 2011. Figure 3.12 revealed that maximum area of coverage fell under insignificant fire danger class and was observed during July (86%), followed by August (80%) and September (64%). Approximately 17% of the area fell under high to extreme high fire danger classes which were observed during September and followed by August (11%) and July (6%). The figures 3.19, 3.20, 3.21 and 3.22 depicted the resultant FPI maps for time periods of the year 2011, 2012, 2013 and 2013 respectively overlaid with the corresponding active fire points.




| | 2011 | 2012 | 2013 | 2014 | Average |
|---|---|---|---|---|---|
| Very Low | 37 | 30 | 34 | 34 | 34 |
| Low | 40 | 51 | 37 | 38 | 42 |
| Medium | 15 | 11 | 12 | 13 | 13 |
| High | 5 | 5 | 10 | 12 | 8 |
| Extreme High | 1 | 3 | 7 | 4 | 4 |

Figure 3:17. Mean Annually distribution of area coverage of Fire Potential Index

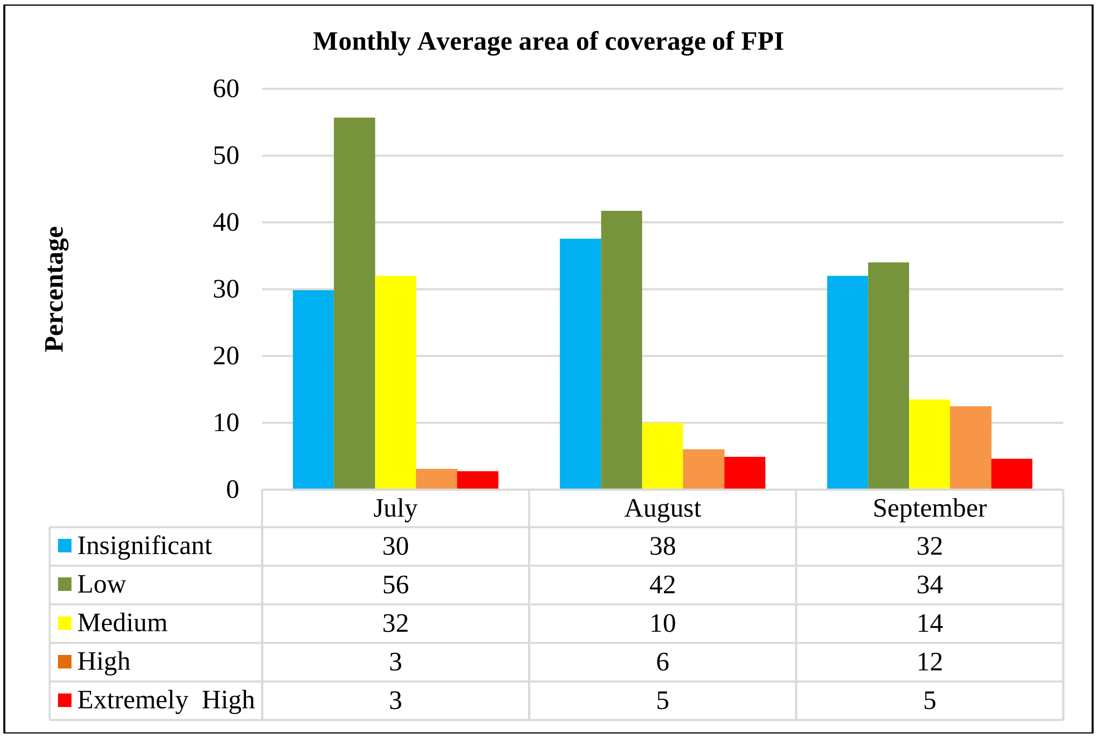



Figure 3:18. Mean Monthly distribution of area coverage of Fire Potential Index

### 3.3.5 Model Validation

According to the South African Fire Danger Rating Systems, fires are likely to occur or ignite from low to extreme fire danger ratings and accuracy assessment (i.e. validation) was done to individual FPI map based on extracting FPI values to the fire point locations. The model revealed an overall accuracy of 89% ranging from 33% to 100% indicating that maximum of fires fell in Low to extremely high fire danger classes. Table 3.7. shows the accuracies of the FPI model for different DOY periods during the fire season of 2011 to 2014 over the study area. GWR analysis show a sound agreement between FPI and the fire points with overall $R^2$ of 0.69 ranging from 0.17 to 0.98 as shown in Table 3.7. Therefore, it is possible to conclude that the model performance is significant.

Table 3.7. Accuracies of Fire Potential Index Model

| **Date** | **Number of fire points for each fire danger classes** | | | | | | **Total Fire Points** | **Accuracy %** | **GWR $R^2$** |
|---|---|---|---|---|---|---|---|---|---|
| | **Insignificant** | **Low** | **Moderate** | **High** | **Extreme High** | **Unclassified** | | | |
| 29 August 2011 | 0 | 1 | 4 | 3 | 2 | | **10** | 100 | 0.71 |
| 30 August 2011 | 0 | 0 | 4 | 3 | 0 | | **7** | 100 | 0.73 |
| 31 August 2011 | 3 | 7 | 0 | 0 | 0 | | **10** | 70 | 0.60 |
| 01 September 2011 | 0 | 2 | 4 | 1 | 0 | | **7** | 100 | 0.17 |
| 03 September 2011 | 5 | 8 | 2 | 4 | 0 | | **19** | 74 | 0.98 |

| Date | Number of fire points for each fire danger classes | | | | | | Total Fire Points | Accuracy % | GWR $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| | Insignificant | Low | Moderate | High | Extreme High | Unclassified | | | |
| 04 September 2011 | 1 | 8 | 5 | 3 | 1 | | **18** | 94 | 0.98 |
| 05 September 2011 | 3 | 3 | 4 | 3 | 0 | | **13** | 77 | 0.73 |
| 30 July 2012 | 0 | 1 | 1 | 4 | 0 | | **6** | 100 | 0.81 |
| 31 July 2012 | 0 | 0 | 1 | 3 | 3 | | **7** | 100 | 0.53 |
| 29 August 2012 | 1 | 2 | 3 | 0 | 0 | | **6** | 83 | 0.93 |
| 30 August 2012 | 1 | 8 | 0 | 0 | 1 | | **10** | 90 | 0.68 |
| 31 August 2012 | 0 | 5 | 6 | 5 | 4 | | **20** | 100 | 0.46 |
| 01 September 2012 | 0 | 3 | 4 | 1 | 5 | | **13** | 100 | 0.67 |
| 02 September 2012 | 0 | 3 | 4 | 0 | 0 | | **7** | 100 | 0.03 |
| 27 July 2013 | 1 | 15 | 2 | 0 | 0 | | **18** | 94 | 0.94 |
| 28 July 2013 | 2 | 5 | 2 | 0 | 1 | | **10** | 80 | 0.55 |
| 29 July 2013 | 1 | 4 | 4 | 12 | 11 | | **32** | 97 | 0.97 |
| 21 August 2013 | 0 | 5 | 0 | 0 | 0 | | **5** | 100 | 1 |
| 25 August 2013 | 3 | 1 | 1 | 0 | 0 | | **5** | 40 | 0.98 |
| 27 September 2013 | 0 | 0 | 3 | 12 | 3 | | **18** | 100 | 0.55 |
| 28 September 2013 | 2 | 5 | 2 | 8 | 7 | | **24** | 92 | 0.69 |
| 23 July 2014 | 0 | 0 | 4 | 1 | 0 | | **5** | 100 | 0.19 |
| 05 August 2014 | 1 | 2 | 3 | 0 | 0 | 1 | **6** | 83 | 0.64 |
| 24 August 2014 | 2 | 1 | 3 | 0 | 0 | | **6** | 67 | 0.82 |
| 05 September 2014 | 8 | 4 | 0 | 0 | 0 | 1 | **12** | 33 | 0.75 |
| 06 September 2014 | 0 | 3 | 6 | 3 | 5 | | **17** | 100 | 0.94 |
| 09 September 2014 | 0 | 2 | 0 | 2 | 1 | 1 | **5** | 100 | 0.7 |
| | **34** | **98** | **72** | **68** | **44** | **3** | **316** | **89** | **0.6937037** |

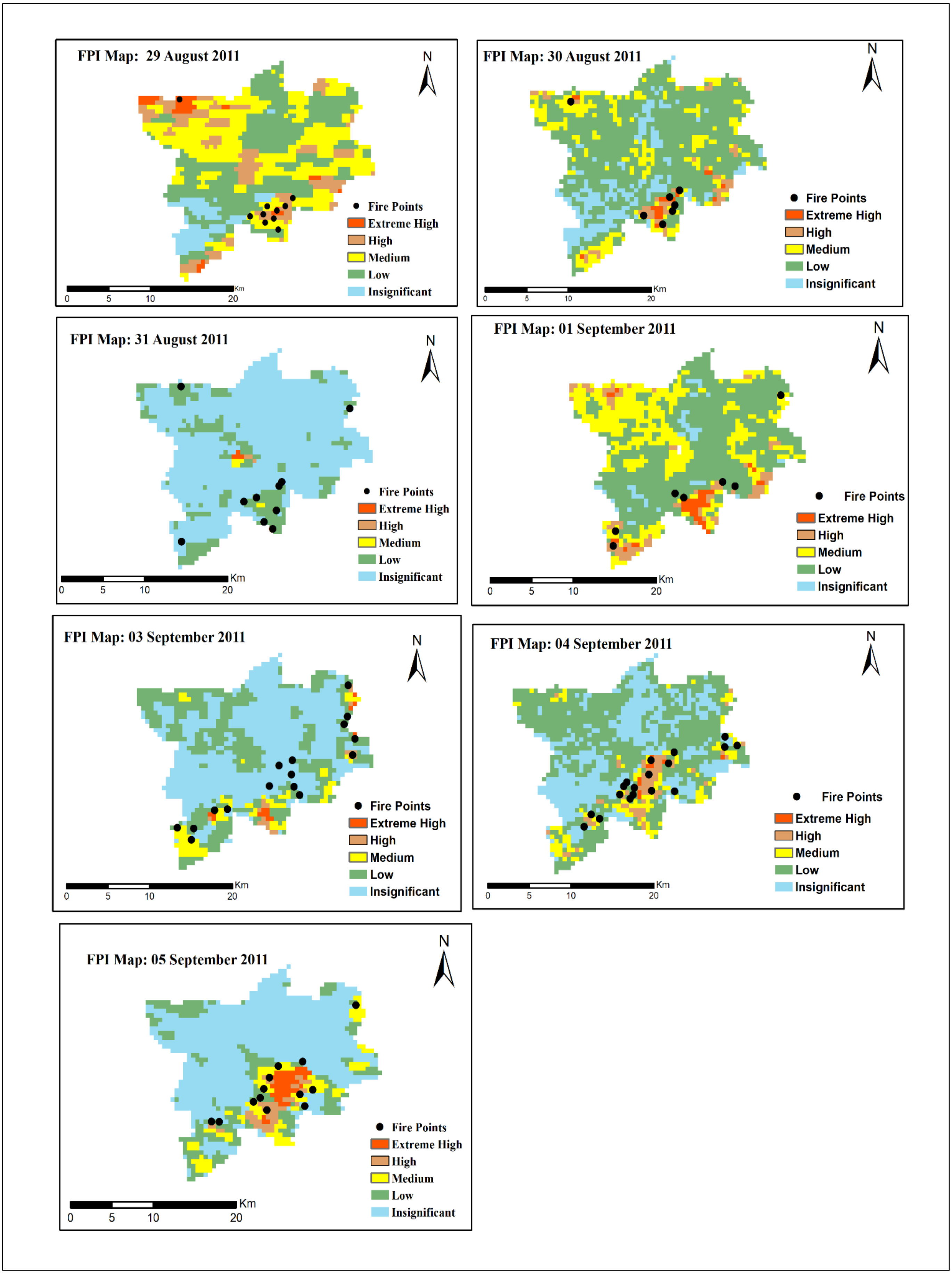



Figure 3:19. Fire Potential Index Map overlaid with corresponding fire point locations for the year 2011.

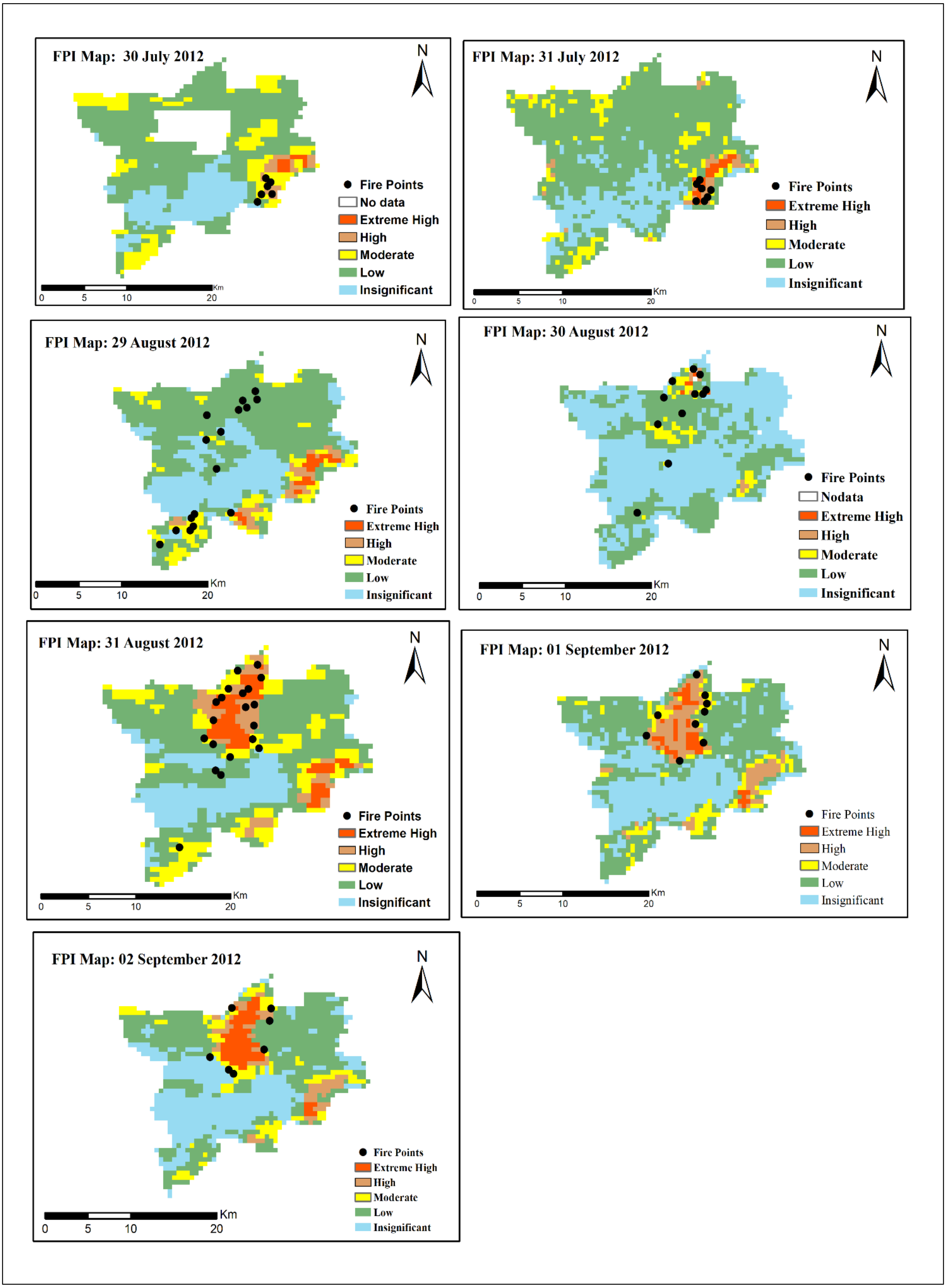



Figure 3:20. Fire Potential Index Map overlaid with corresponding fire point locations for the year 2012

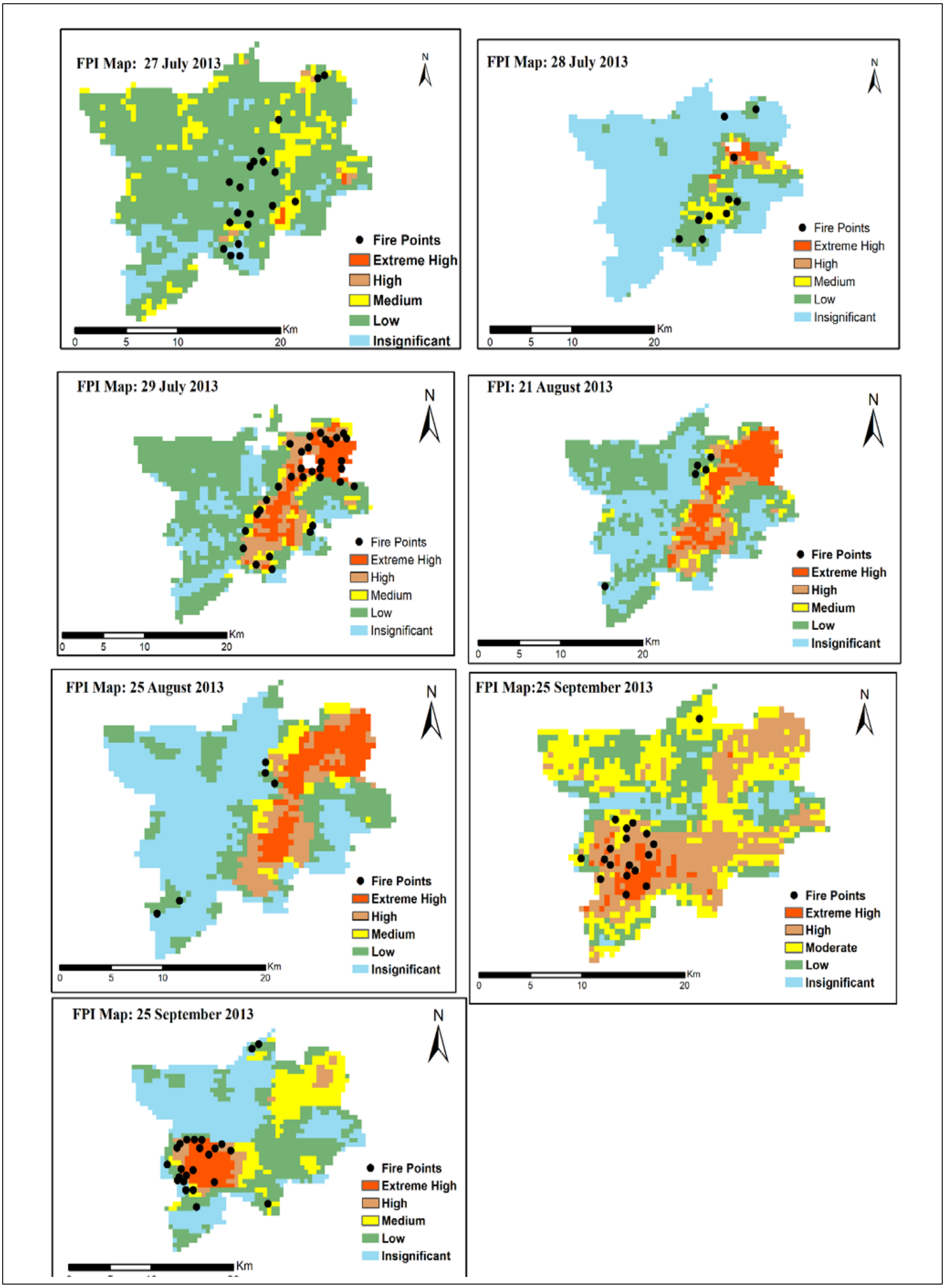



Figure 3:21. Fire Potential Index Map overlaid with corresponding fire point locations for the year 2013

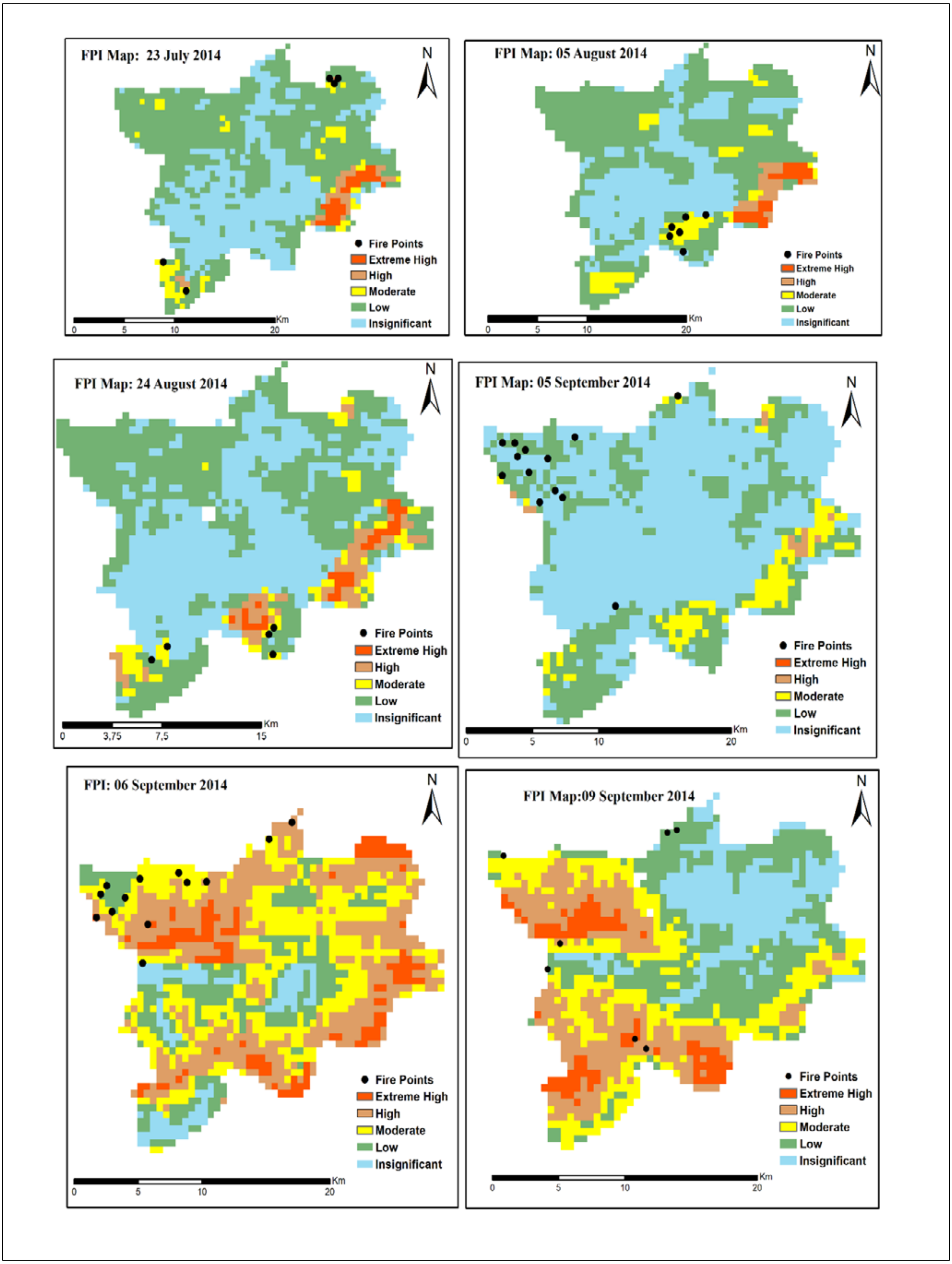



Figure 3:22. Fire Potential Index Map overlaid with corresponding fire point locations for year 2014

## 3.4 Discussion

GGHNP experience winter fire season because of the summer rainfall pattern. Annual fire frequency trends as displayed in Figure 3.3. are revealing in terms of the impact of predicted climate change and inter-annual climatic variation on fire. As displayed in Figure 3.3. 2013, and 2014 experienced the greatest number of fires during the fire season of 2011 to 2014. These years (2013 & 2014) have been cited as the warmest years recorded in the Southern Hemisphere compared to global average (National Centers for Environmental Information (NCEI), 2017). One can assume that GGHNP annual average air temperature would be similar to that of the Southern Hemisphere as a whole. Two possible scenarios have been established for fires under a warming climate (Strydom and Savage, 2016). First scenario states that under warmer air temperatures, heat waves and drought conditions may be more severe which may result in vegetation desiccating at higher rates, leading to drier fuel resulting in increased fire numbers. Secondly, under a warming climate rainfall maybe significantly higher. Higher rainfall totals may lead to increased rates of vegetation growth, leading to heavier fuel loads which results in more available fuel to burn. As both 2013 and 2014 have been marked as the years of above- average air temperature and have high number of fire points therefore these two scenarios are accurate.

Similarly, to other studies, majority of fires occur in August and September during relatively rain-free winter months, when vegetation is dormant and dry and the start of summer rains when lightning prevails (Makhado, 2012, Strydom and Savage, 2016, Van Wilgen, 2009). This may be due to that August is known as “dry and windy month”. Wind is a very powerful drying agent of vegetation, high wind speed dry fuel out much faster and it increases the supply of oxygen and increase the combustion rate of fire. September is the month that coincide with spring warming, a condition that promote fuel desiccation and more severe fire (Arganaraz *et al.*, 2016). Yates *et al.* (2009) have shown in Northern Australia that fire lit in the early dry season are smaller or less than the fire that occur late in the dry season. GGHNP fire pattern does not support this pattern. Monthly distribution of fire points as depicted in Figure 3.4. revealed that fire intensifies at the later stage of dry season. GGHNP falls within the Zone 4 lightning strikes for $km^2$ thus the park is naturally prone to lightning (Govender, 2011). Lightning fires tends to take place after the start of summer rains, one should expect that some of fires might be of lightning-induced fires. The study revealed that no fire recorded in June 2011 however, the only year which experienced late fire was in November and this serves as a challenge to critical decision makers on time of prescribe burning.

According to United States Geological Survey (USGS) (2016), FPI is a fuel-moisture based fire risk assessment tool. Numerous remote sensed derived indices and indicators directly or indirectly estimate moisture content of fuel including those used to measure FMI ($RGI_{NDWI}$ and NMDI) and Potential Surface Temperature (LST and elevation) which were used to prepare the FPI. These indices and variables were fully described in Section 3.2.2.1. Many other remote sensing- derived indices or indicators could not be included during estimation of FPI but the importance of the used indices and variables in fire risk assessment is well documented in numerous previous studies (Bian *et al.*, 2013, Burgan, 1996, Chowdhury and Hassan, 2013, Chuvieco *et al.*, 2002, Huesca-Martínez *et al.*, 2007, Huesca *et al.*, 2014, Maselli *et al.*, 2003, Wang *et al.*, 2008, Wang *et al.*, 2013b, Yebra *et al.*, 2013).

The afore-mentioned parameters used for this study and have proven for their effective contribution for fire risk assessment and mapping. The results of this study is in line with other previous work of different authors (Babu -Suresh *et al.*, 2015, Burgan *et al.*, 1998, Huesca *et al.*, 2014, Martínez *et al.*, 2007, Qin *et al.*, 2008, Schneider *et al.*, 2008, Wang *et al.*, 2013a). Wang *et al.* (2013a) urged that since fuel moisture content is a ratio of water content to dry mater content, single vegetation index may not be used to determine fire potential and used two indices to estimate moisture content hence this study used the linear combination of both vegetation water index ($RGI_{NDWI}$) and drought effect index (NMDI) to estimate FMI. This is because with a ratio of two indices many factors that affect vegetation indices in general such Leaf Area Index and soil noise may be cancelled out resulting into consistent estimation of FMI (Hunt *et al.*, 2012). However, dry-matters requires narrow-band data so monitoring fuel moisture required either a new sensor or combination of two sensors one with high temporal resolution for water content and one with high spectral resolution for dry-matter content (Wang *et al.*, 2013a).

FMI dynamic in GGHNP was influenced by the distribution of precipitation. High values of FMI estimation following relative high rainfalls in 2011 and 2014 as shown in Figure 1.5. This could be explained by the fact that vegetation have received sufficient rainfall for its growth and that the vegetation entered “green-up” period after the growing season, which increased the water content (Liu *et al.*, 2017). On the other hand, the lower values of FMI were observed during 2013 fire season and in September and coincide with the highest number of fire points observed during 2013 fire season and in the month of September. This could be related to loss of foliage due to severe negative rainfall anomaly of 2013.

LST also have influence on fire risk as it controls fuel temperature and moisture content of the fuel. However, in mountainous areas similarly to the study area it is very difficult to quantify LST for fire risk assessment as indirect indicator of fuel moisture owing to a complex interaction between atmospheric and rugged terrain. In line with other previous studies, a novel approach in overcoming terrain-induced variation in LST was adopted by using Potential Surface Temperature in estimation of fire risk assessment. For example, Babu -Suresh *et al.* (2015) used Potential Surface Temperature to estimate FPI for Uttarakand . According to Dasgupta *et al.* (2006), temperature would be expected to increase in drier vegetation on account of reduced evapotranspiration. In comparison of Potential Surface Temperature with FMI values, slight deviation in mean annual was observed in this study (i.e. very dry area only covers 4% vs 7% very high Potential Surface Temperature). This could be that high temperature recorded by satellite might be caused by fire itself and therefore the sensors recording fire has to be of relatively higher temporal resolution than the one for LST (Chifodya, 2014). However, stronger relationship between FMI and Potential Surface Temperature was observed during 2012 fire season.

Estimation and mapping fire potential areas by using GIS and Remote Sensing techniques is a complicated task as different parameters are taken into account for analysing their effects in fire in different indices. AHP was used for calculating weights during ranking of the parameters. Although, AHP is well known and provides a very easy technique for ranking and weight derivation, few drawbacks of this process has been criticized by various researchers. During weight derivation by this process results created by interaction of those parameters may be ignored to its compensational behaviour (Mahdavi *et al.*, 2012). Kordi (2008) also mentioned that the uncertainty associated with the mapping of decision makers' judgement to priority number is not taken into account by AHP.

According to the South African Weather Services (SAWS) (2017), Southern Hemisphere seasons are classified into four: December, January and February are summer months, and the temperature and precipitation are at their highest; March, April and May are Autumn, and the temperature and rainfall decrease; June, July and August are Winter months and are cold and the temperature is at its lowest; and September, October and November are Spring months, and the temperature and rainfall increase slowly. However, throughout South Africa the transitional seasons of Autumn and Spring tend to be very shot and most analysis of climate is done using the assumption that January is mid-summer; July mid-winter (South African Weather Services (SAWS), 2017); August –late winter and September represents early spring and start of growing season. FPI estimates the fire risk or danger quite well. Because according to Dasgupta *et al.* (2006), during the beginning of the growth season (September) fire danger or risk is higher on the average. This is in consistent with this study as shown in Figure 3.18. This is the result of vegetation accumulated during the previous seasons (Chifodya, 2014). Furthermore, the FPI estimation revealed that high to extreme high fire danger decrease during mid-winter (July) when temperature drops and increase during late winter month (August), late dry season (Figure 3.18). The main reason is that during winter temperature in GGHNP drops to the freezing point and snowfalls thus fuel become moist whereas in August strong winds cause vegetation to dry making it susceptible to fire.

## 3.5 Conclusion

FPI was estimated to determine the susceptibility of vegetation to fire of GGHNP area which was the main objective of this chapter. Two parameters namely, Fuel Moisture Index and Potential Surface Temperature were used for estimation of FPI. Total of four remotely sensing derived variables or factors (i.e. RGIndwi, NMDI, LST and elevation) were used to prepare these parameters. FPI map having five danger classes of GGHNP was prepared. Geospatial Techniques such as RS and GIS provided the techniques and tools to conduct complicated integration needed and preparation of FPI map in a fine scale (landscape scale).

The FPI values show that on average there is extreme high to high fire danger area which covers about 4% and 8% respectively whereas moderate fire danger area constitutes 13% of the park area. About 34% and 42% of the park area were identified as insignificant to low fire danger zone respectively. In temporal basis, largest area coverage of high to extreme fire danger classes was observed during 2013 (17%), followed by 2014 (16%), 2012 (8%) and 2011(6%) and was observed in September (17%) followed by August (11%) and July (6%). Assessment of the effectiveness of the FPI model was very important objectives of this chapter. Fire Points data was very helpful for the accuracy assessment. The results indicated that the model is reliable because only 11% of fire points fell under insignificant fire danger class.

The goodness of fit of the model suggests that MODIS products and derived indices have a great potential to predict fire danger in GGHNP. These results indicate that this model might be useful for monitoring spatiotemporal distribution of susceptibility of vegetation to fire. It is imperative to consider that the derived fire potential or danger maps do not completely explain fire occurrence since high FPI values are necessary condition for, but not a cause of fires because fire only occurs when ignition agents is present (Chuvieco *et al.*, 2009)

# Chapter 4

# GENERAL CONCLUSION

## 4.1 Introduction

Though fire is regarded as one of the ecological management tools, still poses negative natural and socio-economic impacts. Fire risk assessment and mapping is still considered a challenge, geospatial technologies such RS and GIS has shown to outperform conventional methods. There have been numerous RS studies focused on fire risk assessment and mapping within Protected and Unprotected areas, however, few of them has focused on the mountainous area. Planned fire or Prescribed fires in the PAs without the knowledge of fire risk conditions lead to serious negative impacts such as loss of biodiversity. In South Africa, Fire Danger Rating System has been adopted and is based on meteorological variables derived from weather station which is well known for ill-posed spatial-interpolation problem. Moreover, RS has not been well explored as tool for FDR. In the course of this study, a simple but unique fully remote sensing-based fire potential Index for fire risk assessment at 500m spatial resolution was developed for the mountainous GGHNP.

The objectives of this study were to:

1. Review previous studies regarding the successes and limitations of utilising remote sensing in monitoring wildfire risk conditions for fire risk assessment/mapping in protected area.
2. Calculate fuel moisture index (FMI) using satellite remote sensed derived variables (Relative Greenness Index derived from Normalized Difference Water Index (NDWI) and Normalised Multiband Drought Index (NDMI).
3. Determine the Potential Surface Temperature from Land Surface Temperature and Elevation.
4. Estimate FPI by using data layers from (2 & 3)

## 4.2 Monitoring fire risk conditions in PAs

RS is a valuable tool for monitoring fire danger or risk conditions as it can explicitly reveal spatial patterns of fire risk in recurrent and consistent way over a large area (Wang *et al.,* 2013b). Chapter two (2) reviewed different remote sensing data and techniques that have been used for predicting and monitoring fire risk conditions and its implication for fire risk assessment and mapping in PA. The review showed the capabilities and the limitations of RS techniques for monitoring fire risk conditions. Image fusion techniques, in particular fusion of optical and hyperspectral data, fusion of hyperspectral and LiDAR data have demonstrated to improve operational use of fire risk models. The integration of GIS and RS data especially broadband multispectral data is emerging as a fashionable research field in fire risk assessment. Regression analyses remained the common effective and easy-to-use techniques for monitoring and estimations of fire risk conditions. Knowledge-based, ANN, AHP and BNN methods has been employed for fire risk assessment. Overall, it can be concluded that monitoring and estimation of fire risk conditions for fire risk assessment can be conducted with reliable accuracy using multi-sensory or multi resolution data or multi-variate fire risk index.

### 4.3 Estimation of Fire Potential Index

Estimation of FPI is an essential process as it is fuel-moisture based index for fire risk assessment and fuel moisture is one of the critical parameters for both fire ignition and propagation (Yebra *et al.*, 2013). The main aim of Chapter 3 was to investigate the potential of remote sensing data in determining the susceptibility of vegetation to fire by estimation of FPI for mountainous GGHNP. The study consisted of four steps: (i) Processing of the input variables ($RGI_{ndwi}$, NMDI, LST, Elevation) and generation of remotely sensed risk variables or indicators in a spatial consistent way (geographical data layers of FMI, Potential Surface Temperature and Fire Points); (ii) Determination of variables-specific fire danger into five fire danger classes (iii) Integration of variable into a synthetic FPI. Finally, statistical analysis was conducted to assess the effectiveness of the FPI model in fire danger rating.

The results of this studies indicated that that FPI derived from remote sensed variables can provide useful index of fire potential variability on spatial and temporal scale in the mountainous region. Thus indicated that MODIS-based FPI developed from $RGI_{ndwi}$, NMDI, LST, Elevation is a useful index to estimate the proneness of vegetation to fire in recurrent and consistent manner over a mountainous area of the study area GGHNP. This is critical important because of lack of inaccessibility of area due to the its rugged topography. Despite the good spatial relationship between FPI and past fire occurrences, it is suggested that the proposed methods should be evaluated prior to implementing in other ecosystems across the country according to the variables of that particular ecosystems. Exception could be made for the similar mountainous grassland landscape like this study area,

Fire regimes can be used to understand the past role of fire, current changes in fire regimes due to management actions and as indicators to future management practices and policies. Such dynamic variability of fire potential can have significant implications for defining management strategies. The difference found in the spatial and temporal dynamic of fire potential depends on the model inputs used. This fact can be important in terms of management implication. For instance, FPI can be used for resource allocation early in the fire season and planning fuel load reduction following fire season.

## 4.4 Contributions to knowledge of science

The main contributions resulted from this dissertation are as follows

- Numerous reviews have been conducted on the use of RS on fire management, however, focused on the fire monitoring or post fire products. This study reviewed the literature on pre-fire stage (i.e. monitoring fire risk conditions for fire risk assessment.
- In general, FPI was developed and implemented in United States (Burgan *et al.*, 1998), Europe (Huesca-Martínez *et al.*, 2007) and India (Babu -Suresh *et al.*, 2015)focusing on large scale or continent or regional scale. This study could be first of its kind in South Africa

if not within the African continent which focused on mountainous protected landscape that is prone to fire.

- Previous researches computed live fuel moisture content using NDWI derived from MODIS SWIR band 5 or 6. Here, NDWI was derived from MODIS SWIR band 7 which shown to be more moisture dependent.
- Both NMDI and Potential Surface Temperature were used to quantify vegetation conditions for FPI for the first time
- The concept of integrating remote sensed derived variables of FMI (RGIndwi and NMDI) and Potential Surface Temperature (Elevation and LST) using GIS techniques in predicting fire potential conditions are unique and applied over the fire prone mountainous grassland protected landscape.

## 4.5. Future research

Despite the effectiveness of the proposed method of combining RS derived variables that characterized vegetation, gathered frequently and continuous in predicting fire potential, the following issues should be considered in order to potentially enhance its capability:

- Vegetation or fuel types and meteorological variables such as relative humidity and precipitation are quite often used in the framework of FPI (Burgan *et al.*, 1998) as well as wind velocity and direction; insolation are cited as the most influential factors of fire occurrence. So thus it will be worthwhile to be investigated
- Estimation of fire risk conditions is currently critical limited because of variance in temporal and spatial dimensions between ground measurement and a sensor. MODIS has high temporal resolution which makes useful for providing fire risk conditions however MODIS spatial resolution of 500m remain a challenge as does not give enough detail for some fire management activities. Therefore, satellite data with high to moderate spatial resolution is desired for upscaling ground measurement before low spatial resolution data can be used to provide estimates of FMC over landscape scale in fine scale.
- Modeling and forecasting of this MODIS based FPI on a pixel basis using time series models in order to develop a robust application for environmental monitoring and forecasting in spatially continuous framework.
- Improved understanding of climatic variation in a complex topography and its influence on spatial and temporal variation in fire potential will be essential if we are to continue to assist PA managers to maintain and restore fire as dominant and beneficial ecological process.

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