Modelling susceptibility to Parthenium *hysterophorus* invasion in KwaZulu-Natal Province, South Africa using physical, climatic and remotely sensed derived variables

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A dissertation submitted in the fulfilment for the degree of Master of Science in Environmental Sciences, in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal.

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Abstract

Invasive alien plants (IAP) are considered as one of the major causes of global change. Parthenium *hysterophorus* is recognized as one of the world's most aggressive, harmful and extremely resilient invasive plant species. It has adverse impacts on the environment, economies, biodiversity, human health and agriculture. Identification and modelling of areas vulnerable to Parthenium invasion is critical for proactive control and site- specific management of its spread. This study sought to test the performance of Maxent algorithm in modelling habitats susceptible to Parthenium invasion using selected environmental and physical variables and remotely sensed data. Specifically, the study sought to identify key physical and bio-climatic variables that influence the distribution of Parthenium. Furthermore, the study sought to determine the value of the freely available Sentinel 2 multispectral instrument (MSI) datasets in concert with environmental variables in modelling habitat susceptible to Parthenium invasion. The Maximum Entropy model (MaxEnt) machine learning algorithm was used to model Parthenium invasion using presence - only records (n = 274). Results showed that landscapes characterized by low elevation, close proximity to roads and high precipitation were the most susceptible to Parthenium invasion. An Area under curve (AUC) value of 0.946 was attained, indicating that the model derived using the aforementioned optimal physical and bio-climatic variables performed better than random. Based on the high AUC values, results also showed that all the model scenarios derived from spectral bands and environmental variables, vegetation indices and environmental variables and a combination of spectral bands, vegetation indices and environmental variables performed better than random, with AUC values of 0.976, 0.970 and 0.974, respectively. The higher accuracy exhibited by the optimal model (bands and environmental variables) can be attributed to the integration of red edge band centered at 705 nm in Sentinel 2 MSI and environmental variables in predicting areas susceptible to Parthenium. Overall, these results demonstrate the potential of integrating the freely available Sentinel 2 MSI data and environmental variables to improve the mapping of habitat susceptibility to Parthenium invasion. These results could be beneficial for early detection, site -specific weed management and long-term monitoring.

Preface

This study was conducted in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, under the supervision of Dr. John Odindi and Prof Onisimo Mutanga in fulfilment of the requirements of Master of science.

I declare that the current work represents my own ideas and has never been submitted to any other academic institutions. Acknowledgement has been duly made for statements originating from other authors.

Arogoundade M Adeola Signed ……………… Date ……………….

1.. Dr. John Odindi (Supervisor) Signed ………………. Date ……………...

2.Prof Onisimo Mutanga (Co-Supervisor) Signed………………... Date……………….

Plagiarism Declaration

I Arogoundade M Adeola, declare that:

1. The research reported in this document is my original work, unless indicated otherwise.
2. This dissertation has not been submitted for attainment of a degree or examination purposes at another university.
3. This dissertation does not contain any data, graphics, and other information from other persons, unless duly acknowledged.
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Publication and manuscripts

The following manuscripts are under peer-review or being prepared for publication.

Arogoundade, M.A, Odindi, J., O. Mutanga, & Sibanda, M. (Under Review). Determining the vulnerability of South African landscapes to Parthenium *hysterophorus* invasion using bio-climatic and physical variables. South African Journal of Science. [Chapter 2]

Arogoundade, M.A, Odindi, J., O. Mutanga, & Sibanda, M. (In preparation). Modelling Parthenium *hysterophorus* invasion in Kwazulu-Natal using remotely sensed data and environmental variables. International Journal of Remote Sensing. [Chapter 3]

A poster presentation titled "Habitat susceptibility modelling of Parthenium *hysterophorus* in Kwazulu-Natal, South Africa" was presented by Arogoundade, M.A. at 11th Society of South African Geographers (SSAG) Conference 2017, University of Mpumalanga, South Africa. [Chapter 2]

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CHAPTER 1

GENERAL INTRODUCTION

1.1 Introduction

Invasive plant species are non-indigenous or exotic plants introduced outside their natural adapted environments and dispersal potential (Baran, 2011, Van Kleunen et al., 2015). According to the World Conservation Union (IUCN, 2000) invasive plant species are defined as organisms that become established in indigenous ecosystems or habitats by rapidly multiplying and modifying the landscape, thereby threatening native biodiversity. Globally, studies have shown that alien invasive species can among others change soil nutrients (Vitousek and Walker, 1989, Daehler and Strong, 1994) and increase carbon absorption rate (Le Maitre et al., 1996) thereby posing a risk to native plant species. Generally, invasive species are a key risk to among others biodiversity, landscape productivity and animal and human health.

Parthenium *(hysterophorus)* is one of the major problematic invasive plant species across the world (McConnachie et al., 2011, Dhileepan, 2007, Mahmoud et al., 2015). It is a noxious invasive species which degrades natural ecosystems, invade agricultural and rangeland habitats and outcompetes native species through allelopathy (Belz et al., 2007, Patel, 2011). Studies have also demonstrated its harmful effects on human health, agriculture, and environment (Dhileepan, 2007, McConnachie et al., 2011). The weed has a major impact on grazing land and expands exponentially to new areas (Bhowmik and Sarkar, 2005, Khan et al., 2012).

Parthenium is an erect and annual herbaceous invasive plant species thought to have originated from South and Central America and Mexico. The weed invasion has been reported in India, Eastern and Southern Africa, the Caribbean, Australia and North America (Dhileepan and Wilmot 2009, Patel, 2011). It is an annual herb growing up to 1.5m high, with longitudinal groove, hairy stem, and deep tap root (Bhowmik and Sarkar, 2005). In climatic conditions characterised by rainfall greater than 500mm per annum and temperature ranging from 10 to 25^{0}C, the weed grows rapidly and produces flowers at any time of the year. Plant growth and seed production are reduced by low temperature, causing a reduction in net assimilation rate and leaf area index (Navie et al., 1996a, Pandey et al., 2003). Flowering starts between 6 to 8 weeks after germination and soil moisture is hypothesized as an important factor of flowering (Navie et al., 1996a). Each plant produces about 20 000 seeds which can survive for years (Khan et al., 2012, Dhileepan and Wilmot 2009).

Parthenium invades roadsides, water courses, cultivated fields and overgrazed lands. Seeds can travel long distances due to their light weight. Seeds can also be easily spread by humans, livestock, winds, flood, farm machinery or flowing water (Navie et al., 1996a, McConnachie et al., 2011, Javaid et al., 2009). The seeds persist in the soil and are viable for long periods (Navie et al., 1996a). Parthenium weed is not easy to eradicate due to its small size, persistence of the seed in soil, germination rate, and adaptability in dry conditions.

Literature has demonstrated the weed's significant impact on human health, agriculture, environment, and biodiversity (Patel, 2011, Strathie et al., 2011, Bromilow, 2001). Dhileepan (2007), for instance, showed that Australian native grazing land has declined due to an increase in Parthenium. The weed releases toxic allelochemicals which inhibit the growth of surrounding vegetation (McConnachie et al., 2011). It's fine hairs and pollens have been found to cause severe allergic reactions in people, and causes dermatitis, hay fever and asthma among other diseases (Bromilow, 2001). Reports of domestic animals, as well as wildlife, feeding on Parthenium with serious health hazards in the animals have been noted. For instance, Patel (2011) reported degenerative liver and kidney changes in wildlife, while Navie et al. (1996a) and Strathie et al. (2011) found a reduction in the quality of milk and death in livestock after consuming a significant amount of the weed. Parthenium is known to cause severe economic losses to agricultural production by invading cropping land and grazing lands**.** Khosla and Sobti (1981) reported a 40% decline in agricultural crops due to Parthenium invasion in India. While Adkins et al. (2010) reported a reduction in Australia's grazing land.

In Africa, Parthenium has widely invaded Swaziland, Mozambique, Zimbabwe, Tanzania, Kenya and Ethiopia. Predictive modelling has shown that most areas of sub-Saharan Africa are suitable for the growth of Parthenium (McConnachie et al., 2011, Kija et al., 2013). In South Africa, Parthenium weed, also known as Maria-Maria and more recently 'famine' weed or "Umbulalazwe", has invaded KwaZulu-Natal, Mpumalanga, North West and Limpopo provinces, and continues to spread rapidly (Belz et al., 2007, Strathie et al., 2011). According to Nanni et al. (2016a), the weed expanded from 3 cells (invasion sites) in 1980 to 76 in 2014 in the country, thereby making it a weed of national significance. Due to its impact on biodiversity, human health and agriculture, a national strategy was initiated by the South African government for its eradication and control. Due to the aforementioned adverse effects, up-to-date information on the weed's distribution and areas of susceptible invasion is necessary for designing appropriate mitigation and landscape rehabilitation measures.

Identification and modelling of areas vulnerable to Parthenium invasion is critical for proactive control and management of its spread. Generally, monitoring and modelling of the potential range of Parthenium focuses on the physical and climatic variables that influence its invasion. Hence, these variables could be used model the spatial distribution of invasion under the present environmental conditions and vulnerable areas. Physical and bioclimatic variables (climate, topography, elevation, temperature etc) are quantitative or descriptive measures of different environmental features. These variables can be collected during field sampling (assisted by remote sensing) to produce maps showing their distribution in an area (Keshavarzi et al., 2013). Such maps are important inputs to spatial planning, decision making and land evaluation. According to Franklin (1995), the spatial distribution of species have been modelled using these variables. Hijmans and Graham (2006) and Václavík and Meentemeyer (2012), for instance used climatic and physical variables to predict vegetation patterns globally, while Apan et al. (2008) and Evans et al. (2007) modelled suitable areas for Blackberry (*Rubus fruticosus agg*.) distribution in Australia. The studies showed that Blackberry was affected by factors like mean rainfall, distance from New South Wales border and land use (disturbed areas). In a similar study in the Cape Peninsula, South Africa, Higgins et al. (1999) developed a model to predict the landscape-scale distribution of invasive plant species plants such as *Acacia cylops, P.pinaster, A.longifolia,* using physical and climatic variables. Hence, it can be concluded that the distribution of invasive plant species are influenced by these variables.

Traditional methods e.g. field surveys and map interpretation have been used to acquire spatial data of invasive plant species (McConnachie, 2015). Mapping of plant species for a large area can be laborious, time-consuming, date lagged, and costly, especially in difficult terrain using traditional methods (Taylor et al., 2011). To mitigate these challenges, remote sensing and GIS have been proposed as quicker, timely and economical approaches to determining the distribution of vegetation at a landscape scale (Langley et al., 2001, Odindi et al., 2016, Galidaki et al., 2017).

Remotely sensed image spectral properties are increasingly becoming valuable in the advancement of empirical techniques such as vegetation indices for estimating forest canopy gaps and perimeter, leaf area index and biomass (Merzlyak et al., 1999, Baret and Guyot, 1991). Hence, knowledge of the spectral signatures of invasive plant species allows informed assessment of infested sites before mapping. A growing body of literature has demonstrated the success of hyperspectral remotely sensed imagery in the discriminating and mapping the spatial distribution of invasive plant species (Robinson et al., 2016, Niphadkar and Nagendra, 2016, Skowronek et al., 2017, Gairola et al., 2016). However, hyperspectral sensors are expensive, spatially restricted and require longer processing time. Hence, the shortfalls of hyperspectral sensors have paved way for readily and freely available broadband multispectral sensors with a large swath width, such as Sentinel 2 MSI and the Landsat series (Mathieu et al., 2013).

Sentinel 2 MSI datasets for instance allows for timely and regional mapping of vegetation (Delegido et al., 2011, Clevers and Gitelson, 2013, Majasalmi and Rautiainen, 2016). The sensor is characterised by additional red edge bands that have high potential to discriminate subtle variation in vegetation (Frampton et al., 2013, Delegido et al., 2011, Richter et al., 2012, Atzberger and Richter, 2012, Gil et al., 2013). Successful adoption of Sentinel 2 in several studies has also been achieved using vegetation indices. However, a combination of derived vegetation indices and spectral bands in modelling Parthenium remains largely unexplored.

Studies have previously integrated environmental variables with remotely sensed data to detect and map invasive plant species (Joshi et al., 2005, Malahlela et al., 2015). For instance, Joshi et al. (2005) integrated environmental data with Landsat ETM + imagery to map the likely occurrence of C. *odorata* in south central Nepal forest while Malahlela et al. (2015) integrated World View-2 vegetation indices and ancillary environmental data to map Chromolaena *odorata* in South Africa. In a similar study, Bradley and Mustard (2006) mapped Cheat grass (*Bromus tectorum*) using Landsat MSS, TM, and ETM remotely sensed data and landscape variables in north central Great Basin .

Existing studies have demonstrated that GIS techniques, integrated with powerful statistical algorithms enables the spatial modelling of invasive plant species and helps in determining environmental variables that determine occurrence of species (Franklin, 1995, Yang et al., 2006). Spatial Distribution Models (SDMs) for instance have been used to describe the relationship between observed species distribution, their environment and the ecological change in the environment (topographic, vegetation and bioclimate). SDMs also relate a species occurrence to environmental conditions for prediction of the species in un-sampled locations. Numerous statistical methods have been used to develop SDMs for modelling the spatial distribution of invasive plants using environmental variables, these include; logistic regression (Gallardo, 2003), fuzzy envelope models (Guisan and Zimmermann, 2000), maximum entropy (Kija et al., 2013), random forest (Adam et al., 2013), and support vector machine (Guo et al., 2005). In most SDMs, presence and absence data are required in modelling species, but where presence only data is available (i.e. the species occurrence points are known but non-occurrence points are not known), pseudo -absences are generated as a substitute for the absence data. Absences could be due to unsuitable location or the site has not yet been invaded, two possibilities that are often indistinguishable for invasive plant species (Jarnevich and Reynolds, 2011).

The Maximum Entropy model (MaxEnt) developed by Phillips et al. (2006) is a presence-only machine learning algorithm with simple arithmetic formulation. MaxEnt estimates the maximum entropy of a target probability distribution based on the input environmental data in predicting areas of likely invasion of the species. The approach has become popular due to its robust predictive performance with a range of sample sizes and ability to reduce overfitting using its regularization setting (Ficetola et al., 2007, Merow et al., 2013, Phillips and Dudík, 2008). Also, the Maxent algorithm has the ability to fit complex responses to environmental variables (continuous and categorical) (Barry and Elith, 2006, Phillips et al., 2006). Several works (Padalia et al., 2014, Truong et al., 2017, Suárez-Mota et al., 2016) have used MaxEnt in modelling invasive plant species. Wakie et al. (2014) for instance, used MaxEnt to map the current and potential distribution of Prosopis using Moderate Resolution Imaging Spectro-radiometer (MODIS) vegetation indices and top-climatic predictors in Ethiopia, while Hoffman et al. (2008) tested the capabilities of the MaxEnt algorithm in predicting the likely occurrence and distribution of five invasive plant species along the North Platte River, Nebraska. Hence, due to adverse socio-economic threat posed by Parthenium invasion in KwaZulu-Natal province, and indeed the rest of South Africa, this study sought to test the performance of MaxEnt to modelling habitat susceptible to Parthenium invasion using bio-climatic, topographic variables and remotely sensed data (Sentinel 2 MSI).

Previously, the potential distribution of Parthenium has been modelled using bioclimatic variables (temperature, rainfall) to predict areas highly susceptible invasion (Kija et al., 2013, McConnachie et al., 2011). However, the relationship between vegetation phenology, physical and climatic variables on the spatial distribution of Parthenium remains unexplored. Hence, the need for this study. Different remotely sensed measure of vegetation such as derived vegetation indices e.g. Normalized difference vegetation index (NDVI), Soil adjusted vegetation indices (SAVI), Enhanced Vegetation Index (EVI) have been explored in evaluating differences in habitat quality at a finer scale. In this study, Sentinel 2 MSI spectral bands and vegetation indices were adopted to model areas susceptible to Parthenium invasion in KwaZulu-Natal using selected physical and bioclimatic variables. To the best of our knowledge, no study has been carried in modelling the likely invasion of Parthenium using the above.

1.2 Aim

The main aim of this study was to test the performance of Maxent algorithm in modelling habitats susceptible to Parthenium invasion using selected environmental, physical and remotely sensed data in KwaZulu-Natal, South Africa.

1.3 Objectives

The objectives of this study were;

1) To determine the performance of Maxent in modelling areas susceptible to Parthenium invasion using physical and bio-climatic variables.

2) To determine the value of freely available Sentinel 2 multispectral instrument (MSI) datasets in concert with environmental variables in modelling habitats susceptible to Parthenium.

1.4 Research questions

1. Which physical and climatic variables best describe the habitats for Parthenium?

2. How do the selected variables influence future invasion of Parthenium?

3. Does the integration of remotely sensed data (Sentinel 2) improve predictions of invasion over models generated from environmental variables?

1.5 Thesis Structure

CHAPTER ONE: GENERAL INTRODUCTION

The chapter presents a general background to Parthenium, its spread and effects. The chapter also presents the benefits of using physical and environmental variables, remotely sensed data and algorithms in predicting areas susceptible to invasive plant species. Furthermore, description of the study area and research objectives are summarised.

CHAPTER TWO: DETERMINING THE VULNERABILITY OF SOUTH AFRICAN LANDSCAPES TO PARTHENIUM *HYSTEROPHORUS* INVASION USING BIO-CLIMATIC AND PHYSICAL VARIABLES.

This chapter focuses on physical and bioclimatic variables in modelling the areas susceptible to Parthenium invasion. The chapter focuses on predicting landscapes vulnerable to Parthenium using bio-climatic and physical variables. A robust machine learning algorithm, Maxent was used to predict the relationship between Parthenium occurrence points, physical and climatic variables. The model performance was evaluated using the area under curve (AUC).

CHAPTER 3: MODELLING PARTHENIUM *HYSTEROPHORUS* INVASION IN KWAZULU-NATAL USING REMOTELY SENSED DATA AND ENVIRONMENTAL VARIABLES.

This chapter explores the utility of integrating the freely available Sentinel 2 MSI and environmental variables in modelling habitats susceptible to Parthenium invasion. In evaluating the strength of Sentinel 2 MSI, this study compared the results obtained using (i) spectral bands; (ii) derived vegetation indices as well as (iii) the combination of spectral bands and vegetation indices based on the Maxent algorithm. The choice of Sentinel 2 MSI was based on the additional unique spectral bands and finer spatial resolution.

CHAPTER 4: SYNTHESIS AND CONCLUSION

The chapter presents a synthesis of the major findings of study, the significance of the results, the limitations and further recommendations.

CHAPTER TWO

DETERMINING THE VULNERABILITY OF SOUTH AFRICAN LANDSCAPES TO PARTHENIUM *HYSTEROPHORUS* INVASION USING BIO-CLIMATIC AND PHYSICAL VARIABLES

This chapter is based on:

Arogoundade, M.A, Odindi, J., O. Mutanga, & Sibanda, M. Determining the vulnerability of South African landscapes to Parthenium *hysterophorus* invasion using bio-climatic and physical variables. *South African Journal of Science*, In Review.

Abstract

Parthenium (*Parthenium hysterophorus*) is one of the most problematic and devastating weed globally. It is a noxious alien plant species which, among others, degrades natural ecosystems, compromises agricultural and rangeland productivity and affects human and animal health. Hence, knowledge on its locality and area of invasion is important to develop early control strategies and site-specific mitigation measures. This study sought to determine areas susceptible to Parthenium invasion using a range of physical and environmental variables in KwaZulu-Natal province. Maximum entropy, a robust machine learning algorithm was used to predict the relationship between Parthenium occurrences and topographic and climatic characteristics. The area under the curve (AUC) was used to assess model performance when different climatic and topographic variables were used. Based on the optimal model, landscapes that were at a low elevation (<1500m), closer to roads and characterized by high precipitation were the most susceptible to Parthenium invasion. The study demonstrates the value of Maxent in providing robust and precise spatial framework to aid policy makers and land managers in controlling and long-term monitoring of areas susceptible to Parthenium invasion, and indeed other invasive species.

Key words: invasive species, Parthenium, MaxEnt, spatial distribution models, modelling, climatic variables, physical variables.

2.1 Introduction

Globally, invasive species are key risks to biodiversity, ecosystem functioning and socio- economy (Barik et al., 2011, Monty et al., 2013). One of such species is *Parthenium hysterophorus* (Parthenium), an annual herbaceous plant native to tropical America but invasive in over 20 countries in five continents (Bhowmik and Sarkar, 2005, Mahmoud et al., 2015). In South Africa, the number of Parthenium invaded sites has steadily increased. Nanni et al. (2016a) for instance, notes that the weed was found in only 3 cells (invasion sites) in 1980, 15 cells in 2000, 62 cells in 2007 and 76 cells in 2014. Its attributes such as rapid growth and distributive ability, allelopathy, high phenotypic plasticity and the ability to adapt to a wide range of environmental conditions aid its aggressive invasive ability (Ayele, 2007, Belz et al., 2007, Navie et al., 1996a). The weed has been reported to reduce rangeland, meat and milk quality and quantity (Bromilow, 2001, Dhileepan, 2007, Evans, 1997, Patel, 2011, Strathie et al., 2011). Severe allergic reactions such as dermatitis, hay fever and asthma have also been reported in people and animals in close contact with Parthenium (Patel, 2011). Hence, identification and modelling of potentially susceptible habitats to Parthenium weed is critical for proactive control and cost-effective mitigation of its spread.

In South Africa, Parthenium has invaded KwaZulu-Natal, Limpopo, North West and Mpumalanga provinces and continues to spread rapidly (Belz et al., 2007, Strathie et al., 2011). Its negative impact on animal and human health, agricultural production and biodiversity (Wise et al., 2007), as well as aggressive growth, have made it a weed of national concern. Hence, up-to date information on its distribution and vulnerable areas to invasion are critical in designing appropriate mitigation measures. In 2003, a national strategy was implemented by the South African government to control the weed (Nanni et al., 2016a, Strathie et al., 2011). This programme involved site specific biological and chemical control, containment plans, usage of competitive plant species and cultural methods (Goodall et al., 2010, Strathie et al., 2011).

In addition to the above-mentioned efforts, monitoring and modelling of vulnerable landscapes and habitats remains critical for designing optimal mitigation approaches. Based on the ecological niche theory, environmental and physical conditions form an important ecological niche appropriate for the survival and reproduction of species (Pearson and Dawson, 2003). Several authors e.g. Cadenasso and Pickett (2001), Soberon and Peterson (2005), Pauchard and Alaback (2004) and Dimitrakopoulos et al. (2017) have demonstated that physical variables (e.g disturbed sites, corridors for disperal and landscape structure) and climate (temperature and precipitation) have significant impact in the establishment and dispersal of invasive plant species (Blois et al., 2013). These variables have become important in predicting current and potential areas of plant invasion. Climate change for instance, alters temperature and precipitation pattern, thereby affecting biomass, land use practices and management decisions (Bradley et al., 2012, Hellmann et al., 2008). According to Pino et al. (2005)**,** several invasive plant species grow in different settings (climate and habitats) , but only under specific ecological conditions do they become agrresive invaders, thus the need to identify key predictor varaiables. Temperature and rainfall variability influence establishment and growth of invasive plant species. Apan et al. (2008) and Evans et al. (2007) for instance modelled suitable habitats for Blackberry (*Rubus fruticosus agg*.) distribution in Australia using climatic and physical variables. These studies showed that Blackberry was affected by factors like mean rainfall, distance from New South Wales border and land use (disturbed areas). A similar study Higgins et al. (1999) in the Cape Peninsula, South Africa, developed a model to predict the landscape-scale distribution of invasive plant species such as *Acacia cylops, P. pinaster, A. longifolia* using physical and climatic variables. In this regard, spatial distribution models (SDMs) have increasingly become popular in describing the relationship between existing physical and environmental conditions and the occurrence of species (Adhikari et al., 2015, Apan et al., 2008, Barik et al., 2011, Rameshprabu and Swamy, 2015, Williams et al., 2009).

A number of spatial distribution models make use of presence and absence data in modelling species (Boyce et al., 2003, Hirzel and Le Lay, 2008). However, due to significant efforts required to collect absence data, there has been a growing awareness in modelling species distribution using presence only data (Phillips et al., 2009, Elith et al., 2011, Fourcade et al., 2014). The Maxent entropy model, a correlative approach has been identified as one of the best SDM for presence-only data analysis (Ficetola et al., 2007, Hernandez et al., 2006, Elith et al., 2011, Yang et al., 2013). The approach has become particularly popular due to its robust predictive performance with a range of sample sizes and ability to reduce overfitting using its regularization setting (Elith et al., 2011, Fourcade et al., 2014, Merow et al., 2013, Ortega-Huerta and Peterson, 2008, Phillips et al., 2006). In this study, we seek to predict landscape vulnerability to Parthenium using bio-climatic and physical variables within the Maxent entropy modelling environment.

2.2 Materials and methods

2.2.1 Study area

This study was conducted in KwaZulu- Natal province, South Africa. The province occupies approximately 92,285 km^2 and lies between 26°50′ and 31°10′ South and 28°50′ and 32°50′ East. Altitudes ranges from sea level to 3400m, with topography ranging from coastal plains to mountain slopes of the Drakensberg mountain range. The study area is characterised by rainfall and temperature ranging from 500 mm to 2000mm and 11 ^{o}C to 28 ^{o}C, respectively. The entire province lies in the summer rainfall belt (Schulze and McGee, 1978). The province is mainly covered by grasslands, savannah woodlands, bush thickets and forest. Geological formations such as Arenite, Basalt, Tillite, Mudstone, Granite, Siltstone, Sand, and Shale underlie the sampling areas. The study area comprises of different land use types i.e. agriculture (commercial and subsistence, crop and animal farming), low and high residential settlements and ecotourism. Parthenium was first noticed in the KwaZulu-Natal province in 1880 and later in 1984 after the flood caused by Cyclone Demoina (McConnachie et al., 2011). Currently, Parthenium infestation is prevalent in among others along the physical infrastructure networks like roads and railways, croplands, plantations, grazing land, homesteads and fallow and abandoned lands. Existing literature (McConnachie et al., 2011, Nanni et al., 2016b) and field surveys have shown that KwaZulu-Natal is heavily invaded by Parthenium.

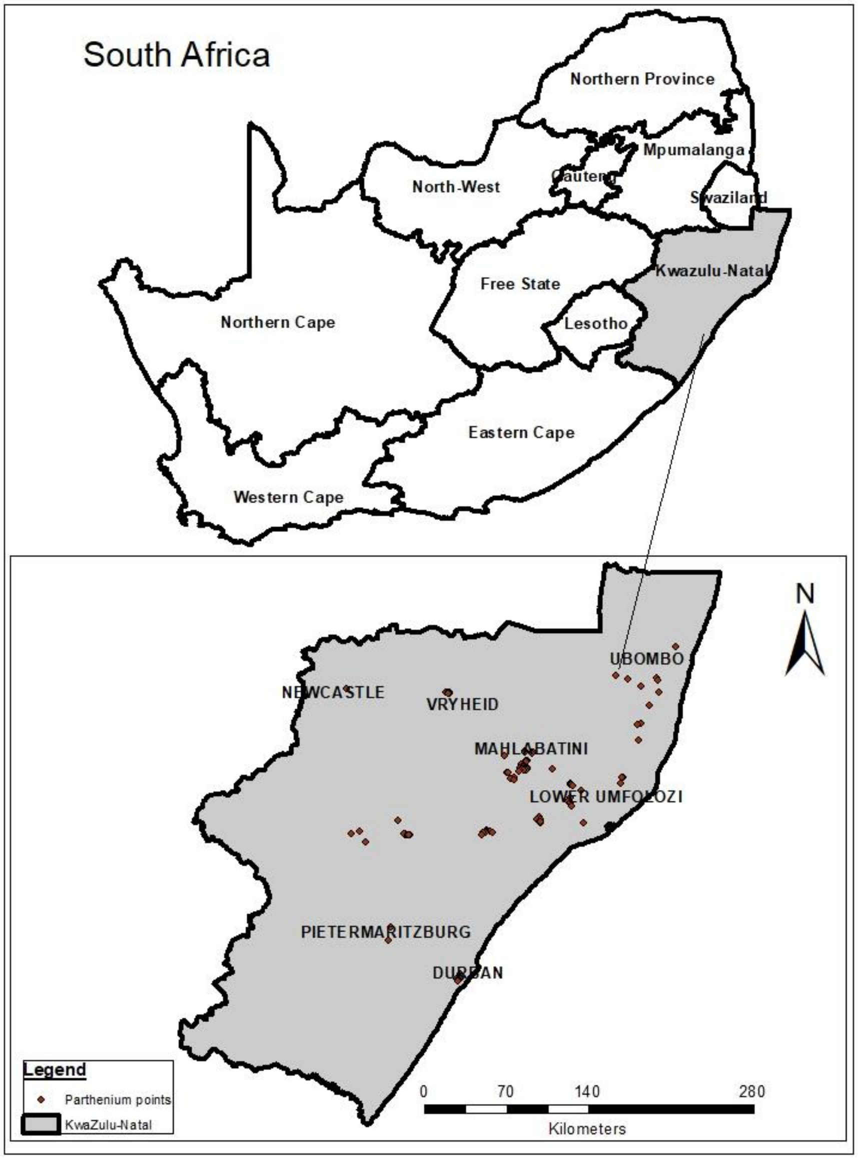

Fig 2.1: Map of the study area and Parthenium invaded areas.

2.2.2 Field data collection

Parthenium occurrence data were collected in various locations in KwaZulu-Natal province including, Mtubatuba, Durban, Vryheid, Richards Bay and Pietermaritzburg during the period between January and March 2017 (Figure 2.1). A total of 274 sites were sampled. Purposive sampling approach was used to identify Parthenium patches greater than $10m^2$, as invasive plants are not uniformly distributed in their habitat. XY co-ordinate records of weed locations were determined using a handheld Trimble GeoXH 6000 global positioning system with a sub-meter accuracy. Also, the percentage cover of Parthenium patches within the quadrat were recorded. Specifically, only Parthenium patches greater than $10m^2$ were considered in this study as they were regarded as hot spots. Data from the field survey were captured in Microsoft excel spreadsheet and used to create point maps in a GIS environment. The dataset (n = 274) was then randomly split into 70% training dataset and 30% test dataset. The GPS points were used to extract weed patches and areas around the patches.

2.2.3 Physical and environmental variables

Environmental variables (Table 2.1) used to determine landscapes susceptible invasion in this study area were chosen based on their biological relevance to Parthenium. The bioclimatic variables were derived from the 30 arc-seconds spatial resolution of the current WorldClim climatic conditions dataset. These climatic datasets are an average of long-term measurements (30 years of data) and contain grids of rainfall, temperature and derived bioclimatic summary variables. The bioclimatic data were resampled to the spatial resolution of the DEM (20m). The 20m spatial resolution DEM was created from the 20m contours extracted from the South African 1: 50,000 topographic maps. Slope (percentage), aspect (Northness and Eastness) and topographic wetness index (wetness index) were then derived from the DEM. Distances from rivers (metres), roads (metres) and households were derived from the river, road shapefile and Eskom database (2016) of KwaZulu- Natal. The distances in meters were calculated using Euclidean distance in ArcGis 10.2 and resampled to DEM's pixel size.

Table 2.1: Variables used in modelling Parthenium

Variables	Abbreviation	Description	Unit	Year
Topographic wetness index	TWI	steady state wetness index	n/a	
Elevation	elevation	ground height	m	
Slope	slope	steepness of the ground	% rise	
Aspect	aspect	slope direction	degrees	
Distance from households	dis_to_hse	Eskom database for households	m	2016
Distance from roads	dis_to_roads	distance from major or gavel roads	m	
Distance from water body	dis_to_river	distance from water bodies	m	
Bio1	bio_1	annual mean temperature	°C	1960-1990
Bio5	bio_5	maximum temperature of warmest month	°C	1960-1990
Bio 6	bio_6	minimum temperature of coldest month	°C	1960-1990
Bio7	bio_7	annual temperature range	°C	1960-1990
Bio9	bio_9	mean temperature of driest quarter	°C	1960-1990
Bio10	bio_10	mean temperature of warmest quarter	°C	1960-1990
Bio11	bio_11	mean temperature of coldest quarter	°C	1960-1990
Bio 12	bio_12	annual precipitation	°C	1960-1990
Bio13	bio_13	precipitation of wettest quarter	mm	1960-1990
Bio14	bio_14	precipitation of driest quarter	mm	1960-1990
Bio 16	bio_16	precipitation of wettest quarter	mm	1960-1990
Bio17	bio_17	precipitation of driest quarter	mm	1960-1990
Bio 18	bio-18	precipitation of warmest quarter	mm	1960-1990
Bio 19	bio_19	precipitation of coldest quarter	mm	1960-1990

2.2.4 Model description

2.2.4.1 Maximum entropy algorithm (MaxEnt)

Parthenium was modelled using the freely available MaxEnt version 3.3.3 software (http://www.cs.princeton.edu/~schapire/maxent) (Phillips et al., 2004). The software is a machine learning algorithm that models the likelihood of species presence based on environmental constraints and estimates the probability distribution with the maximum entropy, which is the distribution that is most spread out. The selection of environmental predictors is a guideline for habitat susceptibility as they clarify aspects that would likely influence susceptible sites (Phillips et al., 2006, Araujo and Guisan, 2006). Typically, MaxEnt produces an estimate of a probability of occurrence that ranges from 0 to 1, with 1 being the highest and 0 the least likely probability. It is a concise mathematical definition, hence amenable to analyse and has efficient deterministic algorithms that are certain to give optimal probability distribution. The model is known to performs efficiently even with small sample sizes (Kija et al., 2013, Hernandez et al., 2006). When absence data exist for the species, a conditional model can be used to enable presence/absence modelling (Phillips et al., 2006, Franklin, 2010, Elith et al., 2011). Maxent uses background /pseudo-absence and presence points that evaluate the environmental space for model testing. Environmental variables (continuous and categorical) and species presence data are used to run the model and the influence of each variable can be determined from the jacknife tool in Maxent (Phillips et al., 2006).

2.2.4.2 Predictor variable selection

The geospatial analyst tool in ArcGIS 10.2 was used to extract points, which were assigned to each variable. Pearson's correlation coefficient was used to minimize highly redundant and correlated variables after data was tested for normality. If two variables had a high correlation ($r > 0.8$), then only one of the pair was selected for further analysis, based on relative importance of each variable and knowledge of Parthenium in the study area (Table 2.2). The collinearity threshold was set at r >.0.8 as recommended by Graham (2003). Removal of highly correlated variables was executed using the Pearson's correlation in IBM SPSS Statistics (Morgan et al., 2012). This process reduced the variables from 21 to 9. The 9 variables were then used for the analysis.

Table 2.2: Pearson’s correlation coefficient for all the environmental variables.

	dis_to_road	dis_to_hse	Aspect	bio1	bio10	bio11	bio12	bio13	bio14	bio16	bio17	bio18	bio19	bio5	bio6	bio7	bio9	dis_to_river	elevation	slope	twi
dis_to_road	1	-0.023	0.025	0.033	.161**	.269**	-0.020	-0.029	-0.004	-0.054	0.019	-0.041	0.018	.150*	0.023	0.035	.269**	0.038	-0.095	0.058	-0.105
dis_to_hse		1	.137*	-.244**	-.206**	.130*	.614**	.601**	.577**	.494**	.625**	.616**	.626**	-.390**	.453**	-.596**	.130*	.520**	-.223**	.148*	-0.079
aspect			1	0.016	0.041	-0.032	0.065	-0.001	.140*	-0.045	.145*	0.040	.145*	-0.044	.155**	-.124*	-0.032	.162**	-.150*	.121*	-0.067
bio1				1	.852**	.607**	-.466**	-.489**	-.190**	-.671**	-.197**	-.559**	-.199**	.827**	.150*	.450**	.607**	-0.065	-.725**	-.236**	.202**
bio10					1	.740**	-.343**	-.402**	-0.040	-.559**	-0.068	-.488**	-0.070	.857**	.328**	.403**	.740**	-.170**	-.714**	-.134*	.133*
bio11						1	0.099	-0.040	.345**	-.182**	.344**	-0.096	.344**	.494**	.622**	-0.064	1.000**	0.072	-.785**	-0.051	0.032
bio12							1	.891**	.926**	.911**	.933**	.946**	.933**	-.680**	.690**	-.922**	0.099	.406**	-.167**	.194**	-.225**
bio13								1	.772**	.907**	.778**	.916**	.779**	-.632**	.498**	-.799**	-0.040	.358**	-0.035	0.106	-.145*
bio14									1	.709**	.994**	.791**	.994**	-.455**	.875**	-.886**	.345**	.411**	-.443**	.168**	-.194**
bio16										1	.709**	.950**	.710**	-.756**	.385**	-.773**	-.182**	.252**	.175**	.168**	-.193**
bio17											1	.805**	1.000**	-.475**	.864**	-.901**	.344**	.459**	-.451**	.177**	-.202**
bio18												1	.805**	-.730**	.495**	-.839**	-0.096	.441**	-0.001	.162**	-.205**
bio19													1	-.477**	.864**	-.902**	.344**	.460**	-.449**	.177**	-.201**
bio5														1	-.118*	.754**	.494**	-.278**	-.429**	-.187**	.261**
bio6															1	-.681**	.622**	.322**	-.694**	.135*	-.133*
bio7																1	-0.064	-.450**	.182**	-.177**	.228**
bio9																	1	0.072	-.785**	-0.051	0.032
dis_to_river																		1	-.256**	0.113	-0.112
elevation																			1	0.082	-0.042
slope																				1	-.212**
twi																					1

2.2.4.3 Model setting

The default MaxEnt settings was used to run the model. To validate the model, 30% of the dataset was withheld as recommended by Phillips et al. (2004). Visual inspection on the response curve and difference between test and train area under curve (AUC) values of the model was assessed to determine over-overfitting. Since, there were no overfitting detected, the default regularization was adopted. For the probabilistic model output, the 10 percentile training presence logistics threshold rule in MaxEnt was used to generate Parthenium binary map of habitat suitability and unsuitability (Escalante et al., 2013, Pearson et al., 2007). This threshold makes certain that 90% of the occurrence data has been predicted as present and omission error does not surpass 10%.

2.2.4.4 Evaluation and validation

Using the random test percentage settings in MaxEnt, 70% of the dataset was used to train and 30% to test the performance of the model. Evaluation and validation of the model was done using the AUC of the receiver operating curve (ROC) to classify the landscape as suitable or unsuitable (Bradley, 1997, Phillips and Dudík, 2008). The area under the ROC curve shows the likelihood that presence (sensitivity) is correctly ordered by the classifier as compared to the absence (specificity) of Parthenium. Sensitivity is the probability of true positive predictions in the actual positive observations. The ROC is generated by a two-dimensional space by plotting the sensitivity as Y and the specificity as X. Sensitivity and specificity were calculated for each of the likely significant thresholds for the entire range of predicted probabilities, 0 – 1 (Pearce and Ferrier, 2000). Models with high accuracy have AUC value close to 1 whereas a value equal or less than 0.5 shows models that perform no better than random (Hanley and McNeil, 1982).

2.3. Results

2.3.1 Predictor variables contribution

Table 2.3 shows the predictor variables and their percentage predictive contribution in the model. The higher the percentage contribution, the higher the influence in predicting the species occurrence. As shown in the table, distance to roads (33.2%) had the highest predictive contribution, hence the most influential variable in modelling areas prone to Parthenium invasion.

Other influential variables were elevation (19.9%) and bio13 (16.2%). Topographic wetness index (TWI) did not have any contribution to the model, whether run on its own or removed. Slope decreased in permutation value, hence a negligible role in predicting habitat susceptibility to Parthenium.

Table 2.3: Showing analysis of variable contribution.

Variable	Abbreviation	Percent contribution	Permutation importance
Distance to road	dis_to_road2	33.2	21.3
Elevation	elevation	19.9	26.8
Precipitation of the wettest month	Bio 13	16.2	10.8
Distance to river	Dis_to river	9.8	6.3
Slope	slope	7.7	23.1
Distance to houses	Dis_to_hse	7.3	4
Mean temperature of driest quarter	Bio 9	3.9	6.4
Aspect	aspect	1.5	1
Topographic wetness index	twi	0.5	0.4

The omission/commission analysis results (Figure 2.2a) showed that omission on test samples (turquoise blue line) matched the predicted omission rate (black line) from the MaxEnt distribution. This showed that habitat that are suitable exists above the threshold. A cumulative threshold value is set by the modeller in Maxent. The omission on training samples (blue line) lies below the predicted omission (black line). Figure 2.2b shows the model evaluation for habitat susceptible to Parthenium invasion using the ROC of the randomly selected training and test data. The area under curve (AUC) results indicates that the model performed better than a random model (P <0.005).

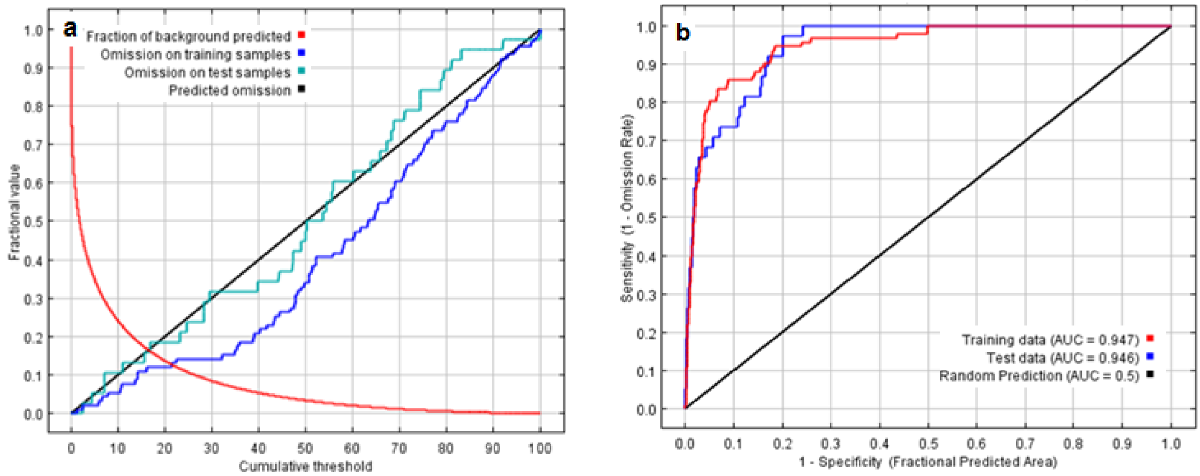

Fig 2.2: MaxEnt testing and training omission analysis and predicted area for Parthenium (a) and receiver operating curve (AUC) for training and test data (b).

Figure 2.3 illustrates the contribution of a variable to the model based on the jacknife of training and the percent contribution table (Table 2.3). The red line represents all the predictors run together, the blue line indicates the amount of model gain with only one variable, and the turquoise line an indication of model gain when a specific variable is excluded. Distance from road had the highest gain when used alone, implying its highest value information compared to other variables. When distance from roads were omitted from the model, it had the highest decrease in gain, showing its significance to the model. Topographic wetness index (TWI) had the least contribution to the model, hence had no significant role in predicting habitat susceptible to Parthenium.

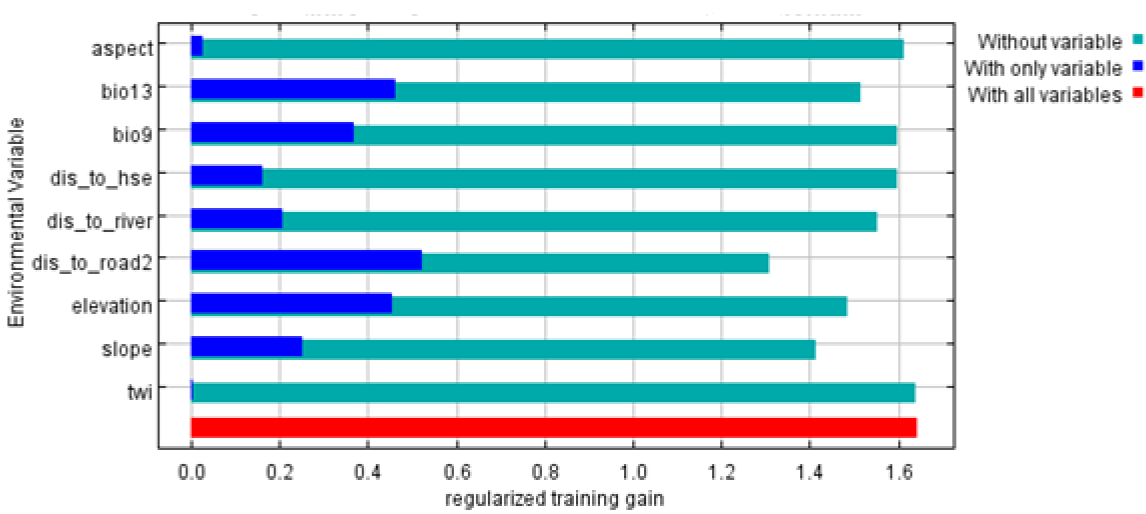

Fig 2.3: The jacknife of variable importance in modelling the spatial distribution of Parthenium

2.3.2 Visualisation of distribution

Figure 2.4 shows the likely occurrence of Parthenium based on the field observation points, environmental and physical variables. An overlay analysis of the resultant map and Parthenium distribution shows that probability of invasion is higher in the interior landscapes than the low-lying coastline, and the north-eastern and south-western parts of the province (Figure 2.4). Also, landscapes of high susceptibility were characterised by low lying to intermediate elevation as well as high precipitation prevalence, which facilitates plant growth compared to higher elevation areas with low susceptibility. Furthermore, the model also predicted potential invasion in the north-western and midlands, where the presence of Parthenium is presently low. However, climatic variable (precipitation of wettest month) and physical variable (low to mid elevation and distance to roads) indicated a high probability of future invasions. Specifically, results showed that these areas have higher probability to Parthenium invasion during precipitation of the wettest months (summer precipitation).

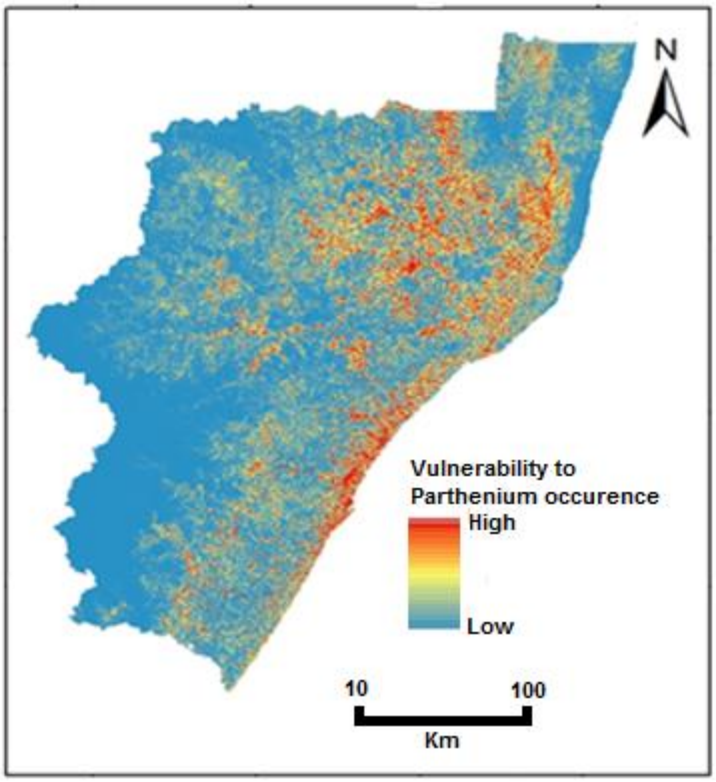

Figure 2.4: Habitat susceptibility to Parthenium invasion.

2.4. Discussion

Results in this study indicate that habitat susceptibility to Parthenium can be reliably modelled using selected climatic and physical variables. In this study, habitat susceptibility to Parthenium was reliably determined as shown by the high AUC value when using 30% test data set. Variables with the highest contributions were; distance from roads, precipitation of the wettest quarter (bio13) and elevation. Since MaxEnt does not explain the relationship between these selected variables and the presence of the weed, the jacknife result test was used to estimate the input of each variable to the likelihood of invasion.

As aforementioned, our model identified distance to roads, with 33.2% model contribution, as the strongest determinant of invasion, indicating that areas close to roads were most vulnerable to invasion. This finding is consistent with Ayele (2007), Navie et al. (1996a) and McConnachie et al. (2011) who noted that the probability of Parthenium invasion increases with proximity to the roads. This relationship can be attributed to the fact that vegetation close to the roads are more disturbed due to increased movements compared to those further away from the road. Furthermore, the highly connected nature of road networks and road construction provides corridors for the expansion of Parthenium from highly infested areas to vulnerable habitats. Auld et al. (1982) and Navie et al. (2004) also reported that the dispersal of the Parthenium was caused by construction vehicles, animals and human movements along tarred and major roads. Several studies e.g. Christen and Matlack (2009), Trombulak and Frissell (2000), Parendes and Jones (2000), and Gelbard and Belnap (2003) have demonstrated that disturbed habitats are more vulnerable to plant invasion due to lack of interspecies competition, regular disturbance, sunlight and soil nutrients availability. Trombulak and Frissell (2000), also noted that invaders may gain a competitive advantage as native species are continually supressed by pollutants and grazing along roadsides. According to Myers et al. (2004), vehicles along roads, surface runoff and increased exposure enables the movement of wind, animals and water that transport seeds of non-native plants along road corridors, hence a higher probability of invasion.

The results in this study also illustrated the influence of altitude on Parthenium distribution. Low probabilities of invasion were predicted for areas with high altitude (>1500m) while high probabilities were predicted for low lying areas (<1500m). In Figure 4, north-eastern and midlands of KwaZulu-Natal, with low lying areas have high probabilities while the south-eastern areas e.g the Drakensberg mountain range, with high altitude have low probabilities of Parthenium invasion. These findings concur with McConnachie et al. (2011) who noted that Parthenium invasion is more prevalent at lower to intermediate altitudes (<1500m) in South Africa. The distribution of Parthenium in our study can be attributed to the fact that low lying areas favour plant growth due to optimal soil development conditions that may include erosion of nutrient rich topsoil from higher grounds that are deposited in low lying areas. As noted by Hijmans and Graham (2006), most low lying areas have deeper soil depth, higher moisture content and soil nutrients compared to higher grounds. Hijmans and Graham (2006) further notes that higher elevations are characterized by extreme environmental conditions which hinder growth of plants due to absence of symbiotic relationships with microorganisms that nourish the soil. In the Drakensberg Alpine Centre, South Africa, Carbutt et al. (2013), noted that at high altitude, there were limited beneficial soil microorganisms resulting in a decline or unavailability of nitrogen content, which is a crucial element for plant growth.

The distribution of Parthenium can also be attributed to the influence of altitude on microclimate, as low-lying areas have optimal temperature for growth, compared to high-lying areas. The relationship between altitude and temperature in this study is consistent with Kija et al. (2013) and Tamado et al. (2002) who tested the viability of Parthenium seeds in Tanzania and eastern Ethiopia. The study concluded that temperatures ranging from 10 °C to 25 °C, that characterise most low-lying areas, are suitable for seed germination. Also, Tamado and Milberg (2000) established that Parthenium infestation were more prevalent in lowland and intermediate altitude (1600m to 1900m) farms, characterised by high temperatures, but rare in highlands (>1900m) of eastern Ethiopia. This is further explained by principle of decreasing temperatures with altitude that hinders the growth of weeds that are adapted to warmer temperatures. In agreement with this study, Navie et al. (1996a) and Pandey et al. (2003) found that low temperature related factors reduces leaf area index and net assimilation rate of Parthenium. Dispersal strategies might explain the association between invasions and increasing elevation through wind, human and animal dispersal, for instance, seeds are easily dispersed by the winds in areas with low altitude. Although wind can transport the seeds to a few meters, whirlwinds at low altitude can carry many seeds to an extensive distance (Okubo and Levin, 1989). Jones (2013), demonstrated that altitude affects wind flow, the amount of shelter and precipitation received by plants.

Our model showed that Parthenium occurrence increased with precipitation of the wettest quarter (bio 13). Precipitation of the wettest quarter (November to January) is in the summer (>500m). During the summer months, there is high rainfall and both rainfall and temperature have little fluctuation, which is conducive for plant growth in the coastal and interior regions (Eeley et al., 1999). Similarly, Parthenium was reported to thrive during flooding, as lack of moisture is a major factor hindering its growth during the dry season (Goodall et al., 2010, Navie et al., 2004). Numerous studies e.g. Baret and Guyot (1991), Adkins et al. (2010) and Laporte et al. (2002) have demonstrated that soil moisture is a strong driver of plant species distribution and an essential factor determining the relative abundance of vegetation. Increased precipitation changes soil water content, thereby favouring plant growth. Ayele (2007) noted that Parthenium seeds germinate at the start of the rainy season, however, when there is adequate soil moisture, germination could occur at any time of the year.

2.5 Conclusion

Understanding the interactions that make the habitat suitable for Parthenium is important to reduce uncertainty in modelling its spatial distribution. Results from this study have shown that the presence of Parthenium is influenced by specific physical and environmental conditions. Based on the findings of this study, it is concluded that landscapes that are in close proximity to roads, characterized by low to mid elevation and higher precipitation are more susceptible to invasion by Parthenium. Results from this study are paramount to the land managers, ecologist and relevant stakeholders in understanding the spatial distribution of alien invasive plants such as Parthenium. These results provide a robust and precise spatial framework to aid policy makers and land managers in control and long-term monitoring of areas highly susceptible to Parthenium invasion. The result will aid in planning and early rapid response to areas susceptible to invasion.

CHAPTER THREE

MODELLING PARTHENIUM *HYSTEROPHORUS* INVASION IN KWAZULU-NATAL USING REMOTELY SENSED DATA AND ENVIRONMENTAL VARIABLES

This chapter is based on:

Arogoundade, M.A, Odindi, J., O. Mutanga, & Sibanda, M., 2018. Modelling Parthenium *hysterophorus* invasion in Kwazulu-Natal using remotely sensed data and environmental variables. *International Journal of Remote Sensing*, (In preparation).

Abstract

Globally, infestations of invasive species impact negatively on the environment and economies. Therefore, modelling their potential distribution is valuable in designing appropriate mitigation measures and efficient management practices. Due to limitations of traditional field surveys, remotely sensed data provides feasible, timely, cost- effective and robust means in mapping and classifying vegetation characteristics. Hence, this study sought to model habitats susceptible to Parthenium invasion using environmental variables and remotely sensed data. The newly launched multi-spectral Sentinel 2 imagery with additional unique spectral bands and finer spatial resolution and the advanced Maximum Entropy (MaxEnt) machine learning algorithm were used to model habitat susceptible to Parthenium invasion. The MaxEnt model was run using occurrence points, selected vegetation indices and bands. In evaluating the performance of Sentinel 2 in modelling habitat susceptible to Parthenium invasion, we tested the utility of (i) spectral bands; (ii) derived vegetation indices and (iii) the combination of spectral bands and vegetation indices based on the Maxent algorithm. The area under curve (AUC) values were used to evaluate the performance of the models. Findings of this study shows that environmental variables combined with spectral bands yielded the best AUC value of 0.976. Sentinel 2 red edge band (705nm) and the normalized red edge vegetation indices were the most influential variables in predicting habitat susceptible to Parthenium invasion. These results illustrate the potential of new Sentinel 2 MSI with strategically positioned bands and the advanced machine learning algorithm (Maxent) in predicting habitats susceptible to Parthenium invasion.

Key words: Parthenium, MaxEnt, Sentinel 2 MSI, modelling, vegetation indices, spectral bands, environmental variables.

3.1. Introduction

Invasive species are the second most important threat to biodiversity after habitat destruction (Holmes et al., 2009). Globally, invasive plant species have spread rapidly impacting ecosystem processes, native species, human health and local and national economies (Vilà et al., 2011, Levine et al., 2003, Mahmoud et al., 2015). According to Richardson et al. (1997), invasive plants are a major environmental problem in South Africa's ecosystem, with nearly two million hectares of land invaded by invasive plants (van Wilgen et al., 2012). According to Richardson and Van Wilgen (2004) invasive plant species have led to a reduction in South Africa's rangelands to feed livestock and wildlife, and significantly reduced biodiversity.

Parthenium *hysterophorus* is an aggressive invader due to its allelopathic characteristics and adaptation to wide environmental conditions (McConnachie et al., 2011, Navie et al., 1996b). It is known to successfully invade disturbed areas like roadsides, crop and fallow lands, home steads and water courses. Parthenium invasion result in among others; decrease in rangelands, biodiversity and ecosystems (Patel, 2011) and affect human and animal health (Dhileepan, 2007). Due to the harmful environmental and economic impacts, Parthenium has been declared a Category One weed in South Africa (invader plant that must be removed and destroyed immediately). Due to the weed's adverse effects, there has been an increased interest in mitigation of its spread as shown by the increasing number of published research papers in the last five years (Kriticos et al., 2015, Mainali et al., 2015, Adkins and Shabbir, 2014, Mahmoud et al., 2015, Jayaramiah et al., 2017, Nguyen et al., 2017).

Due to the weed's adverse impacts on the socio- economy, and biodiversity of grazing lands in Africa, a four-year project on the integrated control of Parthenium was introduced in 2005 in eastern and southern Africa. This project was supported by the United States Agency for International Development (USAID)- which funded the Integrated Pest Management Collaborative Research Support Program (IPMCRSP) (Strathie et al., 2011). This project was able to prove that most of sub- Saharan Africa is prone to invasion by Parthenium (McConnachie et al., 2011). Likewise, in 2003 the South Africa government initiated a nationwide strategy for the management of the weed, developed by key stakeholders to investigate distribution, potential spread of the weed, and containment strategies (Nanni et al., 2016b). Early detection and mapping of the weed is important to formulate effective containment strategies.

Commonly, the detection of invasive plant species has been undertaken using traditional field surveys. Although these approaches are accurate, they are labour intensive, require expert interpretation, time-consuming, and costly for regional mapping (Taylor et al., 2011, Xie et al., 2008). Nevertheless, the advent of remotely sensed data has made ecological studies in large spatial extent achievable (Mansour et al., 2013). In comparison to traditional approaches, remote sensing technology offers feasible, timely, robust and cost- efficient means of mapping and classifying vegetation characteristics (Mansour et al., 2013). Remote sensing provides a wide range of continuous data at high temporal and spatial resolution, which enables the assessment of ecologically relevant processes (Andrew et al., 2014, Lulla, 1981, Mushore et al., 2017, Turner et al., 2003). Hence, datasets from remotely sensed imagery have been used to estimate vegetation biophysical characteristics e.g. chlorophyll estimation (Cho and Skidmore, 2009), leaf area index (Chen and Cihlar, 1996) and plant phenology (Reed et al., 2009).

Numerous authors (Lawrence et al., 2006, Skowronek et al., 2017, Chance et al., 2016, Meijninger and Jarmain, 2014, Bradley, 2014) have demonstrated the importance of vegetation indices and raw bands in the modelling of invasive plant species. Lawrence et al. (2006) for example mapped invasive plants species in North America using hyperspectral datasets with 84 -86 % accuracy while Mutanga and Skidmore (2004) estimated grass biomass using hyperspectral datasets. In a related study, Skowronek et al. (2017) mapped invasive bryophytes using air borne hyperspectral images and Chance et al. (2016) mapped the English ivy (*Hedera helix*) and Himalayan blackberry(*Rubus armeniacus*) using hyperspectral datasets in an urban area. However, hyperspectral datasets are spatially restricted, expensive, and require longer processing time, thus the need for cheap datasets that permit regional mapping (Tong et al., 2014, Eitel et al., 2007).

A large body of literature has demonstrated the potential of freely available multi-spectral remotely sensed imagery in vegetation mapping (Gudex-Cross et al., 2017, Joshi et al., 2005, Bradley and Mustard, 2006). For instance, Gudex-Cross et al. (2017) used Landsat 8 multispectral imagery and ground data to map *Prosopis juliflora* in Somaliland with 84% accuracy. Furthermore, newly launched multi-spectral sensors like Sentinel 2, characterised by additional red edge bands are increasingly becoming popular in discriminating subtle variations in vegetation (Frampton et al., 2013, Delegido et al., 2011, Richter et al., 2012, Atzberger and Richter, 2012, Gil et al., 2013). Delegido et al. (2011), for instance, utilized Sentinel 2 red edge bands in estimating leaf area index and chlorophyll content of crops while Frampton et al. (2013), assessed the strength of Sentinel 2 to estimate biophysical variables in vegetation. Also, Ramoelo et al. (2015) tested the capabilities of Sentinel 2 spectral data to evaluate the quality of range land. However, there is paucity in literature on the adoption of Sentinel 2 in estimating invasive plant species such as Parthenium.

The use of remotely sensed dataset integrated with robust prediction algorithms could provide unique tools for mapping of invasive plant species at local and regional levels. One of the most widely used algorithms is the Maximum Entropy (MaxEnt). MaxEnt utilises presence- only data, thus appropriate in modelling the spread of species when there are no absence data. It is a popular algorithm due to its ability to fit complex responses to environmental variables, predictive accuracy and the use of environmental variables (categorical and continuous) (Phillips et al., 2006, Barry and Elith, 2006). Furthermore, Maxent's popularity is attributed to its regularization settings which is able to reduce over- fit models when using small species occurrences (Phillips et al., 2006, Pearson et al., 2007). A number of studies have used the algorithm in mapping and predicting of invasive plants species. Wakie et al. (2014), for instance, used MaxEnt to map the current and potential distribution of Prosopis using Moderate Resolution Imaging Spectro-radiometer (MODIS) vegetation indices and topo-climatic predictors in Ethiopia. In a related study, Hoffman et al. (2008) tested the capabilities of the MaxEnt algorithm in modelling the occurrence and distribution of five invasive plant species along the North Platte River, Nebraska.

Recent studies have demonstrated that remotely sensed data with the aid of Geographic Information Systems (GIS), enhances the performance of spatial distribution models (Rocchini et al., 2015, Mairota et al., 2015). Whereas various studies have modelled invasive plant species using remotely sensed data and environmental variables (Malahlela et al., 2015, Joshi et al., 2005, Bradley and Mustard, 2006), no studies, to the best of our knowledge has documented vulnerability to Parthenium invasion using geo-information datasets and MaxEnt algorithm. Topographic variables such as elevation and slope have a significant impact in the distribution of invasive plant species, because elevation is an important variable that influences the spatial variability of microclimate, soil nutrient, light availability, and propagule dispersal in plant species distribution

(Wang et al., 2016, Yavitt et al., 2009). Additionally, climatic variables (precipitation and temperature) have strong impact on the growth and distribution of invasive plants species (Merow et al., 2017). Parthenium is likely to respond to climate and topographic variations due to its high reproductive and distributive ability. Hence, the integration of environmental variables combined with multispectral data that contain unique band settings to predict susceptible habitat to Parthenium might be further explored. Hence, this study sought to model the vulnerability to Parthenium invasion in KwaZulu-Natal using Sentinel 2 MSI datasets, environmental variables in a Maxent environment. Specifically, the study sought to determine the value of Sentinel 2 MSI raw bands and selected vegetation indices in modelling Parthenium invasion.

3.2 Methodology

3.2 .1 Study area

This research was conducted in KwaZulu- Natal province, South Africa and covers an area of approximately 92,285 km^2. The province lies between 26°50′ and 31°10′ South and 28°50′ and 32°50′ East (Figure 3.1). Altitudes within the province varies from sea level to 3400m, with topography ranging from coastal plains to mountain slopes in the Drakensberg mountain range. The province receives an annual rainfall ranging from 500 mm to 2000mm. The average midday temperature is 11 ^{o} C to 28 ^{o} C in the winter and summer months, respectively. The area is characterised by geological formations such as Sand, Arenite, Mudstone, Tillite, Basalt, Granite, Siltstone, and Shale. Parthenium infestation was first recorded in the KwaZulu-Natal province, South Africa in 1880 (McConnachie et al., 2011). Hence the province is known for its long history of Parthenium infestation which is prevalent along physical infrastructure networks such as roads, croplands, plantations, grazing land, homestead, as well as abandoned lands (Nanni et al., 2016b).

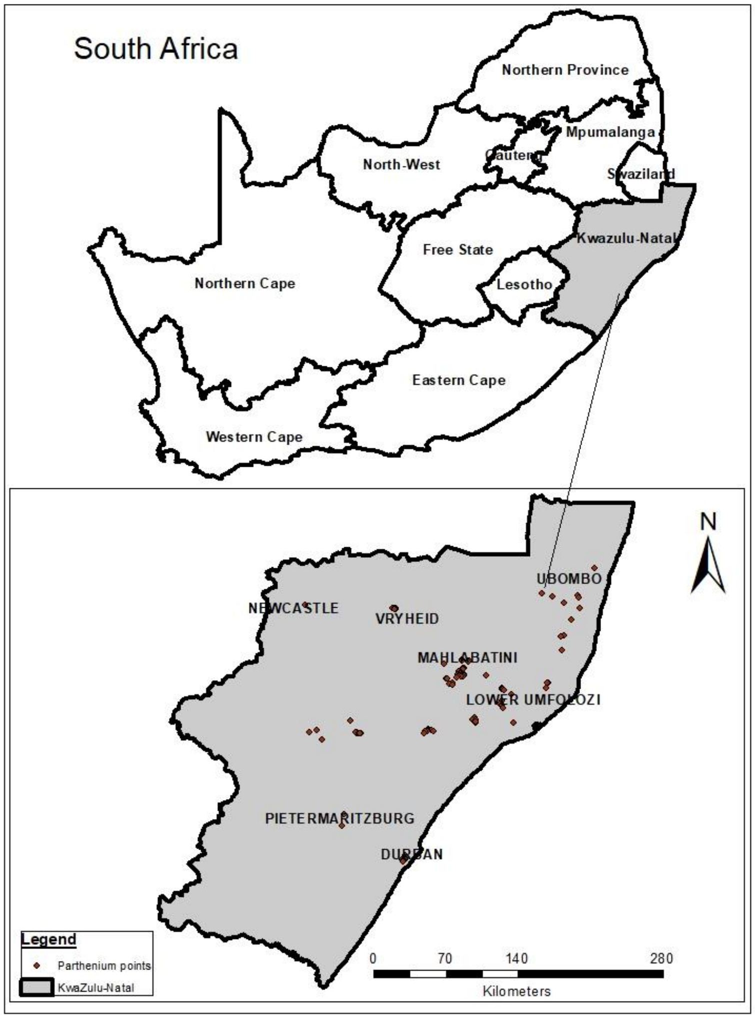

Fig 3.1: Map of the study area

3.2.2 Field data collection

Parthenium occurrence data were randomly collected around Mtubatuba, Durban, Vryheid, Richards Bay and Pietermaritzburg between January and March 2017 (Figure 3.1). Purposive sampling approach was used to identify Parthenium patches greater than 10m^2, because invasive plants are not uniformly distributed in their habitat. XY co-ordinate records of weed locations was taken using a handheld Trimble GeoXH 6000 global positioning system with a sub-meter accuracy. At each Parthenium observation, 10 by 10m quadrat was demarcated to accommodate the 10 by 10-pixel size of Sentinel 2 within the sampling sites, and their percentage cover within the quadrat recorded. A total of 274 Parthenium presence-only sites were sampled. Parthenium co-ordinates were recorded at sampled plots. After the field survey, data were captured in Microsoft excel spreadsheet and used to create point maps in a GIS environment. The dataset (n = 274) was then randomly split into 70% training and 30% test dataset. The training dataset was used to train the Maxent model, while accuracy and validation of the model was tested using the test dataset. The GPS points were used to extract weed patches and areas around the patches.

3.2.3 Satellite image acquisition and processing

Sentinel 2 multispectral satellite was launched on 23 June 2015 by the European Space Agency (ESA), designed with an improved bandwidth and spectral resolution. It provides a global coverage of the earth's surfaces with great potential in coastal and terrestrial mapping application (Delegido et al., 2011). The satellite made up of two sensors with a swath width of 290km, and a 5 days temporal resolution, ideal for frequent and broad scale vegetation mapping (Immitzer et al., 2016). It is positioned at an orbital angular distance of 1800 and images are acquired at a nadir position. The satellite has 13 spectral bands ranging from the visible, near infrared (NIR), red edge and the short-wave infrared-red (SWIR) at 10, 20 and 60m spatial resolutions. Sentinel 2 MSI comprises of four bands at 10m, six bands at 20m and three bands at 60m spatial resolution. The sensor has three novel bands in the red- edge region (705, 740 and 783 nm) of the electromagnetic spectrum, that were absent in former multispectral sensors. The red-edge bands are assumed to have potential in identifying and discriminating subtle variation in vegetation.

The freely-available Sentinel imagery was assessed from the Sentinel Scientific Data Hub website (https://scihub.copernicus.eu/). Twenty scenes of Sentinel 2 imagery were acquired from January to March to cover the study area and were mosaicked using QGIS 2.18 software. Sentinel 2 atmospheric correction was done using the Sen2Cor version 4.0 software (Main-Knorn et al., 2015). This correction converts the TOP-Of Atmosphere level 1C product to Bottom-Of Atmosphere and terrain corrected product (Vuolo et al., 2016). Excluded from this analysis are bands acquired at 60m which are designed for detecting atmospheric features.

Sentinel 2 datasets used in this study are vegetation indices and spectral bands. Tables 3.1 and 3.2 show the vegetation indices and raw bands used in this study. The selected vegetation indices used in this analysis were based on their performance in previous studies on invasive plant species (Matongera et al., 2017, Lambert et al., 2017, Potter, 2017, Liu et al., 2017). Also, these indices were chosen based on their ability to minimize the effect of soil background or to enhance greenness in vegetation. Sentinel -2 MSI bands (2,3,4,5,6,7,8,11,12,13) and vegetation indices (Enhanced Vegetation Index, green chlorophyll index, Normalized Difference Vegetation Index, simple ratio, Red edge normalized vegetation index1, Red edge normalized vegetation index2, and Soil Adjusted Vegetation Index) were used to model habitats susceptible to Parthenium invasion. The Spatial Analyst toolbox in ArcGIS10.4 (Environmental Systems Research Institute) was used to extract Sentinel 2 bands and vegetation indices.

3.2.4 Extraction of Environmental variables

Elevation, distance to roads and precipitation of the wettest months environmental variables were used in this study. These variables were chosen based on their relevance in the ecology and distribution of Parthenium-: distance to roads (Ayele, 2007, Navie et al., 2004, McConnachie et al., 2011), elevation (McConnachie et al., 2011, Tamado et al., 2002), and precipitation of the wettest month (Goodall et al., 2010, Kija et al., 2013). A 20m spatial resolution DEM was created from the 20m contours extracted from the South African 1: 50,000 topographic maps. Distance (in meters) away from roads was calculated using Euclidean distance in ArcGIS 10.2 based on the road shape file of KwaZulu- Natal and resampled to the 10m spatial resolution of Sentinel 2. The bioclimatic variable (precipitation of the wettest months) was derived from the 30 arc-seconds spatial resolution of the current WorldClim climatic conditions dataset. These climatic datasets are an average of long-term measurements (30 years of data) and contain grids of rainfall, temperature and derived bioclimatic summary variables. Precipitation of the wettest months was resampled to fit Sentinel 2 10m pixel size.

Table 3.1: Sentinel bands

Band	Name	Wavelength (nm)	Resolution
Band 1	Coastal aerosol	443	60
Band 2	Blue	490	10
Band 3	Green	560	10
Band 4	Red	665	10
Band 5	Vegetation red edge	705	20
Band 6	Vegetation red edge	740	20
Band 7	Vegetation red edge	783	20
Band 8	Near Infra-red	842	20
Band 8a	Near Infra-red	865	10
Band 9	Water vapour	945	60
Band 10	Cirrus	1,375	60
Band 11	Short wave infra-red	1,610	20
Band 12	Short wave infra-red	2,190	20

Table 3.2: Selected vegetation indices

Indices	Formula	References
Enhanced vegetation index (EVI)	2.5*((NIR-R)/ (1+NIR+6R – 7.5B))	Huete et al. (1997)
Green chlorophyll index (G Ch index)	(NIR/G) - 1	Viña et al. (2011)
Normalized vegetation index (NDVI)	(NIR -R) / (NIR + R)	Tucker (1979)
Red edge normalized vegetation index1 (ndvi _red 1)	(NIR -RE1) / (NIR + RE1)	Kross et al. (2015)
Red edge normalized vegetation index 2 (ndvi _red 2)	(NIR -RE2) / (NIR + RE2)	Gitelson and Merzlyak (1994)
Simple ratio	(NIR/R)	Brown et al. (2000)
Soil adjusted vegetation index (SAVI)	((NIR2 -R) *(1 + L))/ (NIR2 +R + L)	Huete (1988)

*****B, G, R, NIR, RE represent blue, green, red and near infrared and red edge spectral bands of Sentinel 2 respectively.

To test the value of selected predictors in modelling Parthenium, Maxent was run with three different model scenarios (Table3.3). The first model assessed the utility of Sentinel 2 bands and environmental variables, the second model assessed the utility of vegetation indices and environmental variables and the third model integrated al1 variables. The model scenarios were chosen to determine the performance of each dataset and their combined strength in predicting susceptible habitats to Parthenium invasion.

Table 3.3: Parthenium model scenarios with different environmental input.

Model	Variables
Model 1	Distance to roads, elevation, and precipitation of the wettest months, band 2, band 3, band 4, band 5, band 6, band 7, band 8, band 11, and band 12.
Model 2	Distance to roads, elevation, and precipitation of the wettest months, selected Sentinel 2 indices.
Model 3	Elevation slope, TWI, aspect, band 2, band 3, band 4, band 5, band 6, band 7, band 8, band 11, band 12, selected Sentinel 2 indices.

3.3 Model description

3.3.1 Maximum Entropy algorithm

Habitats susceptible to Parthenium invasion were modelled using the maximum entropy algorithm (MaxEnt) (Phillips et al., 2006). MaxEnt is a machine learning approach that estimates the maximum entropy of a target probability distribution based on the input environmental variables in order to predict the areas of likely invasion of the species (Phillips et al., 2006). In previous studies by Elith and Graham (2009) and Phillips et al. (2006), the MaxEnt model outperformed other presence-only modelling methods, like Genetic Algorithm for – Rule set Prediction (GARP), ecological niche factor analysis (ENFA), bio-climatic envelope algorithm (BIOCLIM) and DOMAIN, especially with small sizes (Hernandez et al., 2006). The Maxent model performs a jacknife test to assess which environmental variables contributes most to the distribution of species. Background pseudo-absence and presence points are used by the model to evaluate the environment for model calibration and testing. To identify the most influential variables to the MaxEnt model, each variable was excluded in turn, and a model created with the other variables, then a model created using each variable in isolation. Finally, a model is created using all variables (Phillips et al., 2006).

3.3.2 Model setting

The default settings in MaxEnt were used to run the model. As recommended by Phillips et al. (2004), 30% of the dataset was withheld to validate the model. The model was examined for over fitting by testing regularization values of 1, 1.5 and 2. The default setting of 1 was used, after visual inspection of response curves for complexity and difference between the train and test AUC were checked. The 10-percentile training presence logistics threshold rule was used, as this threshold classifies 90% of occurrence data as suitable and classifies 10% as unsuitable (Escalante et al., 2013).

3.3.3 Model evaluation

The performance of the models were evaluated using the area under curve (AUC) of receiver operating characteristics (ROC) analysis (Phillips et al., 2004). AUC values ranging from >0.6, 06 – 0.7, 0.7 – 0.8, 0.8 – 0.9 or 0.9 – 1.0 , predicts the model to fail, poor, fair, good or excellent, respectively (Hanley and McNeil, 1982).

3.4 Results

3.4.1 Model accuracy

The threshold independent AUC values from the ROC analysis model scenario in figure 2 indicate that all models performed well with AUC values greater than 0.9, which is excellent. The sensitivity and specificity test show the AUC values for each model, (Figure 3.2a) using the Sentinel bands and physical variables yielded a value of 0.976. Figure 3.2b shows that using indices and physical variables yielded an accuracy of 0.970 while, figure 3.2c shows that a combination of all variables produced a value of 0.974. Our results show that the highest accuracy was obtained using the Sentinel 2 bands and environmental variables, with a slight decrease when all variables are combined.

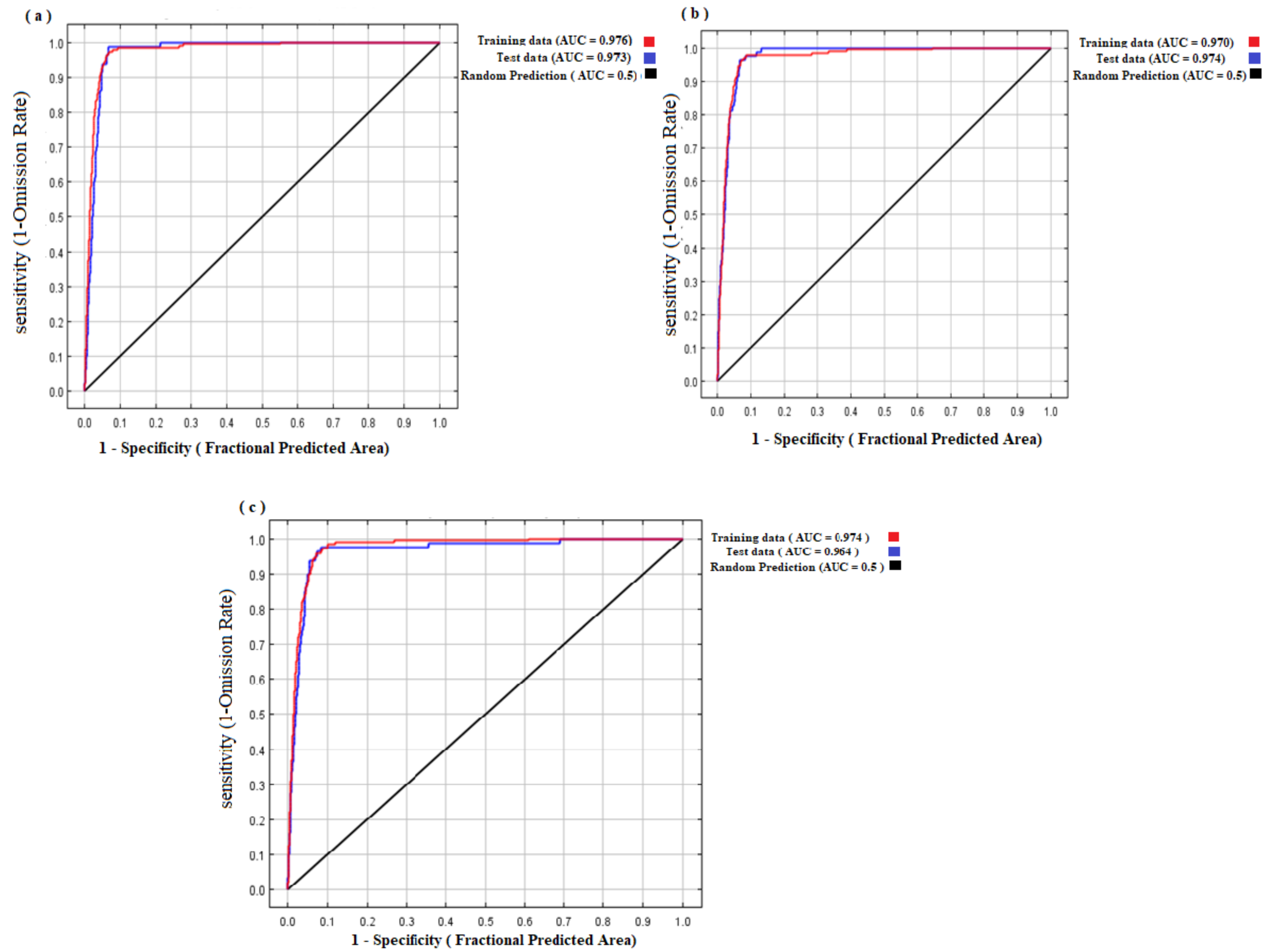

Figure 3.2: The receiver operator characteristic curve derived usng the(a) environmental variables and bands (0.976) (b) environmental variables and vegetation indices (0.970) (c) as well as all variables combined (0.974)

3.4.2 Jacknife result

The jacknife of training (Figure 3.3) illustrates that across all the training models, the most influential variables were elevation, distance to roads and precipitation of the wettest months. The results in Figure 3.3a shows that the blue band (490nm) and the red edge band centred at 705nm, were the most influential variables in the model, while band 6 had the least contribution to the model. Figure 3.3b, illustrates that Sentinel 2 red edge bands indices (NDVI red1 and NDVI red2) were the most influential in the model. SAVI had the least contribution to the model, hence had no significant role in predicting the habitat susceptible to Parthenium.

Notably, figure 3.3c indicates that elevation is the principal determinant of Parthenium distribution. Furthermore, results from the analysis (Figure 3.3c) confirmed that NDVI-red 2 indices and band 5 (red edge band) of Sentinel 2 MSI data outperformed the other input variables when all variables were combined. These results show that the red edge normalized difference vegetation indices contributed the most to the model, implying its vital role in discriminating invasive plant species.

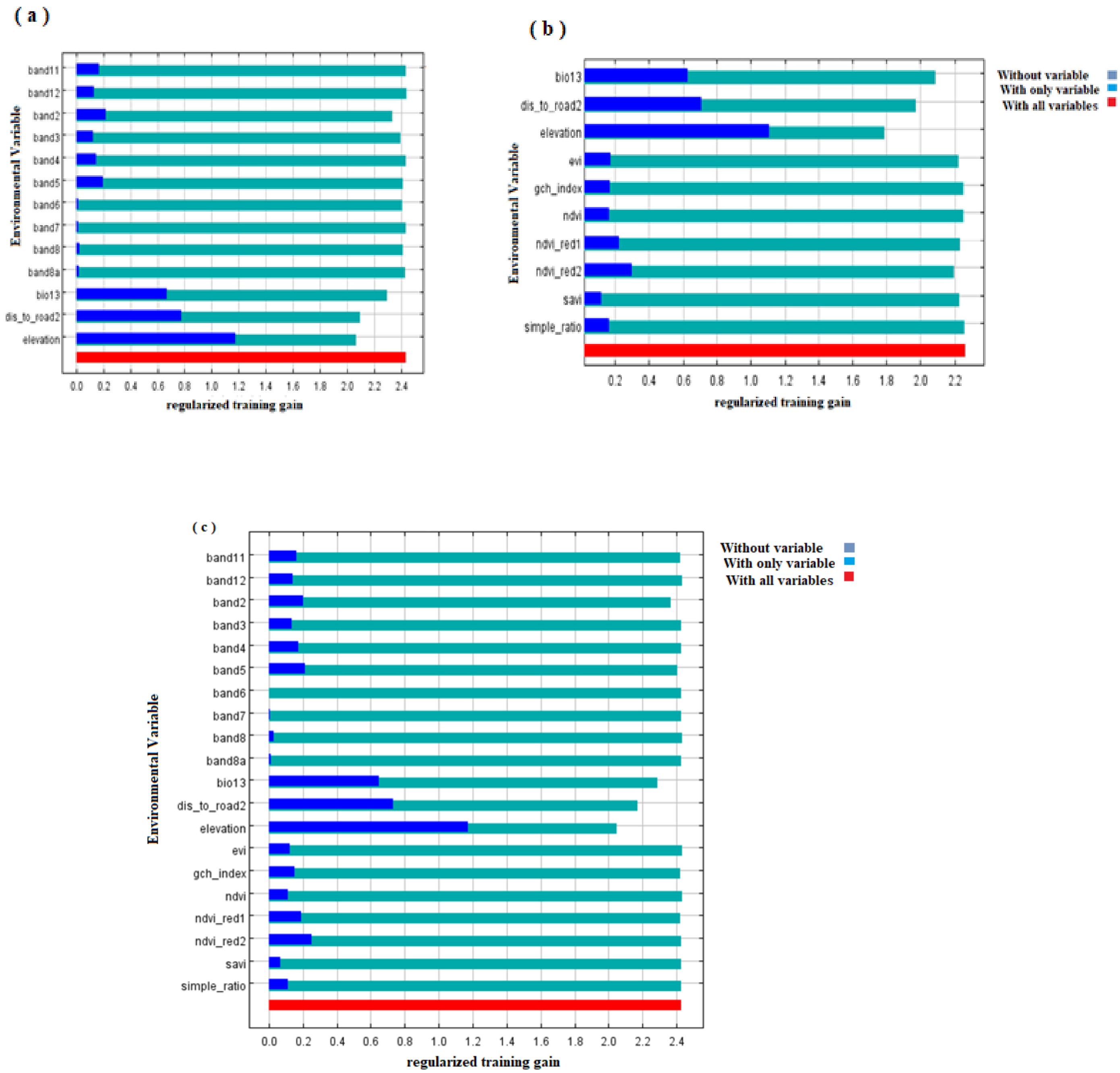

Figure 3.3: Jacknife variable contribution for (a) bands (b) vegetation indices (c) combined variables. The dark blue colour shows the regularized training gain for each variable, light blue without the variable while the red show the regularized training gain with all the variables.

An overlay analysis of the habitat susceptibility maps indicates that the model output maps were visually similar, which makes comparison between the three models difficult. However, from all the predicted maps (Figure 3.4), high susceptibility was predicted in the north-eastern part and the midlands of KwaZulu-Natal. The south-western part of KwaZulu-Natal has low probability of Parthenium invasion. All model scenarios also show that the south-western part has low invasion as they are in higher altitude with lower precipitation and higher population compared to the north-eastern part and the midlands region.

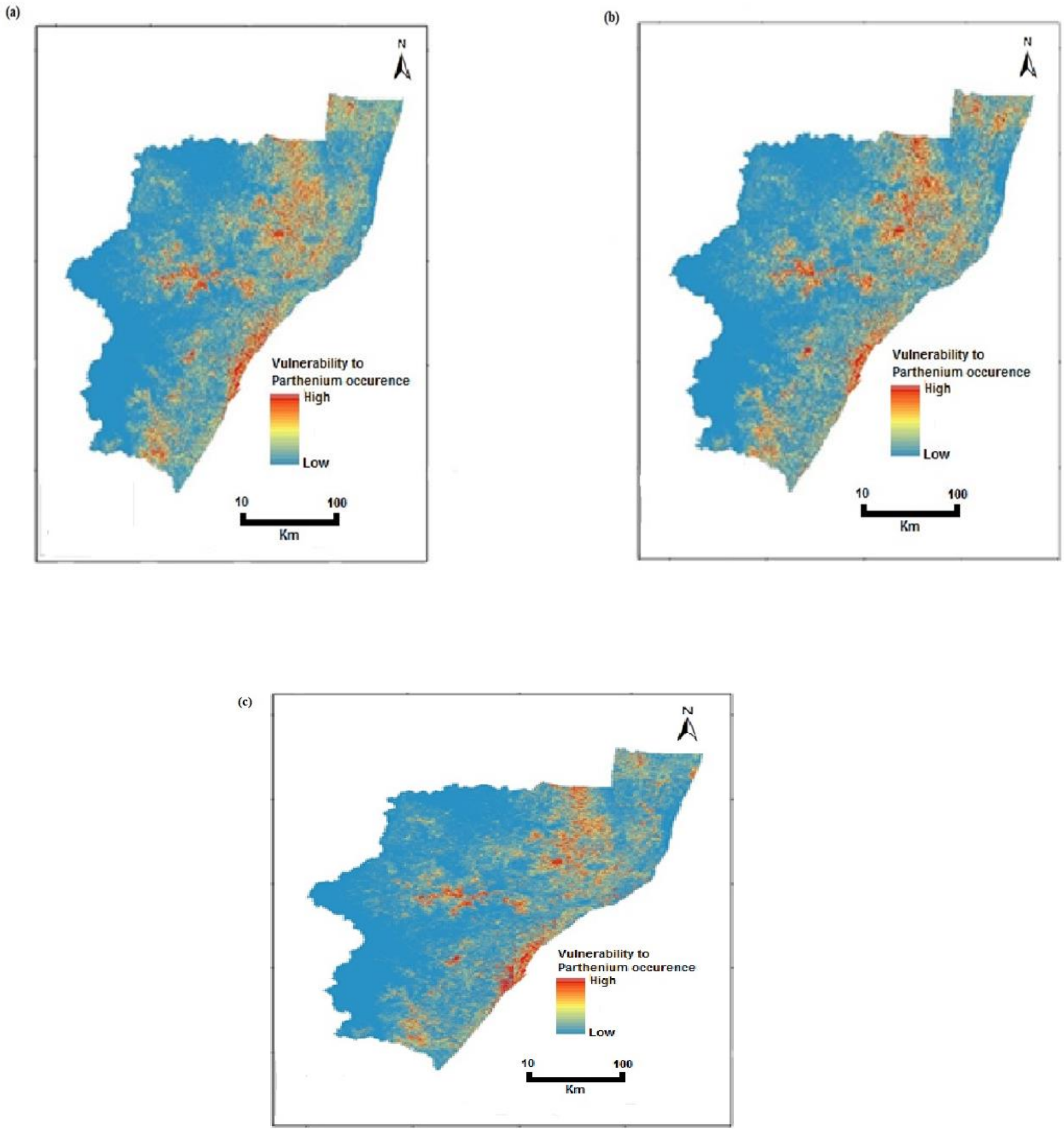

Figure 3.4: Map of the predicted potential distribution of Parthenium (a) environmental variables and bands (b) environmental variables and indices and (c) as well as all variables combined.

3.5 Discussion.

The aim of this study was to test the value of integrating Sentinel-2 multispectral imagery and environmental variables in modelling habitats susceptible to Parthenium invasion in KwaZulu-Natal. Results in this study prove that Sentinel-2 imagery, with strategically positioned red edge bands can be used to reliably map and model Parthenium invasion. All the models had AUC values >0.9, which illustrates that our models were able to predict suitable and unsuitable habitats for Parthenium establishment.

This study shows the potential of integrating Sentinel 2 datasets and environmental variables to improve the mapping and prediction of habitat susceptible to invasive plant species. Sentinel 2 datasets and environmental variables yielded a value of 0.976, the integration of vegetation indices and environmental variables yielded a value of 0.970 and, all variables combined yielded 0.974. The results from this study show that the model with bands and environmental variables yielded the highest accuracy of 0.976 at predicting Parthenium. This model gave the highest accuracy compared to vegetation indices or a combination of all variables with environmental variables. The high accuracy can be attributed to the integration of environmental variables (elevation, distance to roads and precipitation of the wettest month) and the red edge band (band 5) in modelling habitats susceptible to Parthenium invasion.

The results show the importance of the jacknife in Maxent algorithm in identifying the most important variables which illustrates the differences in the models. Environmental variables (elevation, distance to roads and precipitation) which were the important predictor variables are shown to be crucial in mapping and predicting the likely invasion of Parthenium. The high predictive power of environmental variables is because variables used are of essential importance to the distribution of the species being modelled. A body of literature has been able to prove the influence of elevation (McConnachie et al., 2011, Tamado et al., 2002), distance from roads (Ayele, 2007, Navie et al., 2004) and precipitation (Auld et al., 1982, Kija et al., 2013, Tamado et al., 2002) in the spatial distribution of Parthenium. As stated by Lambert et al. (2017) and supported by Othman et al. (2015), elevation is an important variable that influences the spatial variability of microclimate, soil properties, propagule dispersal and plant species distribution. Parthenium has been documented to establish in lowlands and intermediate altitudes farms with high temperatures, and rare in the high lands (Tamado and Milberg, 2000). Also, road networks have been demonstrated to serve as corridors of invasion and distribution to Parthenium invasion (Ayele, 2007, McConnachie et al., 2011). Additionally, moisture availability is a major determinant in the distribution of Parthenium. For example, Ayele (2007) and Goodall et al. (2010) found that the growth and distribution of Parthenium was highly influence by high rainfall.

The red edge band, which is also an important predictor to Parthenium invasion, is sensitive to subtle vegetation changes and characteristic variations which are prominent in these portions of the electromagnetic spectrum. In a previous study, Immitzer et al. (2016) successfully mapped crop and trees in Europe with the red edge bands of Sentinel 2. Numerous studies have highlighted the potential of Sentinel 2 red edge bands in vegetation mapping (Delegido et al., 2011, Dhau et al., 2017, Immitzer et al., 2016, Sibanda et al., 2015, Ramoelo et al., 2015, Richter et al., 2012). Our results concur with Majasalmi and Rautiainen (2016) who also reported that the red edge spectral bands in Sentinel 2 yielded optimal results in estimating boreal forest canopy cover and LAI, whereas Delegido et al. (2011) and Cho and Skidmore (2006) demonstrated that the reflectance near 705nm was sensitive to changes in chlorophyll concentration. According to Gitelson and Merzlyak (1994) the band has shown great potential for detecting subtle difference in vegetation species. Young et al. (2015) demonstrated that the red edge band in Worldview-2 imagery successfully mapped tamarisk invasive plants while, Tesfamichael et al. (2017) noted that Sentinel 2 red edge band were able to map and detect invasive plant species from morphologically similar plants. In a related study, Lantz and Wang (2013) demonstrated that Worldview2 imagery red edge bands have high capacity of detecting *Phragmites australis* (common reed) with an accuracy of 94%. In addition to the aforementioned, the model's high accuracy can be attributed to the strategically positioned and additional bands in improving the ability of Sentinel 2 MSI in discriminating plant species and vegetation monitoring (Frampton et al., 2013, Immitzer et al., 2016).

Interestingly, in the models with vegetation indices and all variables combined (Figure 3c), the red edge vegetation indices from the jack knife results performed better than individual bands, albeit not giving the highest accuracy. This could be due to their ability to minimize atmospheric effects and soil background better than individual spectral bands (Adelabu et al., 2014, Byrd et al., 2014). Also, in figures 3b and 3c the EVI, NDVI, SAVI, simple ratio vegetation indices have little contribution in predicting the occurrence of Parthenium. Our result also shows that all variables combined did not improve model accuracy among all the models. This defies our hypotheses, as we projected a stronger response to this model combination both in terms of training gain and higher AUC. According to Adam et al. (2012) and Adelabu et al. (2014), this may be attributed to the introduction of unnecessary noise into a model as the input variables increases, thereby reducing the model accuracies.

This study illustrates the utility of incorporating remotely sensed data and environmental variables to improve the prediction of invasive plant species. Previous studies have modelled habitats susceptible to Parthenium invasion using bio-climatic and environmental variables (Kija et al., 2013, Nanni et al., 2016b, McConnachie et al., 2011, Tamado et al., 2002), without incorporating remotely sensed data. According to our results, these variables have individual high contribution in all the models compared to remotely sensed data, indicating their significance to the ecology of Parthenium. Similar results were obtained by Malahlela et al. (2015), who used ancillary environmental variables and Worldview2 datasets to map and predict Chromolaena *odorata* (L.). Malahlela et al. (2015), showed that environmental variables (distance from rivers and distance from roads) and mPSRI, SAVI and EVI generated from Worldview2 demonstrated the potential to predict the invasive plant *C. odorata* in forest canopy gaps with 71% accuracy. Habitat susceptibility maps serve as a spatial guide to relevant stakeholders and ecologist to make timely and cost-effective decisions in mapping invasive plants. This study also demonstrates the importance of advanced machine learning algorithm such as Maxent in identifying the significant predictor variables which improve the prediction and mapping of invasive plant species.

3.6 Conclusion

The aim of this study was to examine the strength of the freely available new generation multispectral imagery (Sentinel 2) and environmental variables in modelling invasive plant species. Thus, the results are important for early detection, monitoring and mitigation with minimal cost. This study concludes:

- The newly launched Sentinel 2 imagery provide more bands that are capable of mapping and modelling invasive plant species.

- The red edge band in Sentinel 2 performs better in predicting areas susceptible to Parthenium invasion.
- Environmental variables (elevation, temperature and distance from roads) are important predictor variables in predicting habitat susceptible Parthenium invasion.
- The integration of Sentinel 2 spectral bands and environmental variables yielded a high AUC value of 0.976 in predicting habitat susceptible to Parthenium invasion using the Maxent algorithm.

CHAPTER 4

SYNTHESIS

4.1 Introduction

Invasive plant species are a global problem that requires repeatable monitoring to design appropriate mitigation measures and efficient management practices. Parthenium is prevalent in northern KwaZulu-Natal, thus affecting crop production, animal husbandry, eco-system functioning, human health and biodiversity. Its aggressive distribution can be attributed to reproductive ability, as well as tolerance to a wide range of physical and environmental factors. The weed has been reported to have adverse effects on biodiversity, sustainable development, economic growth, poverty alleviation and food scarcity (Matthews and Brand, 2004). This study focused on the use of bioclimatic, physical variables and multi-spectral remotely sensed data in modelling landscapes that are susceptible to invasion by Parthenium. In this chapter, the aims and respective objectives which were set out in the first chapter are reviewed against the major findings. Also, major conclusions, recommendations for future research are highlighted.

4.2 Objectives of the study

The first objective, presented in chapter two, was to model Parthenium weed distribution and potential areas of future invasion using physical and bio-climatic variables. To achieve this objective, firstly, landscapes that are susceptible to Parthenium invasion were modelled using physical and climatic variables based on the Maxent algorithm and secondly, the key predictor variables that best describe the habitat of Parthenium were identified.

The second objective, presented in chapter three, was to test the accuracy of integrating remotely sensed data and environmental variables in modelling susceptible habitat to Parthenium invasion. To achieve this, two specific objectives were assessed. First, the utility of integrating Sentinel 2 MSI spectral bands, derived vegetation indices and environmental variables in predicting susceptible habitat to Parthenium using Maxent algorithm was evaluated. Secondly, the relative importance of Sentinel 2 datasets and environmental variables in modelling Parthenium invasion were determined.

4.3 General findings of the study

Identification and modelling of vulnerable habitats to Parthenium weed infestation is important for early detection, cost effective and appropriate mitigation measures. Selected physical and climatic variables were used to model vulnerable habitats to Parthenium invasion. The jacknife results from this study shows that physical and climatic variables have different percentage contribution to the model. The results indicate that areas closer to roads, with low elevation (<1500m) and high precipitation had the most influence and play a crucial role in explaining the spatial distribution of Parthenium. From the high AUC value, the Maximum entropy algorithm was able to successfully model susceptible and insusceptible habitats to Parthenium invasion. Findings in this study also showed that the model with integration of spectral bands and environmental variables had the highest AUC value amongst all the models. This can be attributed to the Sentinel 2's strategically positioned and additional. The results illustrate the value of integrating the red edge bands and environmental variables for predicting habitats susceptible to Parthenium invasion. In determining the most important variables influencing the spatial distribution of Parthenium, results showed that the relative significance of environmental variables was generally consistent across all the models. These results illustrate that environmental variables play a more crucial role in explaining the distribution of Parthenium compared than Sentinel 2 data.

In conclusion, this study has demonstrated the value of integrating freely available Sentinel 2 MSI with environmental variables in monitoring and modelling of Parthenium. The results are valuable to policy makers and environmental mangers for early detection and appropriate mitigation measures. Furthermore, the results in this study illustrates the ability of Maxent algorithm to determine the relative importance of the predictor variables.

4.4 General Conclusion

The essence of this study was to assess the utility of the newly launched multispectral imagery and environmental variables in modelling susceptible habitat to Parthenium using the Maxent algorithm. Based on these findings, the following conclusions were drawn:

1 The Maxent algorithm was effective in predicting areas susceptible to Parthenium invasion with models having AUC values > than 0.9.

2 Sentinel 2 data improved the model accuracy; however, environmental variables had a higher individual influence in predicting Parthenium invasion.

3 The freely available Sentinel 2 MSI is cost effective for mapping and modelling of Parthenium at a regional scale, especially in resource scarce areas. Hence, this study is useful for future researchers and policy maker in early rapid response and long-term monitoring of invasive plant species.

4.5 Limitations and recommendations of the study

- ❖ Future research should include more predictor variables like soil, the use of high resolution time series images and future landscape dynamics, which may change the occurrence of Parthenium and give new insights on current and potential distribution of the weed. Moreover, climate change may result in conditions that facilitates the growth of invasive plant species, hence, future studies should consider changes in climatic conditions to understand how it affects the invasive plant species.

- ❖ This study can be further refined by testing different sensors across numerous spatial scale. Also, the performance of other presence only algorithm in comparison to Maxent should be tested.

- ❖ It is important to note that some predictor variables may not accurately represent current conditions (e.g bioclimatic represent mean values from 1960- 1990). Also, bioclimatic variables are interpolated datasets from the global weather station and developing countries do not have good weather station, thereby producing generalized description of environmental variability. Accurate datasets of current conditions can be included into Maxent model to improve results. Climate changes continuously across broad spatial scales, thus capturing climatic variations of species diversity at landscape level is difficult.

- ❖ The Maxent model requires enough space for storage of raw and processed data, and longer processing time (resampling) for each model to run.

- ❖ To improve model and management utility, dispersal variables should be evaluated. Predictor variables that influence dispersal processes directly e.g road density, grazing pressure, precipitation volume should be assessed. For example, propagule pressure (Rouget and Richardson, 2003) that explain with ease how invasive plant species overcome environmental barriers to become invasive are not included. These variables can produce models that have direct impact on management of invasive plant species.

- Extrapolation of results to new areas may be problematic because spatial distribution models such as Maxent are correlative and not mechanistic, thus limiting the inference we can draw from them. Hence, transferability of predicted model from a sampled area to broad geographic area may not be reliable.

- The mapping of Parthenium in this study was carried out during the summer. The weed has different stages of phenology which influence their spectral response, and subsequently discrimination. Thus, identifying the optimal period to map these invasive species is important to provide a better knowledge of their spatial and temporal distribution for effective monitoring.

- Spatial data from different sources rarely have the same spatial resolution which is a requirement of spatial distribution models. Uncertainties might be introduced when resampling datasets to same spatial resolutions in SDMs. Hence, a careful selection of spatial, temporal and spectral data used in SDMs should be undertaken with caution.

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