Modeling and explaining the distribution of *Lantana camara* in South African savanna ecosystems

by

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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

Globally, the Invasive Alien Plant (IAPs) species pose a great threat to global biodiversity, agro-ecological systems and socio-economic development. In particular, *Lantana camara* (*L. camara*) is amongst the most notorious and problematic of all invasive plants globally. Its threats and effects are undeniably recognizable and it is ranked amongst the world's ten worst weeds. As a result, it is one of the most documented weeds in the world. Most studies have focused mainly on detecting and mapping the spatial distribution of *L. camara*. Although its spatial distribution remains rudimentary, the mechanisms driving its distribution are not yet fully understood, especially in savanna rangelands. This study aimed at modelling and explaining the distribution of *L. camara* in South African savanna ecosystems (the Kruger National Park and Bushbuckridge communal lands). Specifically, the study sought to identify the environmental factors influencing the spatial distribution of *L. camara* in savanna ecosystems using the Maximum Entropy (Maxent) algorithm, coupled with remotely-sensed derivatives from Sentinel-2 satellite data. The performance of the model was assessed by using the Area Under Curve (AUC), the True Skills Statistic (TSS) and the Kappa Statistic. From the findings, the Bushbuckridge communal lands had the highest *L. camara* infestations, with the weed covering an area of 10%, when compared to the Kruger National Park, which had an estimated coverage of 7%. The derived spatial distribution maps from Maxent revealed that communal lands of Bushbuckridge are more vulnerable to *L. camara* invasion than the protected area. The study also demonstrates that bioclimatic factors influence the occurrence, spread and infestation of this invasive weed species. Comparatively-speaking, elevation was found to have the greatest influence on the infestation and spatial distribution of *L. camara*. The model that was derived from a composite of all the variables yielded the highest AUC score of 0.96. Subsequently, the model based on indices alone (Model 4) achieved the lowest accuracies, with an AUC score of 0.85. This work is critical for providing the necessary information to assist in effective management and clearing practices by informing the strategic planning, control and rehabilitation of the affected areas.

Keywords: agroecosystems; bioclimatic data, bush encroachment; satellite data; species distribution.

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 Prof Onisimo Mutanga and Dr. Timothy Dube 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.

Xivutiso Glenny Maluleke Signed Date …15/12/2019….

1. Prof Onisimo Mutanga (Supervisor) Signed ………………….. Date ……………….

2. Dr. Timothy Dube (Co-Supervisor) Signed…………………...... Date……………….

Plagiarism Declaration

Declaration Full names of student: Xivutiso Glenny Maluleke

1. I understand what plagiarism is and I am aware of the University of Kwazulu-Natal's policy in this regard,

2. I declare that this dissertation is my own original work. Where other people's work has been used (either from a printed source, Internet or any other source), this has been properly acknowledged and referenced in accordance with departmental requirements,

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Publications and Manuscripts

The following manuscripts are under peer-review or being prepared for publication. They include the work of my Supervisors. However, the contribution of the first author was the greatest, and it is therefore appropriate for the authors' names to appear as they are presented.

Xivutiso G. Maluleke., O. Mutanga. and T. Dube. (Manuscript under Review). Advances and future prospects in monitoring *Lantana camara* in the semi-arid savanna agroecosystems of South Africa. *Geocarto Journal.* [Chapter 2]

Xivutiso G. Maluleke., O. Mutanga. and T. Dube. (Manuscript under review). Modelling localities vulnerable to *Lantana camara* infestation in semi-arid savanna ecosystems of Bushbuckridge communal lands and Kruger National Park, South Africa. *Journal of Arid Environments* [Chapter 3]

Dedication

This dissertation is dedicated to my grandfather, the late William Khoza, to my mother, Mudjadji Cecilia Maluleke, and my father, Gezani Norman Maluleke, and last, but not least, to my two brothers, Nicholas and Herbert Maluleke.

For my family

"For I know the plans I have for you" declares the LORD "plans to prosper you and not to harm you, plans to give you hope and a future" (Jeremiah 29:11)

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I would like to give my sincere appreciation to my supervisors, Professor Onisimo Mutanga and Professor Timothy Dube, who sacrificed their time to assist me in the production of this research. Their professional knowledge, passion, commitment and patience towards supervising my work was outstanding. It is always a pleasure working with you.

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CHAPTER ONE

General Introduction

1.1 Introduction

Savanna rangeland ecosystems remain one of the most significant natural ecosystems, globally. They cover almost half of the world's land surface and provide numerous ecosystem services. For instance, they mitigate climate change through carbon sequestration, serve as forage for wildlife and livestock and store generic diversity, to name a few (Mutanga *et al*., 2004). The intrusion of non-indigenous plant species is one of the most formidable and growing threats to these natural ecosystems. Invasion by Invasive Alien Plant (IAP) species is among the leading non-climatic drivers of global change. The intrusion of these species influences the modification of disturbance regimes, as well as the metabolism of various ecosystems. The impacts of IAP species on savanna ecosystems include the diminution of nutrients, modifications in vegetation succession, the enrichment of fire frequency and sternness, the reduction of native plant species richness, as well as changes in the microclimates, amongst others. In addition, IAP species, such as *L. camara*, result in extreme economic losses (Ayele, 2007). For example, Australia alone loses approximately USD 2.2 million per annum (Goncalves *et al*., 2014), while the United States experiences an estimated loss of 120 US billion dollars annually (Pimentel *et al*., 2005). In South Africa the financial losses associated with cattle being poisoned by *L. camara* are estimated to be R 1 728 900 per annum (Kellerman *et al*., 1996).

L. camara is a small bushy shrub that continues to intrude vast masses of land. It is usually found in forest ecosystems where it is known to substitute native understory vegetation (Ghisalberti, 2000). However, *L. camara* is now commonly found in various areas, such as agricultural fields and grazing lands, as well as alongside rivers and roads. The weed has rich leaves with unstable vital oils and its intrusion has resulted in a significant reduction of the biomass and thickness of the native vegetation (Grice, 2006). Furthermore, it releases different toxic chemicals from its leaves, remains as well as its vital oils which is capable of affecting the native species negatively (Dobhal et al., 2010). In grazing areas, *L. camara* causes major forage shortages, which affect livestock. Its fruit is poisonous to livestock and children, and its toxicity may eventually cause mortality after consumption. *L. camara* has a wooden stem, which is a fire hazard increasing the occurrence fires, due to its high lignin content (Kohli *et al.*, 2006).

The devastating effects of *L. camara* have led to it being one of the most documented weeds globally. Traditional methods, such as field surveys, are labor-intensive, time-consuming, costly, and therefore limited, in terms of the detection and mapping of *L. camara* (Wakie *et al.*, 2014; Taylor *et al.*, 2011; Thamaga and Dube, 2018). Previously, various studies have successfully used remote sensing (RS) strategies in modeling the spread of *L. camara*, but they have not explained the reasons behind its invasion in the environments of concern. According to literature, various environmental factors (soil conditions, topography, climatic conditions) have an effect on the performance of IAP in an environment (Wang *et al.*, 2017; Guisan and Thuiller 2005). Understanding the nature of the interaction between *L. camara* and the environment can help to enhance the knowledge of its versatility in the intrusion of new environments. Furthermore, this information can assist and improve the performance of Spatial Distribution Models (SDMs) in the estimation of the likelihood of the species occurring in the areas of concern.

SDMs have been introduced as feasible tools that are able to identify, summarize and estimate areas suitable/vulnerable to IAPs invasion. SDMs statistically relate the identified distribution of a species (presence/absence) with selected environmental variables (Martins *et al.*, 2016). The incorporation of SDMs with advanced GIS, RS and predictive algorithms can determine the foremost variables responsible for the spatial distribution patterns of IAPs in areas of concern (Adhikari *et al.*, 2015). For instance, Zhu *et al.* (2007) and Ramírez-Albores *et al.* (2016), successfully used SDMs to identify and predict areas vulnerable to the invasion of IAPs. However, to our knowledge, the most significant environmental variables responsible for the invasion of *L. camara* in South African savanna ecosystems have not been fully explored. Vulnerability maps as well as identifying key environmental factors influencing the distribution and spread of IAPs may serve as valuable tools in preventing species invasions, controlling their spread and improving the knowledge of IAPs invasion. It is, therefore, on this premise that this research seeks to map and explain the spatial distribution of *L. camara* in South African savanna ecosystems.

1.2 Aims and objectives

The main goal of this research was to model and explain *L. camara*'s spatial distribution in South African savanna ecosystems, and it was achieved through the following objectives:

- To review the advances and future prospects of monitoring *L. camara* in semi-arid savanna agroecosystems.
- To model localities vulnerable to *L. camara* infestation in semi-arid savanna ecosystems of Bushbuckridge communal lands and Kruger National Park, South Africa

1.3 Key research questions

- Which environmental variables significantly influence *L. camara*'s spatial distribution?
- Which areas are most susceptible to be invaded by *L. camara*?

1.4 Main hypothesis

The distribution of *L. camara* is influenced by bioclimatic variables such as moisture.

1.5 Study area

This research was carried out in the communal area of Bushbuckridge and Kruger National Park (KNP). Bushbuckridge (-24.82789° S, 31.0464° E) is located between the Drakensberg escarpment and the Kruger National Park which is close to the Sabie-Sand Game (Tollman, 2009). The precipitation rate is between 1200mm per annum in the western region to 500 mm in the eastern region, while the average yearly temperature is roughly 22˚C, with little or no frost (Govere *et al.*, 2000). The terrain of the area is characterized by flat to undulant surfaces. The dominant soil type in the area is thin sandy lithosol, however, the base the incline is made up of various soil types. The standard vegetation is open extensive grasslands and deciduous forests. The utmost livestock found in the area are domesticated animals, such as cattle and goats, while the agricultural activities include crop planting (Shackleton *et al.*, 2002).

The Kruger National Park known as one of the largest in the world (19,485 km^2) is located along the eastern part of Mpumalanga and Limpopo provinces in South Africa. It is about 65 and 360 kilometers in width and length, respectively. The region is characterised by subtropical climate type with hot and humid summer days. Rainy season begins around September all through to the month of May.

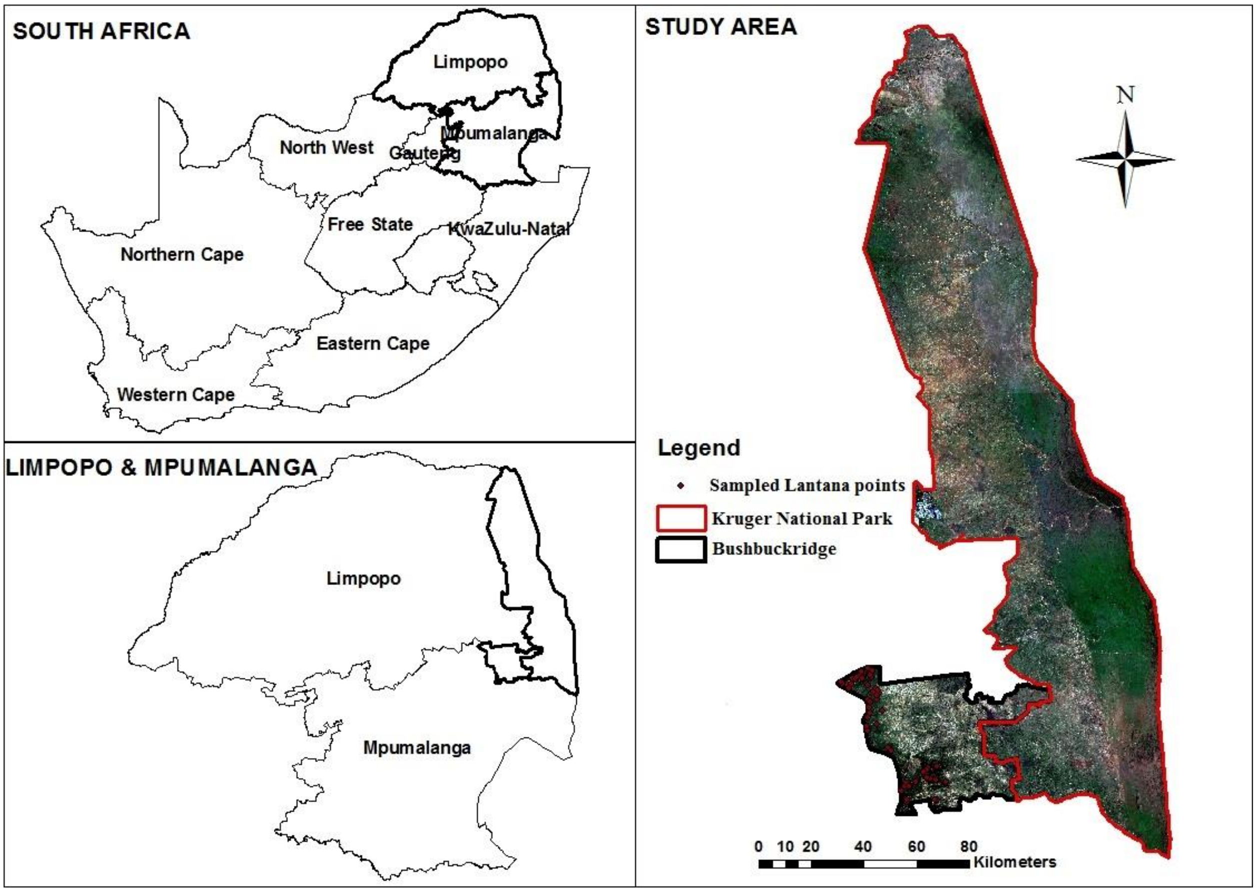

Figure 1.1: Location map of the study area

1.6 Structure of the research

CHAPTER ONE: General introduction.

This chapter presents an overview of the study, stressing the global environmental and socio-economic impacts of IAPs including the role of SDMs in identifying areas vulnerable to them. Moreover, the main aim, objectives, hypothesis and structure of the study are outlined.

CHAPTER TWO: Advances and future prospects in monitoring *L. camara* in semi-arid savanna agroecosystems.

This chapter has been submitted to a journal and is under review, it is therefore presented in the form of a publishable paper. The chapter reviews the advances and future prospects in monitoring *L. camara* in semi-arid savanna agroecosystems. It highlights RS techniques and classification algorithms previously utilized in modeling *L. camara* and their short comings. The study discusses the influence of environmental factors on the distribution and spread of *L. camara*. Finally, the chapter also highlights gaps and potential future directions in understanding the spatial distribution of *L. camara*.

CHAPTER THREE: Modelling localities vulnerable to *L. camara* infestation in semi-arid savanna ecosystems of Bushbuckridge communal lands and Kruger National Park, South Africa

This chapter will be submitted to a peer review journal and has therefore been presented in form of a publishable paper. The chapter discusses various SDMs used in estimating areas likely to be invaded by IAPs. Maximum Entropy (Maxent) is used to investigate the most significant environmental variables influencing *L. camara*'s spatial distribution as well as the areas vulnerable to its invasion.

CHAPTER FOUR: Synthesis

Chapter four summarizes the findings of the research, discussions and overall conclusions. Based on the limitations outlined in the study, the chapter draws recommendations for future research.

CHAPTER TWO

Advances and future prospects in monitoring *Lantana camara* in semi-arid savanna agroecosystems

This chapter is based on a review paper under review.

Xivutiso G. Maluleke., O. Mutanga. and T. Dube. (Under Review). Advances and future prospects in monitoring *Lantana camara* in semi-arid savanna agroecosystems of South Africa. Geocarto Journal.

Abstract

The intrusion of natural ecosystems by notorious Invasive Alien Plant (IAP) species is among the most important environmental concerns globally. Biological invasions are usually a natural process; however, anthropogenic activities have enhanced the process. *Lantana camara* (*L. camara*) is one of the major contributors to global rangeland ecosystem change. It has been classified to be among the world's 100 worst IAP species and is also amongst the world's 10 worst weeds. It threatens ecological systems and the socio-economic status due to its ability to colonize diverse ecosystems. We review the progress in RS *L. camara*'s spatial distribution in South African rangeland ecosystems. In the quest of understanding *L. camara*, various available methods used in detecting and mapping the weed were assessed, in order to help gain adequate knowledge on its distribution and configuration. Previous studies have noted that conventional strategies including field surveys are unable to accurately detect and map *L. camara*'s spatial distribution. Since the introduction of RS techniques, the field of research has greatly improved, and more work has been done on the weed. RS offers well-documented advantages, including multispectral data, synoptic views, multi-temporal coverage as well as cost-effectiveness amongst others. Previous work has mainly focused on the detection and mapping of the distribution of *L. camara*. However, it is not enough as it does not fully explain the occurrence of these species in the affected areas. Therefore, there are shortcomings on the explanation of the mechanisms that drive its occurrence. According to the literature, environmental variables, such as soil moisture, light and climate, influence the occurrence of *L. camara*. The current study recommends that future research incorporates environmental variables for understanding some of the abiotic reasons behind the occurrence of the weed.

Keywords: *agroecosystems; ecosystem restoration; environmental variables; invasive species; rangelands; satellite data; species distribution*.

2.1 Introduction

Rangelands are defined as all those environments where natural ecological processes prevail and where values and benefits are based primarily on natural resource areas which have not been intensively developed for primary production (Foran *et al.*, 2019). These ecosystems cover almost half of the world's land surface and, as such, they provide various important ecosystem services and functions, including sources of forage for livestock and wildlife, mitigating climate change through carbon sequestration, storing generic diversity, eco-tourism, as well as opportunities for ranching and mining (Mutanga *et al.*, 2004). In South Africa alone, these ecosystems cover an estimated of 70% of the land, which contributes roughly R2.88 billion to the country's Gross Domestic Product (GDP) per year (Shoko *et al.*, 2016). The protection and management of these ecosystems is therefore vital for ecological, socio-economic and the survival/livelihoods of the entire human species. The degradation of these ecosystems is occurring at an alarming pace, due to the increasing level of invasion of notorious IAP species, including anthropogenic activities as well as climate variability and change, amongst others (Dlamini, 2016).

As an ornamental and medicinal plant, *L. camara* was introduced in South Africa for landscaping and horticultural purposes. More specifically, the introduction of invasive alien plant species in South African rangelands has had a devastating effect, as it affects human health, as well as the biodiversity and the functionality of ecosystems (Dvorak, *et al.*, 2015). For example, Van Wilgen *et al.* (2008) indicated that if IAP spread to their full potential without disturbance, large grazing and pasture lands could be reduced by about 71%. *L. camara* is considered to be the principle IAP species, and it is thus classified as one of the world's top 100 invasive species by the invasive species specialist group (IUCN 2001) as well as ranks amongst the top 10 weeds in the world. This has resulted in it being one of the most documented IAP species globally (Qin *et al.*, 2016; Sharma *et al.*, 2005). Its invasive ability is evident, as it occurs in diverse habitats with a variation of soil types. According to Shackleton *et al.* (2017) the intrusive ability of *L. camara* is derived from the following biological attributes: its phenotypic plasticity, its fitness homeostasis, its dispersal benefits from destructive foraging activities, its widespread geographic range, resilience to fire, vegetative reproduction, highly competitive ability, as compared to its native vegetation as well as allelopathy.

The spread of *L. camara* is encouraged mostly by anthropogenic activities including cultivation, road construction and changes in fire regime. The spreading of the species is further exacerbated by climate change (Sharma, *et al.*, 2005). Sahu and Singh, (2007) found that *L. camara* has invaded a vast area of native forest and protected land in India, and that it has become the dominant understory species, as well as a major threat. It reduces the availability of resources and microhabitats essential for various native plants and animals. Furthermore, Belay and Hailu, (2017) reported that communities have lost their productive assets including pasture land, arable lands and local medicinal plant species since the introduction of *L. camara* in Bahir Dar Nile River Millennium Park in Ethiopia. Various methods have previously been utilized to map and monitor *L. camara*'s spread. Initially, traditional methods were used to map invasive species, but they have proved to be spatially restricted, time-consuming and labor-intensive (Thamaga and Dube, 2018; Taylor *et al.*, 2011). The introduction of RS techniques has since proved to offer better results in terms of mapping the spatial distribution of IAP species and it has become a great tool for assisting ecologists, environmentalists and land managers as well as other disciplines.

Most researchers have focused mainly on successfully mapping *L. camara*'s spatial distribution. For instance, Dhau, (2008) utilized Landsat TM and Aster datasets for mapping and monitoring the invasion of *L. camara* in Zimbabwe across three different land tenure systems. Kimothi and Dasari, (2010) also explored the Indian satellite data in mapping the spatial distribution of the intrusive *L. camara* in forest landscapes. Furthermore, the study demonstrated the ability of Linear Imaging Self-Scanning Sensor (LISS) IV and Cartosat-1 data for the detection and mapping of *L. camara*. Regardless of the successful mapping of *L. camara* worldwide, there is a lack of understanding regarding the factors that affect its versatility in the adapting to new environments. As such, the mapping of *L. camara* alone is not enough as it does not explain why the species occurs in these regions; hence, there is need to incorporate environmental variables in the RS of *L. camara* in rangeland ecosystems.

This review draws attention to the advent of RS strategies in the detection, mapping as well as monitoring of *L. camara* in rangeland ecosystems. Firstly, information on the impacts of *L. camara* on rangelands is provided, followed by a discussion on some characteristics that RS data provide for the mapping of *L. camara*. An overview of previous techniques utilized to map *L. camara* and their limitations is also provided. The influence of environmental variables on the distribution of the species is then discussed and, finally, suggestions are provided regarding the direction that is to be taken in future.

2.2 Origin and geographic distribution of *L. camara*

L. camara belongs to the Verbenaceae family and is a genus of both shrub and herbaceous plants with about 150 species (Khan, *et al.*, 2015). It is of the genus *Lantana* and an evergreen climbing aromatic woody shrub with the ability to grow up to 2 m when supported by the surrounding flora (Day *et al.*, 2003). *L. camara* is originally from the tropical regions of South and Central America. However, the weed is currently being used for the purpose of aesthetics (ornamental plants) in South Africa and other parts of the world. It has been totally naturalized in most tropical and subtropical parts of the world due to its capability to easily and rapidly grow as well as thrive in harsh weather conditions (Sharma et al., 2007). Additionally, in a recent global review by Richardson and Rejmánek (2011), 12 of the 15 regions evaluated depicted the invasion of *L. camara*, hence, making it one of the topmost wide spread IAP species globally.

L. camara's natural range stretches from Mexico to Brazil, however, the species has been reported to have established populations in more than 60 nations globally, resulting in massive economic losses in most of those countries (Goncalves *et al.*, 2014). Initially, the species was introduced in Europe from Brazil in the 17th century. One hundred years after its introduction, the weed was exported to other regions including Africa, America, Asia and Oceania. However, the weed only became intrusive in the tropical, subtropical and warm temperate areas (Goncalves *et al.*, 2014; Vardien *et al.*, 2011). According to Taylor *et al.* (2012). The appropriate climatic regions for *L. camara* in Africa are anticipated to be only within parts of Angola, Ethiopia, Tanzania, Gabon, Zambia, Uganda, and the Republic of Congo remain suitable in 2070 however, some parts of South Africa are currently heavily-infested with the species.

Thus far, there have been only three recorded cases of its introduction into South Africa, with the earliest dating back to 1858 in Cape Town, Western Cape Province. By the year 1998, *L. camara* was found over a total area of over two million hectors (Vardien *et al.*, 2012; Urban, 2011). More than fifty variations of *L. camara* are predicted to occur in South Africa. The wide breeding and intra- and inter-specific hybridization have resulted in structural varieties of the weed. The effective distribution of the weed has therefore been backed by its biological and structural features. This includes its generation of fleshy fruits and it being able to flower all year, with some birds acting as the chief dispersal factors. Furthermore, *L. camara* can reproduce asexually.

L. camara is present in the major biomes of most countries, where it is naturalized in the warm, moist subtropical and temperate areas of Kwazulu-Natal, Eastern Cape, and Mpumalanga provinces. It is not found in the dry and heavily-frosted areas of the country (*Vardien et al.*, 2011). Mukwevho *et al.* (2018) reported that the provinces of KwaZulu-Natal, Mpumalanga, Limpopo and Gauteng in South Africa are the provinces that are severely invaded by *L. camara*. This was further confirmed by Urban *et al.* (2011), who reported that the species is increasing in density and spreading mainly in the provinces of Mpumalanga and Limpopo, as well as in the Gauteng, Eastern Cape, and North West the southern part of Western Cape.

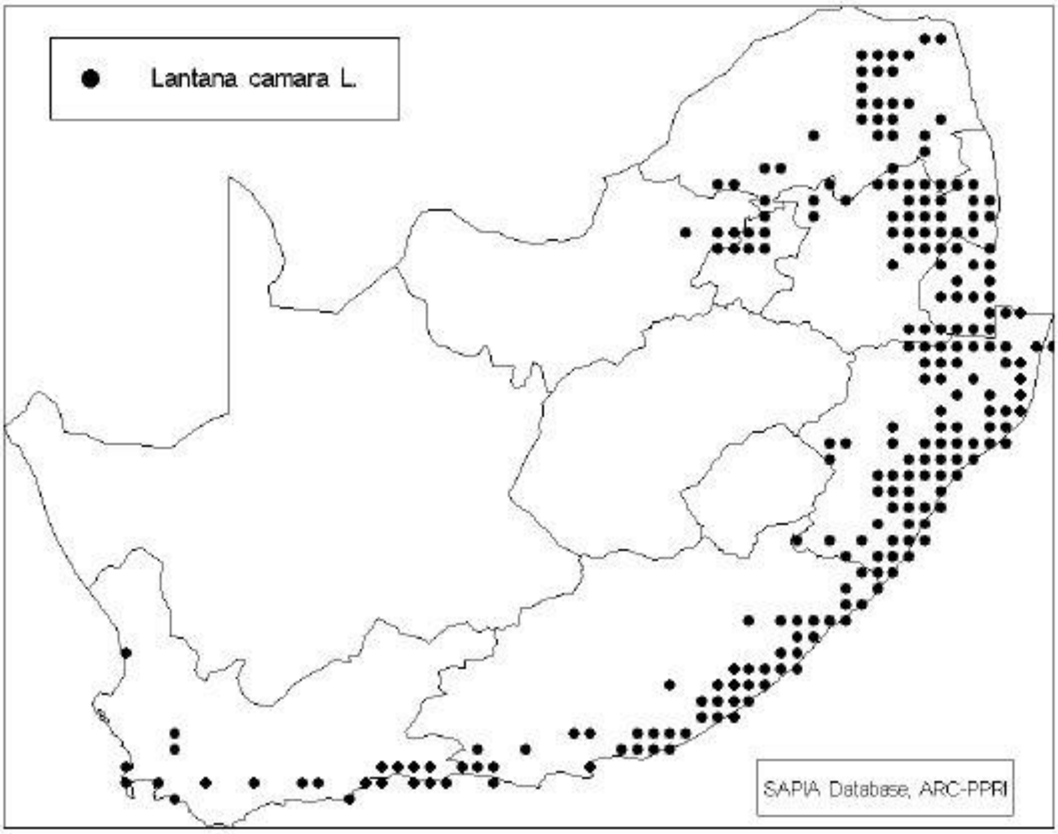

Figure 2.1: Recorded localities of *L. camara* in South Africa, as on Southern African Plant Invaders Atlas (SAPIA) Database (Henderson, 2001)

2.3 The impacts of *L. camara* on rangeland ecosystems

Savanna rangeland ecosystems are one of the largest ecosystems globally. They are made up of a mixture of trees and grasses that are of ecological importance and play an enormous role in ecosystem services (Adjorlolo, 2008). The impacts of *L. camara* on rangelands are several, diverse and undeniable. On a broad scale, these impacts include alterations to the native disturbance regimes, changes in the native diversity, as well as changes in the ecological processes. *L. camara* is a threat to biodiversity and can dramatically affect the structure and functioning of rangelands. For example, *L. camara* has been known to replace native vegetation such as grass, a vital source of food for herbivores (Prasad, 2013). This affects the carnivores that depend on the herbivores and thus a threat to important wildlife populations as well as endangered species which may even lead to the extinction of some species. For example, the Global Invasive Species Database (2020), reported that *L. camara* competition may have caused the extinction of the shrub *Linum cratericola* Eliasson (Linaceae), and is a major threat to other endangered species in the Galapagos Archipelago (Day *et al.* 2003).

According to Priyanka and Joshi, (2013), in the presence of soil moisture, light and soil nutrients, *L. camara* can be a vicious competitor to native colonizers. In regions infested by *L. camara*, the weed is capable of shifting and outcompeting native vegetation for various resources namely, sunlight, moisture and soil nutrients leading to the reduction of biodiversity (Chatterjee 2015; Taylor *et al.*, 2012). For instance, in a study conducted by Fernando *et al.* (2016), it was found that the impacts of the *L. camara* on the Udawalawe National Park included the out-competing of the native species, resulting in decreased biodiversity and a reduction in the richness of the species, which caused the malnutrition of elephants and a disturbance of the succession process in the areas that it covered. Furthermore, results in a study conducted by Gooden *et al.*, (2009) revealed that species richness of native species in North Coast Wet Sclerophyll Forest along the south-east Coast Ranges of New South Wales, Australia, declined significantly with an increase in the area covered by *L. camara*.

The most common change observed to occur due to the understory plants being replaced is the decrease of the biomass in communities. The characteristic of Allelopathy enables the weed to survive secondary succession and become monospecific thickets. Reduced or no growth has been observed in species such as *Lolium multiflorum* L. (rye), *Christella dentata* (fern), *Morrenia odorata* L. (milkweed vine), as well as on other vicious crops such as corn (*Zea mays*), wheat (*Triticum aestivum*) and soyabean (*Glycine max*) results due to the allelopathic effect in various areas (Sharma *et al.*, 2005). *L. camara* outcompetes the pasture species by affecting the frequency, density and dominance of the natives. This is possible as the leaves and flowers of *L. camara* release some phenolic acids and volatile oils. Under environmental stress, *L. camara* has extra selective advantages over the native species as it can release vast amounts and types of secondary metabolites. As such *L. camara* is able to quickly colonize at the cost of the surrounding native species (Kohli *et al.*, 2006). Furthermore, the species has the ability to pollute the gene pool of native as well as rare plant species resulting in the endangerment of those plant species (Chatterjee, 2015). According to Lyons and Schwartz, (2001) native and or rare plant species are important for maintaining ecosystem processes in ecological communities. Tilman *et al.* (1998) and Doak *et al.* (1998) also suggested a variation of species in rangeland ecosystems results in a peak of ecosystems processes.

L. camara causes mustering of cattle resulting in the death of livestock by poisoning through incidental consumption of seeds (Urban *et al.*, 2011; Chatterjee, 2015). The field cases have been reported to mainly occur in the young and newly introduced animals in areas infested by *L. camara* (Sharma and Raghubansh, 2007). Besides causing the death of livestock, *L. camara*'s sub-lethal toxin doses are also manifested in abortions, they reduce the potential in production, they induce the loss of milk production in dairy cows and chronic wastage among beef cattle (Kohli *et al.*, 2006). *L. camara* has been found to have direct impacts and consequences on the community structure of various bird species. It is responsible for the decrease in species richness by the allelopathic interaction (El-Kenany and El-Darier, 2013). The dense thickets nature of *L. camara* also houses disease-causing agents, such as mosquitoes and tsetse flies (Glossina sp.), which cause health problems in the society, whereas, direct contact with it may cause irritation and or allergic reactions (Mack and Smith.,2011; Vardien *et al.*, 2012).

L. camara has a wooden stem with a high lignin content, which is responsible for causing fire hazards and increasing the occurrence of fires (Bajwa *et al.*, 2016). As such, the presence of *L. camara* in rangelands alters fire regimes as the weed burns readily in hot and dry conditions (Hiremath and Sundaram, 2005). Furthermore, *L. camara* alters the nutrient cycling and influences burn intensity, which, in turn, leads to the reduced forage quality in the rangelands (Masters and Sheley, 2001). *L. camara* is able to rapidly yield large amounts of biomass due to its high productivity which can fuel more fires. As a result, rangelands that have previously been invaded by *L. camara* can easily be subject to a fire-lantana cycle. (Hiremath and Sundaram, 2005). Furthermore, Hiremath and Sundaram, (2005) also suggest that *L. camara* has characteristics similar to other fire-maintaining and fire-maintained invasive species globally.

L. camara has a negative impact on various water sources. For instance, expanding thickets of *L. camara* barricade access to water sources for various animals also utilizing vast amounts of water and reducing water quality in various river catchments such as Hartenbos and Klein Brak (Taylor and Kumar, 2014). According to Richardson *et al.* (2011) *L. camara* utilizes about 3.300 million cubic meters of water yearly which is more than what is used by native plants and accounts for 7% of the country's runoff. As a result, water scares countries such as South Africa spend more money in importing water from neighboring countries.

The devastating impacts of *L. camara* have become an economic concern globally as the intrusion of the weed has led to large economic losses. According to Goncalves *et al.* (2014) the economic losses caused by the introduction and expansion of *L. camara* have been estimated to be approximately $2.2 million per annum in Australia alone. While in the US the introduction of *L. camara* species has caused economic losses of about $137 billion yearly, with an estimate of $35 billion of that annual cost being due to its intrusion alone (Ustin *et al.*, 2014).

Figure 2.2: Impacts of *L. camara* (replacement of native vegetation by the intrusion of *L. camara* thickets), photograph (Ghisalberti. 2000).

2.4 Remote sensing of *L. camara*

The devastating impacts of invasive species have triggered a global concern and resulted in an urgent need for an essential tool to identify and monitor invasive species. The tool is also needed for obtaining reliable and up to date information for improved management of invaded areas, as well as vulnerable areas (Underwood *et al.*, 2007). RS has proved to be significantly useful for across-the-board environmental studies. As a result, earth observation studies have increased and improved over the years (Martins *et al.*, 2016). RS and Geographic Information Systems (GIS) are convenient tools for the detection, mapping and monitoring of IAP species as well as predicting areas vulnerable to IAP invasion. They enhance the control and monitoring of invaded areas by providing multi-temporal records that can be assimilated and used in the GIS environment (Joshi *et al.*, 2004).

Advantages of RS include multispectral data, synoptic views, multi-temporal coverage, and cost efficiency amongst others. It offers a feasible approach for the study of various remote ecosystems as well as complex geographic terrain types. Aerial photographs, ground-based spectrometer measurements, satellite imagery, high and low spectral resolution and airborne multi-spectral scanners are some of the variety of sensor systems provided by the tool. (Joshi *et al.*, 2004). Furthermore, satellite-borne sensors provide a better means of gathering information on different features on the surface of earth that is from land cover, land use or even the extent of environmental hazards (Thamaga and Dube, 2018; Matongera *et al.*, 2016).

The use of RS in studying the notorious weed *L. camara* has been on a rise over the years. Researchers have attempted using different remote sensors and techniques to study the weed and have been successful, to some extent. For example, Moderate spatial/spectral resolution sensors are one of the data sources previously used to map and monitor *L. camara* in RS. These sensors collect data at a spatial resolution of between 10 and 100 in less than 20 bands (Huang and Gregory, 2009). The data sources include the Advanced Space-borne Thematic Emission and Reflection Radiometer (ASTER), Satellite Pour l'Observation de la Terre (SPOT) and Landsat Enhanced Thematic Mapper Plus (ETM+)/ Landsat Thematic Mapper (LTM). For instance, in South Africa, Oumar, (2016) used vegetation indices which include Simple Ratio and Normalized Difference Vegetation Indices, as well as, SPOT 6 to map *L. camara* within the rangelands of Kwazulu-Natal. The standard bands of SPOT 6 were combined with the two vegetation indices to classify *L. camara*, which produced an overall accuracy of 75%. Similarly, Peerbhay *et al.* (2016) used a fusion of WorldView-2 (a high spatial resolution dataset) with LiDAR and an AISA Eagle airborne hyperspectral dataset for the detection of Bugweed in Kwazulu-Natal's commercial plantation forests. The fusion of LiDAR and AISA produced high classification accuracy results of 78%, while the fusion of LiDAR with WorldView-2 produced a classification accuracy 74%. However, WorldView-2, AISA and LiDAR individually produced classification accuracies of 63%, 68% and 64%. According to Huang and Gregory, (2009) the use of moderate spatial/spectral resolution images on IAP mapping and monitoring is not clearly understood in the background of native vegetation and are therefore difficult to detect. Huang and Gregory, (2009) stated that this data can only be used to detect large patches of weeds that rely more on the phonological time. For instance, Joshi., *et al.* (2004) mapped *L. camara* at the species level, using the 30 m Landsat TM and SPOT data with 20 m spatial resolution and the results were found to be unsatisfactory.

Using high spatial resolution images is one of the greatest intuitive and frank RS approaches in mapping and monitoring IAP species. This approach enables one to locate *L. camara* species based on their unusual spatial patterns (Beck *et al.*, 2008). For example, Adam *et al.* (2017) used high-resolution WorldView-2 imagery to map the invasive *Prosopis glandulosa* (mesquite) in the South African semi-arid environments. The results revealed that P. *glandulosa* was effectively detected and distinguished among the coexisting native species of acacia at 2 m resolution by WorldVview-2 imagery with an overall classification accuracy of 86%. Monitoring studies were conducted in the USA by Evritt and his colleagues using aerial photographs taken during the flowering seasons of Eurasian Euphorbia asula and Asian *Tamarix chinensis*. The results showed that the visible-wavelength (400-700 nm) reflectance of infested locations was significantly higher as a result of the bright-coloured inflorescences

(Everitt *et al.*, 1995; Underwood *et al.*, 2003). Due to its various brightly-coloured inflorescences, it is anticipated that similar results would be observed for the mapping of *L. camara*, if the same method is used.

Most plant species have distinctive features occurring in a narrow bandwidth which is only detectable through the use of narrow-band sensors. As a result, hyperspectral sensors become more advantageous over multispectral sensors as they obtain data in a numerous number of spectral bands, while multispectral sensors only record reflectance in a few number of bands within the electromagnetic spectrum. Therefore, hyperspectral sensors are more suitable for invasive species detection as their narrow bandwidths are able to provide more data on the fine spectral feature of different flora (Taylor *et al.*, 2012).

Hyperspectral RS is able to record electromagnetic radiations at a narrow wavelength interval which then allows the differentiation of vegetation types that appear similar on multispectral data to be observed as a result, hyperspectral RS has been used successfully in several studies to characterize plants including in studies on *L. camara* (Dubula *et al.*, 2016). For instance, Taylor et al. (2012) conducted a study to determine the ideal hyperspectral wavelengths based on the spectroscopy data within the spectral range of 450-2500 nm in order to detect *L. camara* from seven surrounding species in the area. The method was established through the use of statistical analysis of the reflectance and 86 as well as 18 bands were identified by the derivative reflectance. *L. camara* was found to be different from the other coexisting species in the area. Furthermore, it was anticipated that it was more likely for *L. camara* to spread further inland into new parts of South Africa in the future. Hyperion imagery was used to evaluate the efficiency of the acknowledged ideal bands. The original Hyperion image containing 155 bands resulted in an overall accuracy of 80% as compared to 77% and 76% from the 86- and 18-band spectral subsets. No significant variation was found in the accuracy when the three error matrices were compared. Furthermore, the combination of the statistical analysis and the FDR analysis demonstrated the significance of the procedure for the reduction of data by refining the variation to less optimum bands for detection of *L. camara* without any adverse effect on the classification accuracy.

The Landsat 8 OLI sensor offers improved mapping capabilities of IAP species, due to its assortment of spectral, spatial, radiometric and temporal resolutions merged with post-launch calibration. The sensor has a range of spectral bands that make it capable of identifying the spectral responses of various vegetation across the near infrared (NIR) as well as panchromatic band. Furthermore, the sensor is able to characterize various seasonal phenological patterns of vegetation through the use of its radiometric resolution of 8 to 12 bits. Landsat 8 OLI is made up of 11 spectral bands that provide endless seasonal coverage of the landmass worldwide at a spectral resolution of 30 m, with a temporal resolution of 16 days (Matongera *et al.*, 2016). For example, Fernando *et al.* (2016) successfully mapped *L. camara* using Landsat 8 in the Udawalawe National Park, where the weed covered 8.5% of the area within the park.

There have been recent new developments of new-generation imagery, such as Sentinel, Worldview and RapidEye, amongst others. These imageries have enhanced spatial and spectral resolutions which are valuable for the mapping of land use and land cover (Odindi *et al.*, 2014). Sentinel-2 is a multispectral dataset characterized with a high spatial resolution as well as a temporal resolution of six days which is usually higher as it is able to adjust the angle of the image acquisition qualifying the sensor to be among the vital data sources suitable specifically when considering large spatial extent mapping and predominantly in regions with inadequate resources (Sibanda *et al.*, 2016). The spectral characteristics of Sentinel-2 provide better means of mapping invasive species. For example, Rima *et al.* (2017) utilized Sentinel-2, together with Pleiades, to detect IAP species in Kenya whereby the results showed that the IAPs were more profuse in the Sentinel classification compared to Pleiades sensor. Regardless of the success of using Sentinel-2 in detecting and mapping IAP species, little work has been done in using the sensor to detect and map *L. camara*.

Vegetation indices were originally developed to use spectral measurements for the qualitative and qualitative assessment of vegetation cover (Bannari *et al.*, 1995). Vegetation indices (VI) like the Transformed Vegetation Index (TVI), the Normalised Difference Vegetation Index (NDVI), the Soil Adjusted Vegetation Index (SAVI), the Transformed SAVI (TSAVI), etc., have potential in the classification of vegetation. Spectral and statistical analyses have revealed that vegetation indices assist in the discrimination of *L. camara* from other classes such as agriculture, barren and urban water (Kandwalet *et al.*, 2009). In a study conducted by Kandwalet *et al.* (2009), SAVI was found to be the best index for separating *L. camara* from other classes because it produced the highest producer and overall accuracy. The high errors of commission and omission were anticipated to have been caused by the wrong assignment class labels while thresholding. Overall, the success of various RS techniques on the detection and mapping of *L. camara* including that of vegetation indices in separating it from other classes has not been able to explain why the weed occurs in the areas of concern. As such there is need to incorporate environmental variables in understanding some of the abiotic reasons behind the occurrence of the weed.

Table 2.1: A summary of satellite remote sensing sensors mostly in used South Africa

Sensor	Spatial resolution	Spectral resolution	Temporal resolution	Accessibility	Application scale	Accuracy
Aster	15–90m	14 bands	16 days	Free	Local to regional	Very low to low
Landsat 5 TM	30–120m	7 bands	16 days	Free	Regional	Low to moderate
Landsat 7 ETM+	15–60m	8 bands	16 days	Free	Local to regional	Moderate
Landsat 8 OLI	15–100m	11 bands	16 days	Free	Local to regional	Moderate
Quickbird	65 cm to 2.90m	5 bands	1–3 days	Expensive	Local	Very high
Sentinel 1A and 2	10–60 m	13 bands	5 days	Free	Local to regional	High
Spot 5	2.5–20m	4 bands	2–3 days	Free in South Africa	Local to regional	Moderate
Spot 6		4 bands	Daily	Free in South Africa	Local to regional	High
Worldview	0.46–2.4m	8 bands	1–3 days	Expensive	Local	Very high

2.5 Classification algorithms used to map *L. camara* and their challenges

Numerous variations of IAP such as *L. camara* species in South Africa are now entrenched and cause critical harm, while others are at the early phase of introduction (Rouget *et al*., 2004). Therefore, the monitoring and management of not only well-established IAPs, but also the newly-introduced invaders through mapping, are important in managing these species. Initially, conventional strategies including field surveys, visual interpretations, literature reviews, map interpretation and ancillary and collateral data analyses, were used to map IAP (Gil *et al*., 2002). These methods are time-consuming, costly and labor-intensive as they require intensive field work with large volumes of ancillary data for analysis, and are therefore ineffective (Thamaga and Dube 2018). Moreover, the methods are environmentally distractive and impractical for large-scale implementation (Dube *et al*., 2016). For example, within the Kruger National Park, Martin and Foxcroft (2002) used historical to map invasive species. However, the data used were largely disjoined, resulting in loss of information and significant gaps. However, the data captured in the GIS database were the first of their kind to be used for alien biota section. The data proved to be reliable and has the potential to be a useful reference database of invasive species within the park in future (Martin and Foxcroft, 2002). For mapping areas invaded by *L. camara*. Le Maître *et al.* (2002) used field mapping for the Sonderent and Sanbie-sand catchments. GPS was used to map invaders in the Keurbooms River catchment. Lastly, high spatial resolution aerial photographs were used to map invasion on the upper part of Wilge river catchment (Le Maître et al. (2002).

According to Shackleton, *et al.* (2017) roadside surveys provide a better and quick understanding of the distribution of IAP species, particularly where data is rare and missing due to their cost effectiveness. Shackleton, *et al.* (2017) used Roadside surveys for detecting and mapping status of *L. camara* in countries such as Kenya, Uganda, Ethiopia, Tanzania and Rwanda. However, the degree of the surveys was restricted due to inaccessible roads in some areas of these countries. Furthermore, the distance of the IAP from the road made it very challenging and time-consuming for recoding the precise locations of the species. A hand-held GPS unit was used to record coordinates of areas within 1 km where *L. camara* was either present, intrusive or naturalized. As such, it is therefore highly likely that *L. camara*'s precise distribution in eastern Africa was under-represented.

RS is currently one of the most commonly-used methods for mapping. Since most vegetation has a similar spectral signature, the spectral discrimination between the different vegetation can be challenging. However, the inclusion of different classification algorithms provides a better means of discriminating between different vegetation types (IAP's included) species from other lands cover classes (Xie *et al.*, 2008). Generally, images are classified through the use of either unsupervised or supervised classification algorithms (Lass *et al.*, 2005; Strand *et al.*, 2007). The categorization of image classification algorithms is based on various parameters, accessible data from the sensor as well as the nature of the training dataset (Nath *et al.*, 2014; Royimani *et al.*, 2019).

Examples of supervised classification are the Minimum and distance Maximum Likelihood (ML) classifiers. The Maximum Likelihood is a supervised classification algorithm which is commonly used for satellite images laying on statistical distribution patterns. (Thamaga and Dube, 2018; Hara *et al.*, 1994). These supervised algorithms operate by training the classifier extracting evaluations of applicable statistics or parameters for each class and using measured exemplars. It becomes difficult to achieve the automatic operation of supervised classifiers, due to the necessity for operator intervention to designate the training areas of identified terrains, from which the characteristics of each class might be determined (Hara *et al.*, 1994).

The Migrating Means clustering method (alternatively known as ISODATA method) and Random Forest (RF) are some of the examples of unsupervised classification algorithms. ISODATA has been widely used for images attained by infrared or optical sensors and thus, historically, it is the most popular unsupervised classification algorithm (Kumara *et al.*, 2011). ISODATA reduces the requirements on image analyst and has been mostly used processing supervised classification techniques (Hara *et al.*, 1994). Unsupervised classification makes use of algorithms as well as the information found in the measured data to automatically classify the landscape. Furthermore, these classifiers do not require specification of training regions (Gil *et al.*, 2011). Unsupervised classifiers identify the clustering of feature vectors that are measured and designate each separate cluster as a new class, which is why they are preferred for various applications specifically for those whereby real-time processing is required (De Ca´ceres and Wiser, 2012).

Classification algorithms can further be divided into parametric and non-parametric image classifiers. Spectral angle mapper (SAM), Maximum Likelihood (ML) and Minimum Distance to Mean (MDM) are examples of parametric classifiers. These algorithms are recommended for the discrimination of IAP species due to their ability to decrease the level of redundancy in remotely-sensed data (Lu and Weng, 2007). In addition, algorithms are easily accessible and have been successfully used however, there are challenges associated with their overall performance (Fernández *et al.*, 2013; Matongera *et al.*, 2016). For example, parametric classifiers are prone to mixed pixel problems, these increase on heterogeneous terrain. They also make assumptions that the selected dataset used in training the model in the classification procedure represents an ideal (100%) cover of the feature or surface (Campbell and Wynne, 2011). Furthermore, parametric image classifiers compromise the accuracy of the classification by providing the output of the classification at a pixel level (Kumar and Min, 2008).

Support Vector Machines (SVM), Random forest (RF) and Artificial Neutral Networks (ANN) are examples of non-parametric classifiers. These classifiers have the capability of retrieving the biophysical features in various vegetation and are also able to recover single pixels as end-members and combinations of pure materials (Curatola Fernández *et al.*, 2013). For example, Naidoo *et al.* (2012) used a composite of hyperspectral and Light Detection as well as Ranging (LiDAR)-derived structural parameters, in a form of predictor datasets using the approach of automated Random Forest modeling for the classification of eight savanna tree species commonly found in the Kruger National Park region. The results of the study revealed that the hybrid predictor dataset Random Forest model provided the best prediction and classification accuracy of 87.68% for the vegetation of interest. Artificial neutral network is an example of a non-parametric classifier that is effective in extracting vegetation type data including in heterogeneous terrain as it is not driven by statistical properties (Gil et al., 2011). This makes these classifiers more suitable for the classification of change, unlike the parametric classifiers (Royimani *et al.*, 2019).

2.6 Influences of environmental variables on *L. camara*

Environmental factors affect plant species in various ways; they are known to either limit, disturb or provide resources to the species (Guisan and Thuiller, 2005). For example, results in a study conducted by Masocha *et al.* (2017) revealed that rainfall had a positive effect on the rate of spread of *L. camara* in Southern Africa whereby during wet periods, *L. camara* spread faster than during dry periods. Habitats with poor resources have also been found to favor the performance of IAP species over native species (Burke and Grime, 1996). However, this is reversed in some areas (Funk and Vitousek, 2007). The mortality rate of *L. camara* is known to be low under conditions such as low soil moisture, poor soil nutrients and high light, therefore, areas that are moister are more likely to be vulnerable to invasion than areas that are more arid (Sharma *et al.*, 2005). From figure 2.1, it can be seen that the invasion of *L. camara* is more pronounced in the eastern parts of South Africa, which is more humid, rather than in the arid western parts of the country. On the other hand, in arid regions *L. camara* benefits from its proximity to stream-side habitats. Thus, invasion in unsuitable areas could be enabled by a combination of temporal and spatial in moisture.

Light plays a significant role in the regulation of various processes in vegetation. For example, light is vital for the process of photosynthesis in plants, it is also a vital sign for seed germination and seedling development (Nishii *et al.*, 2012). *L. camara* is a shade intolerant species which has an adaptive mechanism enabling it to avoid low light environments. In a study done by Matsoukis and Chronopoulou-Sereli, (2003), it was reported that there was a significant decrease in the amount of flower heads of *L. camara* plants due to an increase of shading from 0% to 66% in the area. It was anticipated that the great reduction of flowering was due to the low light level, which, in general, causes such effects (Matsoukis and Chronopoulou-Sereli, 2003). The significance of disturbance, topography as well as environmental gradients for the spatial distribution of IAP species has rarely been explored in a single study. However, it has been noted by McConnachie *et al.* (2011) and Tamado *et al.* (2002) that elevation has an influence on the spatial distribution of spatial distribution of IAPs such as *L. camara*. Furthermore, Lambert *et al.* (2017) and Othman *et al.* (2015) also stated that elevation is a significant variable that has an effect on the spatial variability of the top soil properties as well as microclimate. This is supported by the findings of Priyanka, (2013), who observed the predominance of elevation gradients in accordance with the expected species, *L. camara* thrives at lower altitudes, whereby there is a decline in species occurrence as a result of an increase in *L. camara* infestations. Similar trends have been observed in South Africa. For example, Ndlovu *et al.* (2018) used remotely sensed data combined with topo-climatic data to map the potential occurrence and spread of the invasive bramble (*rubus cuneifolius*), in the Kwazulu-Natal Drakensberg, South Africa. Results revealed that elevation was identified as one of the strongest predictors of the species. Similarly, Adeola. (2017) found similar results for the invasive *Parthenium Hysterophorus*.

According to the study conducted by Vardien *et al.* (2012), environmental factors, such as climate, have an influence on the distribution and spread of *L. camara*. The weed is already present in several parts of South Africa specifically those with sub-optimal climatic conditions, typically in human-modified habitats or riparian zones having a minimal effect from macro-climatic parameters as compared to natural habitats (Vardien *et al.*, 2012). Although climate sets favorable conditions for the spatial distribution of *L. camara*, its life history is highly influenced by near-term weather conditions. The invasiveness of *L. camara* is also influenced by its ability to respond swiftly to prevailing weather conditions (Raghu *et al.*, 2014). Rivers, natural disturbances, extreme weather events, as well as anthropogenic disturbances such as land use, have been shown to be significant vectors of the distribution and abundance of the weed (Catford *et al.*, 2012; Foxcroft and Richardson, 2003).

The episodic occurrence of unexploited resources, such as fresh water and nutrients in space and time, are assumed to facilitate biological invasions. These resource occurrences are due to the disturbances caused by anthropogenic activities as well as inherent variability in the environment, which then creates the atmosphere for IAP species to grow and thrive in an introduced range. Moreover, this kind of variation in resources availability has been reported to favor invasion in cases where there is heterogeneity in the resources in space or time, or both (Ramaswami and Sukumar, 2014).

Ecological Heterogeneity regulates the occurrence of a larger amount of IAP species within an ecosystem, specifically on the larger scale. Ramaswami and Sukumar, (2014) assumed that the presence of environmental variables, including periodic disturbances influences the spatiotemporal distribution in resources such as moisture, light and nutrients. Habitat boundaries are usually characterized by advanced availability of resources, such as light, and propagules in comparison to adjoining areas and as such are prone to invasion. According to Kumar *et al.* (2006) invasive species richness is associated with the number of boundaries in landscapes. Boundaries naturally occur along riparian habitats whereby invasive species often occur more than adjoining habitats. These riparian ecosystems are prone to flooding making them extremely vulnerable to invasion by *L. camara* as they are influenced by various processes including removal of existing vegetation and sedimentation (Richardson *et al.*, 2011).

2.7 Future research direction

Spatial analysis of plant invasions continues to show incredible growth in the field of research. The use of RS for mapping ecological invasions is a relatively specialized research topic, where the spatial cover, morphology and seasonality of various invaded versus native ecosystems suggest that more IAP species could be detected using RS. (Bradley, 2014). RS has proved a vital tool for large-scale ecological studies in the past three decades, however, it was not commonly utilized in modeling IAP species until the mid-1990s.

With the increasing improvement of the RS technology, this tool has been increasingly utilized in studies related, not only to invasive species, but specifically to *L. camara*. *L. camara* is regarded as being one of the most significant IAP species worldwide and has been the target for intensive management efforts for over a century (Raghu e*t a.*, 2014). The studies done on the species have been successful; for example, several authors, such as Dhau, (2008), Kimothi and Dasari, (2010) and Taylor *et al.* (2011), have successfully mapped the species. However, more work needs to be done in terms of long-term monitoring and seasonal mapping of the species (Matongera *et al.*, 2017). Researchers are advised to explore the freely available and accessible new generation multispectral sensors such as Sentinel-2 and Landsat 8 which are characterized with high to moderately fine spatial-resolution. These sensors possess strategically positioned spectral bands and improved temporal and radiometric properties capable of discriminating IAP species. It is further advised for researchers to weigh and select optimal bands appropriate for mapping *L. camara* as these bands can inform optimal spectral indices to use for reliable model predictions of the species.

Advanced and robust classification algorithms have been valuable for the detection and monitoring of *L. camara*. However, it has been argued that land cover maps usually comprise a component of uncertainty resulting from classification errors. These algorithms are able to significantly improve the classification accuracy of *L. camara* and to advance the precision mapping of the species. Therefore, it is advised that future research explores the potential of the above-mentioned classifiers with the newly-launched multispectral data sets. These datasets have upgraded spectral and spatial characteristics for improved functional scale detection and mapping of *L. camara*. In addition, it is recommended that future research investigates the similarities and differences in the *L. camara* reflectance quantities, and those of other vegetation types.

The several studies done on the *L. camara* have not given much information on the reasons behind the location and/or spatial distribution of the species. Understanding whether environmental factors have an influence on the spread of *L. camara* may enhance the understanding of species invasion dynamics, leading to informed and improved decisions in IAP species management (Masocha *et al.*, 2017). To the best of our knowledge, there is paucity in literature as regards the use of a Composite of RS datasets, species distribution models and environmental variables in detecting, mapping and predicting the spatial distribution of invasive *L. camara* in rangeland ecosystems. Therefore, there is need for research that will incorporate RS, species distribution models and environmental factors to give clear direction on the cause of the distribution of *L. camara*. This is a necessity, as it will give ecologists, environmental managers and decision-makers the means to adequately manage *L. camara*.

2.8 Conclusions

This study successfully reviewed existing literatures on the application of RS to modeling *L. camara* in Rangeland ecosystems. Literature has shown that the use of traditional methods such as field surveys in *L. camara* detection, mapping and distribution has been a challenge in most parts of the world. RS strategies have proved to be able to provide better means of detecting and mapping *L. camara*. The majority of the studies have focused mainly on mapping the spatial distribution of *L. camara*; this then leaves a gap in fully understanding the mechanisms of the species' diverse ability to invade various ecosystems. There is a need to incorporate environmental factors to give a clear understanding of the spatial spread of *L. camara*, therefore future research should focus on assessing the factors that play a role in this.

CHAPTER THREE

Modelling localities vulnerable to *Lantana camara* infestation in semi-arid savanna ecosystems of Bushbuckridge communal lands and Kruger National Park, South Africa

This chapter is based on:

Xivutiso G. Maluleke., O. Mutanga. and T. Dube. (Manuscript under review). Modelling localities vulnerable to *L. camara* infestation in semi-arid savanna ecosystems of Bushbuckridge communal lands and Kruger National Park, South Africa. Journal of Arid environments

Abstract

We mapped and modelled the potential areas vulnerable to *Lantana camara* (*L. camara*) infestation in the semi-arid savanna ecosystems of Bushbuckridge communal land and Kruger national park, South Africa. To achieve this objective, first we modelled the potentially vulnerable areas based on remotely sensed data and selected environmental variables using the Maximum entropy (Maxent) algorithm. The performance of the model was evaluated, using True Skills Statistic (TSS) Area Under Curve (AUC) and Kappa statistic. Results showed that the Bushbuckridge communal lands are more vulnerable to the highest *L. camara* infestation with a prediction of 10% of the area anticipated to be covered by the weed as compared to the 7% in the Kruger National Park. The optimum model was derived from a composite of all variables, yielding an AUC score of 0.95. Model 4, which was developed based on the indices alone, achieved the lowest accuracies, with an AUC score of 0.85. The spatial distribution maps derived from Maxent indicated that *L. camara* was more likely to invade the communal lands, rather than the protected area. The overall findings of this study showed that elevation is the variable which highly influences the spatial distribution of *L. camara*. The study is critical in providing pro-active planning tools for prioritising areas for urgent control intervention

Keywords: environmental variables; invasive plants encroachment; *L. camara*; Maxent; Mpumalanga province, rangelands; rangeland ecosystems.

3.1 Introduction

Non-native species are important agents of global ecological modification. They are perceived as the worst threat to worldwide biodiversity, after anthropogenic environmental damage and natural ecosystem destruction (Gooden *et al.,* 2009). Plant intruders of natural environs, similarly named environmental weeds, change ecosystem structure and utility as well as influences the size and variety of native vegetation (Mack *et al.,* 2000). *L. camara* is recognised to be one of the predominant invasive alien plant (IAP's) species globally and has become a major invader of agricultural areas as well as natural ecosystems (Dobhal *et al*., 2011). Once established, this species poses a serious threat to savanna rangelands and become extremely difficult to manage, maintain and eradicate. Therefore, preventing its introduction or rehabilitating of the affected areas may be the most cost-effective management strategy (Gallien *et al*., 2012).

L. camara has been introduced as an ornamental plant in various countries globally. It has become invasive in most countries including South Africa whereby the invasive species specialist group (IUCN 2001) has ranked it amongst the world's top invasive species (Sharma, 2005). The invasion of *L. camara* in South Africa has been associated with the reduction of grazing pastures, invertebrate diversity and it has been known to result in the mortality of some livestock and humans the after consumption of its fruit (Vardien *et al*., 2012). By the year 2000, *L. camara* had invaded an area of about two million ha in South Africa, with increasing thickets obstructing pathways to sources of water and reducing the quality of water within various river catchments such as Hartenbos and Klein Brak (Taylor and Kumar, 2014). A good example is Bushbuckridge, which is an area located at the edge of the Kruger National Park, where most of the land is reserved for wildlife and livestock grazing. The intrusion of *L. camara* in this area has resulted in increased replacement of natural ecosystems such as grasslands, which are vital for the provision of forage for livestock and wildlife (Masocha *et al*., 2017).

The distribution of the *L. camara* species differs, depending on the biotic and abiotic conditions (West *et al*., 2016). These environmental factors affect the plant species in various ways and are known to limit, disturb or provide resources to them (Guisan and Thuiller, 2005). Environmental variables such as topography and climate impact on the spatial distribution of alien invasive plants (Guisan and Thuiller, 2005). For example, topographic variables such as slope, elevation and aspect influence the amount and quality of soil nutrients and light availability, therefore, influencing the microclimate (Wang *et al*., 2017). In addition, rainfall and temperature have a significant effect on the establishment and dispersal of the IAP's species (Zhu *et al*., 2007). The relationship between the species and their overall environment can result in a variation of spatial trends, which can be witnessed at various scales (Pearson *et al.*, 2004). Hence, for the estimation of the potential niche of the IAP's species and their spatial distribution, it is important to establish precise environmental factors limiting its distribution as well as those that favour its growth. However, such detailed information is lacking for most species (Priyanka and Joshi, 2013). As such, the inclusion of environmental factors in explaining the spatial distribution of *L. camara* can enhance an understanding of these species.

To date, two broad approaches namely field traditional based methods and RS techniques have been developed to quantify alien invasive species. Although traditional methods based on visual interpretations and field surveys are highly accurate, they are often difficult to conduct across large regions and are time consuming, expensive, as well as labour intensive (Odindi *et al.*, 2014; Thamaga and Dube, 2018; Taylor *et al.*, 2011). In contrast, RS technique offers the ability to acquire valuable and relatively cheap primary data that is necessary for timely and accurate quantification of different species (Thamaga and Dube, 2018). Additionally, RS has successfully overcome the challenges associated with conventional approaches, such as time, cost and the accessibility of large geographic unit (Dube *et al.*, 2017). The increasing number of sensors have provided ecologists with spatial data, creating opportunities to advance the use of RS together with Geographic Information System (GIS) strategies in mapping and modelling the distribution of invasive species

The utilization of RS technologies in mapping invasive species has gained increasing attention globally (Dube and Mutanga, 2015). Over the years, many types of sensors have been used by researchers in *L. camara* modelling, with different degrees of accuracy. However, there has been paradigm shift from sensor to sensor, because of their limitations and challenges and the need for continuous improvement in mapping (DeFries *et al.*, 2004). The application of medium spatial resolution in *L. camara* modelling has been limited by insufficient spatial and spectral capabilities (Xie *et al.*, 2008). The application of moderate spatial resolution sensors including Landsat 8 OLI, Landsat 7 ETM+ and Spot 5 to name a few has been restricted to some extent when dealing with the world's worst understory plant species such as *L. camara*, mainly because they are unable to detect species found in smaller patches (Zhang and Foody, 1998). For example, Müllerová *et al.* (2013) tested the effects of image classification as well data resolution on the detection of the invasive *Heracleum mantegazzianum* (Giant hogweed). Between the two tested satellite data sets, the results revealed that the high spatial resolution VHR performed better than the Rapid Eye 2010 which is a medium spatial resolution in detecting the invasive Giant hogweed.

According to Huang and Gregory, (2009), the use of the above-mentioned moderate spatial resolution images on IAP mapping and monitoring is not clearly understood in a background of native vegetation and it is therefore challenging, in terms of detection. Huang and Gregory, (2009) further noted that this data can only be used to detect large patches of weeds that rely more on the phonological time. For instance, a study done by Fernando *et al.* (2016), produced low accuracies in mapping *L. camara* at the species level, using the 30 m Landsat TM and SPOT data that have a spatial resolution of 20 m. Nonetheless, the spatial, spectral and temporal characteristics of Sentinel-2 provide unique opportunity (Addabbo *et al.*, 2016). Sentinel-2 is a high spatial resolution (10–60 m) sensor with a temporal resolution of five days, which is usually higher due to its image acquisition angle adjustment capability. Hence making the sensor a key data provider appropriate for large-scale mapping especially in resource scares zones (Sibanda *et al.*, 2016). It is also the first optical sensor to have red edge bands which increases the sensitivity of vegetation and its spectral response. The use of a sensor with a wider width and spectral characteristics such as those of Sentinel-2 may provide an improvement on detecting and predicting the geographic distribution of *L. camara* across a landscape from mapped environmental variables. The integration of RS data in Species Distribution Models (SDMs) has improved the estimation of likelihoods of species occurrence in areas of concern as well as the performance of SDMs (Kazak *et al.*, 2008; Rocchini *et al.*, 2015).

SDMs have been introduced as tools that can aid in understanding and predicting current and future species invasion. SDMs are a fixed portrayal of habitats that are suitable for species (Bateman *et al.*, 2012). They are based on straightforward correlation between the occurrence of species and ecological features, whereby their functionality is built on the establishment of a relations between a species identified range and environmental variables in the area. Thereafter, the relationship is used to detect other areas that may be inhabited by the species. (Beaumont *et al.*, 2008). The spatial distribution of IAPs species has previously been modelled using different SDMs. Most SDMs use presence and absence data however; there has been a limitation with regards to acquiring absence data (Phillips *et al.*, 2009). In the research conducted by Hernandez *et al.* (2006), Maximum entropy (Maxent) was the best modelling method compared to Multivariate distance (DOMAIN), GARP and Envelope model (BIOCLIM). The four modelling methods were compared with sample sizes of 5, 10 and 25 occurrences. It was anticipated that Domain, GARP and Bioclim performed poorly due to the small sample sizes. In a study done by Wisz *et al.* (2008) it was found that Boosted decision trees (GBM), Regression; multivariate adaptive regression splines (MARS) AND Regression, a rapid application of a GAM (BRUTO) performed exceptionally well and superior to other techniques especially when dealing with bigger sample sizes. However, they performed very poorly in reduced sample sizes. Rule and DOMAIN sets determined by genetic algorithms as well as open modeller version (OM-GARP) were some of the foremost performers when considering smaller sample sizes. However, they produce average results with bigger sample sizes. Additionally, Maxent was found to be less sensitive to different sample size and was the best model to predict species distribution with the use of both large and small sample size.

Maxent is an SDM with great potential for identifying invasive species distribution. Maxent is a correlative approach that has been identified among the best SDM for present-only data analysis (Ficetola *et al.*, 2007). Maxent requires present-only data and a low number of locations to construct models. It has a higher performance compared to other present-only models due to its sensitivity to spatial errors that are related to low data (Phillips *et al.*, 2006). Furthermore, Maxent allows the usage of both continuous and categorical variables. Its regularization procedure makes it prone to overfitting as it compensates for small occurrence data (Phillips *et al.*, 2006; Merow *et al.*, (2017).

As aforementioned, there has been considerable level of success recorded in modelling the spatial spread of *L. camara*. However, regardless of the recorded success, there are still shortcomings in understanding the factors affecting its versatility in the invasion of new environments. As such, the mapping of *L. camara* alone is not enough as it does not explain why the species is occurring in those regions, hence there is need to incorporate environmental variables in RS of *L. camara* in Savanna rangelands. Therefore, the objective of this study was to determine the environmental variables influencing the spatial variability of *L. camara* in savannah ecosystems, utilizing the Maxent algorithm in concert with remotely-sensed data derived from the Sentinel-2 satellite.

3.2 Materials and methods

3.2.1 Field data collection

The filed data was collected in the month of July 2017. Stratified random transects were generated in ArcGIS 10.4 using the study area map. The generated points were then uploaded on a Trimble Juno 3B hand-held Global Positioning System (GPS), and subsequently used to locate the sampling sites on the field. A systematic sampling procedure was adopted. This was done through the measurement of a quadrant within the 30-40 transect after every 10 m interval. Eighty (80) sample points were generated from the field and then divided into 70% for model training and 30% for model validation. GPS captured coordinates were presented in a table format using Microsoft Excel Version 4.0 and then imported into the ArcGIS 10.4 software environment to be overlaid on the study area shape file. For the compatibility of

Maxent, the measured GPS points for *L. camara* were changed to comma-separated values (csv) and used for the modelling of potential vulnerable areas.

3.2.2 Image acquisition and processing

The freely-accessible Sentinel-2 imagery was used in this study. A cloudless satellite dataset of Sentinel-2 covering the study area was accessed from Geocento portal for analysis (https://imagery.geocento.com). The acquired images coincided with field data collection period. Sentinel-2 is a multispectral sensor that was launched on 23 June 2015. It comprises two indistinguishable satellites, namely, Sentinel-2A and Sentinel-2B. The satellite is characterized by a high temporal resolution with five-day intervals in the image acquisition. The satellite collects data at 10 m (blue, green, red and near-infrared-1) and 20 m (red edge1 to 3, close infrared-2, short waves infrared 1 and 2) respectively. For this study, bands 1,9 and 10 were excluded due to the course spatial resolution of 60 m (Table1). Atmospheric correction of the acquired images was carried out with the aid of a toolbox called Sen2cor within the Sentinel Application Platform (SNAP) tool Version 4.0.

Table 3.1: Sentinel-2 spectral characteristics used in this study

Band no	**Band name**	**Band width (µm)**	**Resolution**
2	Blue	0.490	10
3	Green	0.560	10
4	Red	0.665	10
5	Vegetation red edge	0.705	20
6	Vegetation red edge	0.740	20
7	Vegetation red edge	0.783	20
8	Near infrared (NIR)	0.842	20
8a	Vegetation red edge	0.865	10
11	Shortwave infrared (SWIR)	1.610	20
12	Shortwave infrared (SWIR)	2.190	20

3.2.3 Topographic data

A 30m Digital Elevation Model (DEM), which is a 3D representation of the terrain, was acquired freely from the Advanced Space-born Thermal Emission and Reflection Radiometer (ASTER) which covers 99% of the globe. The spatial analyst tool in ArcGIS was used to derive the following topographic variables from the DEM; Topographic Wetness Index (TWI), slope, aspect elevation, and Topographic Position Index (TPI). Sentinel-2 data was used to generate four vegetation indices (Table 2) namely; Normalized Difference Vegetation Index (NDVI) (Rouse *et al.*, 1973), Transformed Vegetation Index (TVI) (Deering, 1975), Ratio Vegetation Index (RVI) (Baret, 1991), and Green Normalized Difference Vegetation Index (GNDVI) (Gitelson, 1998). From the electromagnetic spectrum, NDVI is derived utilizing the red and near-infrared bands to evaluate changes in the phenology of vegetation which therefore uses the utmost absorption and reflection and reflectance of the chlorophyll. Additionally, TVI is utilized in the elimination of negative values as well as the transformation of NDVI histograms to an ordinary distribution (Deering *et al.*, 1975; Mroz and Sobieraj, 2004). RVI is based on the principle that leaves absorb more red wavelengths than infrared light. RVI is sensitive to vegetation and also have a significant relationship with plant biomass; as such it is mostly used for estimating and monitoring vegetation (green) biomass (Xue and Su, 2017). GNDVI is an index of plant and one of the most generally-utilized indices to assess canopy variation in biomass (Gitelson *et al.*, 1996).

Table 3.2: Selected vegetation indices used in this study

S/N	Indices	Formula	References
1	Normalized Difference Vegetation Index(NDVI)	$\frac{NIR - RED}{NIR + RED}$	Rouse 1974
2	Transformed Vegetation Index (TVI)	$\sqrt{(NDVI)} + 0.5$	Deering 1975
3	Ratio Vegetation Index (RVI)	$\frac{NIR}{RED}$	Baret 1991
4	Green Normalized Difference Vegetation Index (GNDVI)	$\frac{NIR - GREEN}{NIR + GREEN}$	Gitelson *et al.*, (1996)

3.2.4 Bioclimatic data

Bioclimatic variables were derived as raster grid format of a 30 arc-seconds spatial resolution from the current WorldClim climatic conditions database (http://www.worldclime.org./). 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 (Hijmans *et al.*, 2005). The variables were categorized into temperature and moisture variables, where those that are biologically-relevant were used. As such, all other variables were resampled to 30m spatial resolution and projected to the Universal Transverse Mercator (UTM) projection to match topographic variables. To ensure that all variables match, the variables were converted from raster format to ASCII so as to ensure their compatibility with Maxent in order to run the model (Jarnevich and Reynolds 2011).

Table 3.3: Bioclimatic variables from WorldClim database (Hijmans *et al.*, 2005)

Abbreviation	Name	Units
	Temperature variables	
Bio01	mean annual temperature	^{o}C
Bio02	mean diurnal range in temperature	^{o}C
Bio03	Isothermality (bio 02/bio 07) X100	^{o}C
Bio04	temperature seasonality	^{o}C
Bio05	maximum temperature warmest month	^{o}C
Bio06	minimum temperature coolest month	^{o}C
Bio07	annual temperature range	^{o}C
Bio10	mean temperature warmest quarter	^{o}C
Bio11	mean temperature coolest quarter	^{o}C
	Moisture variables	
Bio12	mean annual rainfall	mm
Bio13	rainfall wettest month	mm
Bio14	rainfall driest month	mm
Bio15	rainfall seasonality (coefficient of variation)	mm
Bio16	rainfall wettest quarter	mm
Bio17	rainfall driest quarter	mm

3.2.5 Modelling *L. camara* distribution

The freely available maximum entropy (Maxent) was downloaded from (http://biodiversityinformatics.amnh.org/open_source/maxent/) and used to model areas vulnerable to the inversion of *L. camara*. The remaining model parameters were set to default replication of 1 with 500 iterations using cross-validation run type. To reduce over fitting, regularization multipliers were set to 4 (Ndlovu *et al.*, 2018). The clog-log output format was used due to its ability to strongly predict area of moderately high output as compared to the logistic output (Kumbula *et al.*, 2019). Furthermore, a jack-knife test was used to assess the relative importance of predictor variables that explain the spatial distribution of the species, including the unique information provided by each variable (Phillips and Dudík, 2008). This method was used to analyse the effects of environmental variables on model results to indicate influential variables as it can estimate parameters and adjust the deviation without assumptions of distribution probability (Kumbula *et al.*, 2019).

Table 3.4: Model scenarios with selected environmental inputs

Model scenario	**variables**	**No of variables**
Model 1	Aspect, elevation, slope, TPI, TWI.	5
Model 2	Bands 2, 3, 4, 5, 6, 7, 8, 8a, 11, 12.	10
Model 3	Bios 01, 02, 05, 06, 07, 12, 13, 14, 17.	9
Model 4	GNDVI, NDVI, RVI, TVI.	4
Model 5	Aspect, elevation, slope, TPI, TWI, bands 2, 3, 4, 5, 6, 7, 8, 8a, 11, 12.	15
Model 6	Aspect, elevation, slope, TPI, TWI, bios 01, 02, 05, 06, 07, 12, 13, 14, 17.	15
Model 7	Aspect, elevation, slope, TPI, TWI, Bands 2, 3, 4, 5, 6, 7, 8, 8a, 11, 12, Bios 01, 02, 05, 06, 07, 12, 13, 14, 17, GNDVI, NDVI, RVI, TVI.	28

3.2.6 Model evaluation

To evaluate the model's performance and accuracy, AUC which is a threshold-independent measure of accuracy was used as well as TSS and Cohen's Kappa, which are threshold-dependent measures of accuracy. The AUC tests the agreement between the observed species presence and the estimated distribution, indicating whether the probability of presence (sensitivity) versus absence (specificity) was correctly ordered by the classifier (Phillips *et al.*, 2006). An AUC value of 0.5 shows that model predictions are not better than random; <0.5 are worse than random; 0.5–0.7 indicates poor performance; 0.7–0.9 reasonable/moderate performance; and >0.9, high performance (West *et al.*, 2016). Kappa has been previously used to measure model performance; however, it has been highly criticized for dependence on prevalence (Allouche *et al.*, 2006). As such, TSS has been presented as an alternative measure of accuracy as it corrects this dependence while retaining the advantages of Kappa. Furthermore, the error matrix was used to derive specificity, sensitivity, Kappa and TSS values using background samples as absence data. The 10 percentile threshold value was used to evaluate classification accuracy.

3.3 Results

3.3.1 Model accuracy

Table 3.5 shows the values of AUC, which are threshold-independent, as well as those of TSS and Kappa, which are threshold-dependent. The model that used all variables achieved the highest predictive accuracies and had the highest performance, attaining an AUC of 0.96, a TSS of 0.77 and a Kappa of 0.39. On the other hand, the model developed based on indices alone achieved the lowest accuracies, yielding an AUC of 0.854, a TSS of 0.549 and a Kappa 0.295.

Table 3.5: Evaluation results for all model scenarios

MODEL SCENARIOS	AUC	TSS	KAPPA
MODEL 1	0.924	0.667	0.338
MODEL 2	0.906	0.621	0.328
MODEL 3	0.925	0.751	0.397
MODEL 4	0.854	0.549	0.295
MODEL 5	0.952	0.773	0.401
MODEL 6	0.928	0.698	0.367
MODEL 7	0.955	0.765	0.387

Figure 3.1 shows the results of the jack-knife test of variable importance. The findings ranked elevation as the overall most influential variable in predicting areas most vulnerable to the invasion of *L. camara*. As observed in Models 1(a), 5(e), 6(f) and 7(g), elevation is the environmental variable with the highest gain, when it is used in isolation, and it therefore appears to have the most useful information by itself. Furthermore, it is also the only environmental variable with the highest mean decrease in accuracy omitted from the model and it also appears to have the most information that is not present in the other variables. Models 3 (c) and 4 (d) depicted bio 12 (mean annual rainfall) and GNDVI yielded the highest gain when used in isolation and leads to poor model performance omitted, whereas Model 7 (g) depicted band 5 (vegetation red edge) as the most important variable.

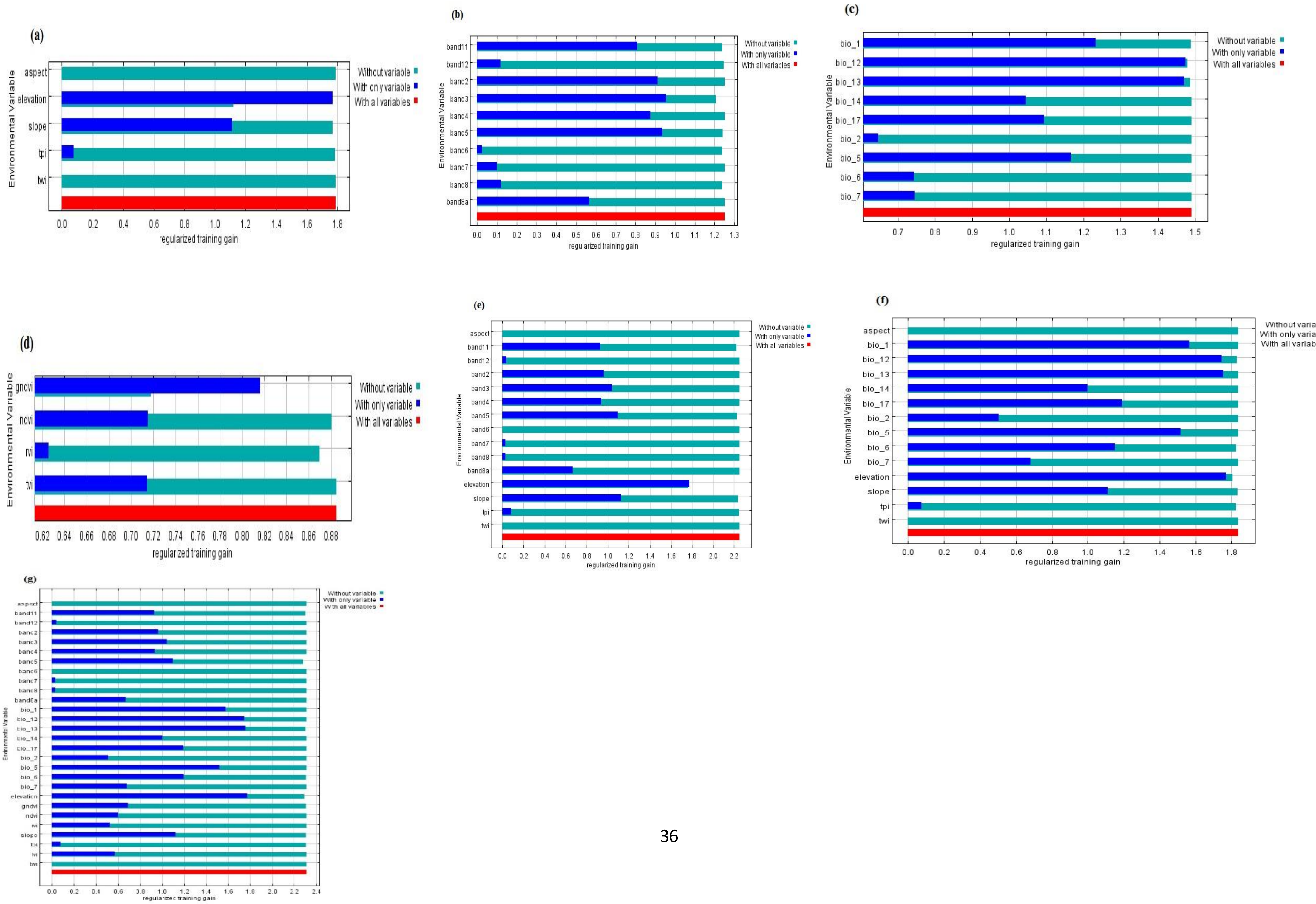
(a)
Environmental Variable
aspect
elevation
slope
tpi
twi
Without variable
With only variable
With all variables
0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 1.8
regularized training gain
(b)
band11
band12
band2
band3
band4
band5
band6
band7
band8
band8a
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0 1.1 1.2 1.3
(c)
bio_1
bio_12
bio_13
bio_14
bio_17
bio_2
bio_5
bio_6
bio_7
0.7 0.8 0.9 1.0 1.1 1.2 1.3 1.4 1.5
(d)
gndvi
ndvi
rvi
tvi
0.62 0.64 0.66 0.68 0.70 0.72 0.74 0.76 0.78 0.80 0.82 0.84 0.86 0.88
(e)
elevation
slope
tpi
twi
0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 1.8 2.0 2.2
(f)
0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 1.8
(g)
gndvi
ndvi
rvi
slope
tpi
tvi
twi
0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 1.8 2.0 2.2 2.4

Figure 3.1: Jacknife test of variable importance (a) topographic variables, (b) Sentinel bands (c) bioclimatic variables (d) selected vegetation indices (e) topographic variables and sentinel bands (f) topographic and bioclimatic variables (g) composite of all variables.

3.3.2 Spatial distribution of *L. camara*

Figure 3.2. shows the predicted potential habitats suitable for *L. camara*. The warm colours illustrate high level of invasion while the cooler colours illustrate low level of invasion. The resultant map shows that invasion is more likely to occur in the communal area of the study area, that is Bushbuckridge, specifically within areas that are moister. Although invasion is taking place in the protected area, the level of invasion is lower. Dry areas within the protected area have low level of invasion while the areas that have more moisture have some invasion taking place, specifically the central eastern part of the protected area. Overall, the maps seem to agree with the areas that are most vulnerable to the invasion of *L. camara*.

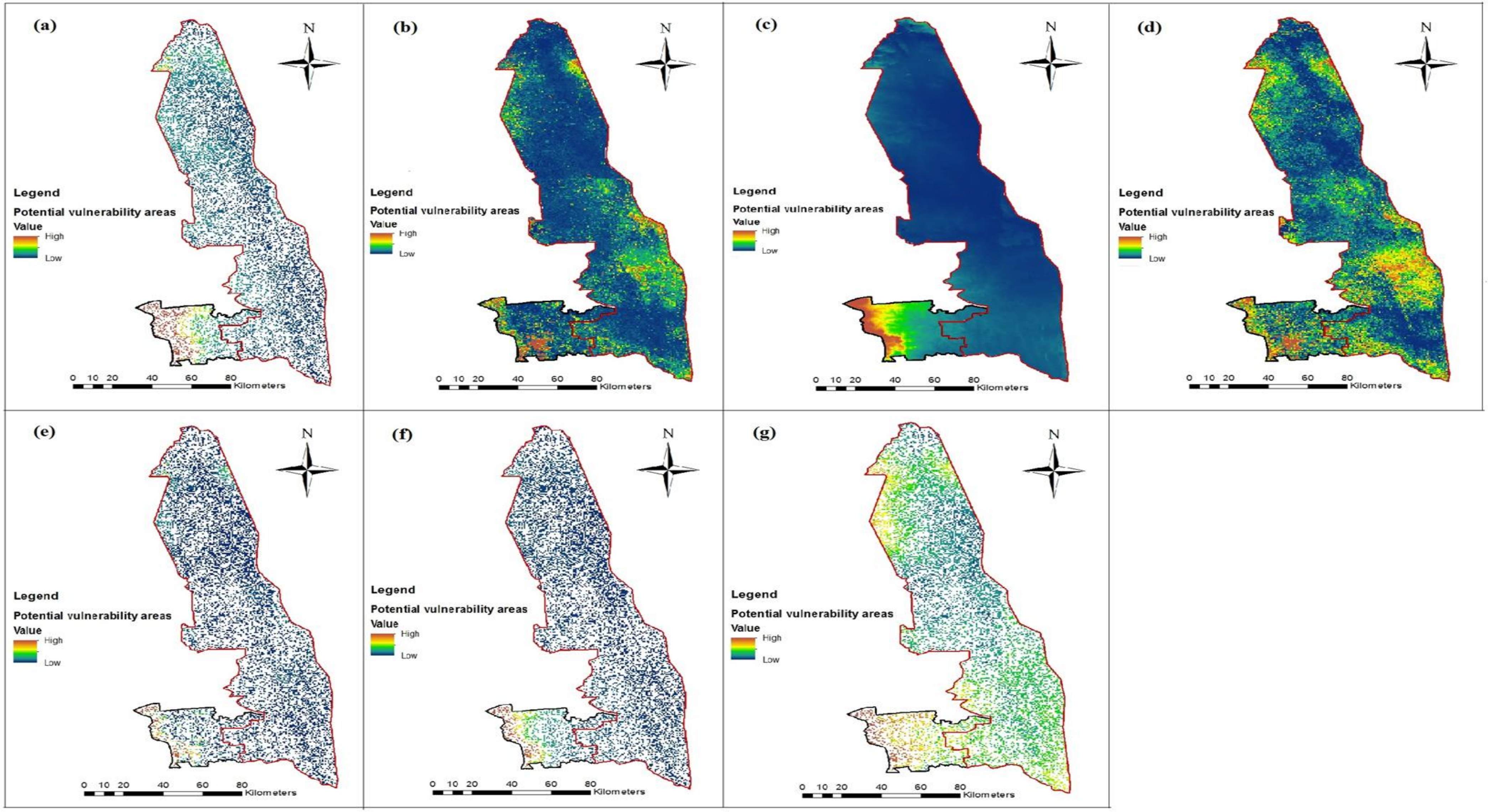

Figure 3.2: The spatial distribution of *L. camara* as predicted by Maxent where the following variables were used for each model: (a) topographic variables, (b) Sentinel bands (c) bioclimatic variables (d) selected vegetation indices (e) topographic variables and sentinel bands (f) topographic and bioclimatic variables (g) composite of all variables.

3.4 Discussion

The aim of the study was to model the potential spatial distribution of *L. camara* in savanna ecosystems using Maxent. Results revealed that the communal lands of Bushbuckridge are more vulnerable to the invasion of *L. camara* when compared to the protected area. Similar trends have been observed in other studies; for example, Rodgers *et al.* (2003) compared two tourist islands (the St. Simons Island and Jekyll Island) and two protected National Wildlife Refuge Islands (the Blackbeard Island and Wassaw Island) to find the island that is the most highly invaded by alien plants. It was found that Alien plant cover was appreciably greater in severely disturbed sites than in less disturbed sites on all islands and within both habitats. This is further supported by a study done by Lin, (2005) whereby major roadsides of Moorea, French Polynesia, were surveyed for *L. camara* cover in association with environmental factors. It was found that the roadside area covered by *L. camara* was 1.99% whereby the presence was correlated to the roadside habitat type with the highest being in areas of agricultural disturbance. The area covered by *L. camara* was also positively correlated to soil moisture and slope. According to Shrama *et al.* (2005), disturbed areas such as railway tracks, roadsides and canals, are more favourable for the species distribution. This is because the performance of IAPs is increased by the availability of more resources, and the altered disturbance regimes that are caused by anthropogenic activities increases the performance of the invading species over that of native species (Daehler, 2003). As a result, IAPs are usually invading disturbed areas (Hobbs, 1992). Disturbance decreases the cover and the vigour of competitors, and it increases the resource levels, which, in turn, facilitate invasions (Kneitel and Perrault, 2006).

Results further indicated that some variables highly influence the spatial distribution of *L. camara* while others have no significant contribution. The model built with all variables yielded the highest predictive accuracies and had the highest performance. Previous studies have established similar results where by models built with a composite of various variables performed better than those based exclusively on one set of variables (Parviainen *et al.*, 2013; Parra *et al.*, 2004; Buermann *et al.*, 2008; Saatchi *et al.*, 2008). Furthermore, all the models achieved AUC values of above >0.85. These results are consistent with those of Phillips and Dudík, (2008) and therefore indicate that the models were able to predict areas vulnerable to *L. camara* invasion.

In addition, the findings of this study have indicated that the elevation was the only environmental variable with the highest gain, when used as independent model dataset in modelling the distribution of *L. camara*. Our results are in line with those of Ndlovu *et al.* (2018) and Adeola. (2017) whose work demonstrated that elevation explained probability of occurrence ($p > 0.5$). According to Adeola. (2017) elevation is a variable that has an influence on the spatial distribution of plant species as well as soil properties amongst others. This is supported by the findings of Priyanka, (2013) who observed the superiority of elevation gradients in accordance with the expected species since *L. camara* flourishes well at lower altitudinal ranges and as it increases, the species occurrence tends to diminish.

Furthermore, Band 5 (vegetation red edge) derived from Sentinel-2 was depicted as another variable that is important in modelling invasive *L. camara*. According to Delegido *et al.* (2011) the inclusion of red edge bands is important for Sentinel-2 to enable the delivery of an accurate green canopy and chlorophyll. The red edge is important for the prediction of *L. camara* as the sensitivity of its presence to the red-edge bands is in line with the assertion that subtle vegetation changes and characteristics or variations are prominent in some portions of the electromagnetic spectrum (Zhu *et al.*, 2007). Hence, its attributes can be probabilistically determined in terms of the red-edge band reflectance. Vegetation red edge bands contribute to vegetation mapping and offer broader discrimination. The potential of vegetation red edge in vegetation mapping and prediction has been stressed by authors such as Dhau *et al.* (2017).

3.5 Conclusions

The findings of this work demonstrate that communal areas of Bushbuckridge are more likely to be infested by invasive *L. camara* when compared to the protected park area. Almost 10% of the communal area is more likely to be infested, whereas only 7% of the park is anticipated to be infested. Further, findings of this study revealed that the models performed exceptionally well with AUC scores >0.85. The model developed using all the variables yielded the highest predictive accuracies and had the highest performance. Further, the results demonstrated that elevation plays a critical role in the spatial distribution of *L. camara* when compared to other variables considered for this study. The findings of this study could assist in conservation planning and management of invasive species and also protected areas. Moreover, such information is vital for ecologists, land managers and policy-makers in the monitoring of areas that are vulnerable to the invasion of *L. camara* and where early response mechanisms could be put in place.

CHAPTER FOUR

Synthesis

4.1 Introduction

The main aim of this study was to explain the spread of *L. camara* and to assess the environmental factors influencing its spatial distribution in the semi-arid savanna rangelands of South Africa. This chapter therefore reviews the aims and objectives presented in chapter one, and it also highlights the major conclusions and future research recommendations.

4.2 Objectives reviewed

To review the advances and future prospects in monitoring *L. camara* in semi-arid savanna agroecosystems.

The study reviewed the advances and future prospects in monitoring *L. camara* in semi-arid savanna agroecosystems. Rangeland ecosystems are one of the largest ecosystems in world, they play a significant role in the global economy, in sustaining livelihoods and in combating global warming. The encroachment of *L. camara* into these ecosystems has had a devastating effect, which requires a reliable and operational monitoring framework. Traditional methods have in accurately detecting and mapping invasive species, such as *L. camara*, have proved to be limited. RS techniques have been presented as an alternative tool that is able to precisely detect and map the spatial distribution of *L. camara*. Various studies have successfully used the RS datasets, in conjunction with classification algorithms, to detect and map the spatial distribution of the weed. However, there is limited knowledge about the reasons behind the invasion of the weed in rangeland ecosystems. Previous studies such as Burke and Grime, (1996), Sharma *et al.* (2005), Funk and Vitousek, (2007) and Masocha *et al.* (2017) have investigated the effect of various biotic and abiotic factors on invasive species. The effects of these variables on invasive species could thus fully explain the dynamics of the ability of *L. camara* to intrude into new environments, which is an aspect that, to our knowledge, remains rudimentary in savanna rangelands.

To model localities vulnerable to *L. camara* infestation in semi-arid savanna ecosystems of Bushbuckridge communal lands and Kruger National Park, South Africa

This work aimed at identifying the most significant environmental variables influencing the distribution of *L. camara* in savanna ecosystems. The obtained results demonstrated that selected environmental variables play a significant role in the spatial distribution of *L. camara*. For instance, the mean annual rainfall (Bio12) and the calculated GNDVI yielded the highest gain, when used in isolation, and led to poor model performance, when omitted. However, elevation is the prime influencer of the spread of *L. camara*. Furthermore, the study appraised areas that are most vulnerable to the invasion of the weed, and it showed that the area between the communal lands of Bushbuckridge and the Kruger National Park (KNP), had the least *L. camara* infestation. The areas covered by *L. camara* within the KNP was estimated to be approximately 7% whereas 10% of Bushbuckridge is covered by the weed. The high infestation rates observed in the communal lands is believed to be caused by the various anthropogenic activities or land management practices in the area and they thus serve as a disturbance. Our study demonstrated that environmental variables as well as environmental disturbance play a significant role in the spatial distribution of *L. camara* in semi-arid savanna ecosystems. This study provides the basis for identifying areas in which the management and monitoring of invasions should be focused

4.3 Conclusions

The aim of the study was to model and explain the spatial distribution of *L. camara* in South African savanna ecosystems. Findings of the study highlighted that the derived topographic, bioclimatic and remotely sensed variables significantly influence the spatial distribution of *L. camara*. Based on these findings, the following conclusions are drawn:

- All models had better than random predictions where by the strength of model predictions varied with use of different variable. However, the model based on the composite of all variables yielded the highest AUC score.
- Vulnerability maps derived from Maxent revealed that *L. camara* infestation is predominant in the communal lands of Bushbuckridge than the protected area of Kruger National Park whereby the area covered by *L. camara* in the communal lands is 10% while in area covered *L. camara* in the protected area is 7%.

- Although other selected environmental variables play a significant role in the spatial distribution of *L. camara*, elevation is the major variable that influences the distribution of *L. camara*.
- The information derived from the results of this study form as a basis for identifying areas where control and management interventions of the weed should be focused.

4.4 Recommendations

The results obtained in this study provide an insight into the spatial distribution of *L. camara*, as well as the utility and potential of SDMs, and they provide useful information about the factors that influence the distribution of *L. camara* in vulnerable areas. There is a need to explore eco-hydrological impacts of invasive species on rangeland ecosystems. This study makes the following recommendations for future research:

- There is need to estimate the amount of water used by *L. camara* as well as the amount of water loss from this weed over time, especially along rivers or in water-scares countries like South Africa. This information will be useful for prioritizing the removal of the species in highly affected areas.
- There is need for long-term monitoring and the seasonal mapping of *L. camara* on a larger scale this is crucial for monitoring the rate of infestation taking place and the level of control strategies required.
- It is advised for future studies to strive to detect other pre-visual physiological indicators of vegetation, stress like chlorophyll and leaf area index, using RS.

References

Adam, E., Mureriwa, N. and Newete, S. 2017. Mapping Prosopis glandulosa (mesquite) in the semi-arid environment of South Africa using high-resolution WorldView-2 imagery and machine learning classifiers. *Journal of Arid Environments* 145: 43: 51.

Addabbo, P., Focareta, M., Marcuccio, S., Votto, C. and Ullo, S. L. 2016. Contribution of Sentinel-2 data for applications in vegetation monitoring. Acta IMEKO, 5(2).

Adeola, A.M. 2017. Modelling susceptibility to *Parthenium hysterophorus* invasion in KwaZuluNatal Province, South Africa using physical, climatic and remotely sensed derived variables. Unpublished MSc Thesis, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal. Pietermaritzburg, RSA.

Adhikari, D., Tiwary, R. and Barik, S. K. 2015. Modelling hotspots for invasive alien plants in India. *PloS one*, 10(7), e0134665.

Adjorlolo, C. 2008. Estimating Woody Vegetation Cover in an African Savanna using remote sensing and Geostatistics.

Allouche, O., Tsoar, A. and Kadmon, R. 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *Journal of applied ecology*, 43(6), 1223-1232.

Ayele, S. 2007. The Impact of Parthenium (*Parthenium Hysterophorus* L.) on the Range Ecosystem Dynamics of the Jijiga Rangeland, Ethiopia. Department of Animal Sciences, School of Graduate Studies, Haramaya University, pp. 134.

Bajwa, A.A., Chauhan, B.S., Farooq, M. et al. 2016. What do we really know about alien plant invasion? A review of the invasion mechanism of one of the world's worst weeds. *Springer Berlin Heidelberg* 244 (1), 39–57

Bannari A., Morin D., Bonn F. and Huete A. R. 1995 A review of vegetation indices. *Remote Sensing Reviews* 13:1-2, 95-120

Baret, F., and Guyot, G. 1991. Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment* 35(2-3), 161-173.

Bateman, B.L., Van Der Wal, L., and Johnson, C.N. 2012. Nice weather for bettongs: using weather events, not climate means, in species distribution models. *Ecography* 35: 306–314.

Beaumont, L.J., Hughes, L., and Pitman, A.J. 2008. Why is the choice of future climate scenarios for species distribution modelling important? *Ecology Letters* 11: 1135–1146.

Beck, P. S. A., Wang, T. J., Skidmore, A.K. and Liu X. H. 2008. Displaying remotely sensed vegetation dynamics along natural gradients for ecological studies. *International Journal of Remote Sensing* 29:14, 4277-4283

Belay, T. B., and Hailu, A.A. 2017. Assessment of the Invasive Alien Plant Species L. camara in Nile River Millennium Park, Bahir Dar, Ethiopia. *Global Journal of Science Frontier Research: C Biological Science,* 17(1), 18-26.

Bradley, B.A. 2014. Remote detection of invasive plants: a review of spectral, textural and phenological approaches. *Biological Invasions* 16:1411–1425

Buermann, W., Saatchi, S., Smith, T. B., Zutta, B. R., Chaves, J. A., Milá, B. and Graham, C. H. 2008. Predicting species distributions across the Amazonian and Andean regions using remote sensing data. *Journal of Biogeography* 35(7), 1160-1176.

Burke, MJW. and Grime, JP. 1996. An experimental study of plant community invasibility. *Ecology* 77:776-90

Campbell, J.B. and Wynne, R.H., 2011. Introduction to Remote Sensing. Guilford Press. Hyperion data. Proc. Int. Archiv. Photogram. *Remote Sensing. Spatial. Information. Science*. 37, 249–254.

Catford, JA., Vesk, P., Richardson, DM. and Pyšek, P. 2012. Quantifying levels of biological invasion: Towards the objective classification of invaded and invasible ecosystems. *Global Change Biology* 18: 44–62.

Chatanga, P. 2007. Impact of the invasive alien plant species, *L. camara* (L.) on native vegetation in northern Gonarezhou National Park, Zimbabwe. MSc thesis, University of Zimbabwe, Zimbabwe.

Chatterjee R. 2015. Impact of *L. camara* in the Indian society. *International Journal of Environment*. 4 (2): 2091-2854

Daehler, CC. 2003. Performance comparisons of co-occurring native and alien invasive plants: implications for conservation and restoration. *Annual Review of Ecology, Evolution, and Systematics* 34:183-211.

Davis, A. S., Dixon, P. M., and Liebman, M. 2003. Cropping system effects on giant foxtail (Setaria faberi) demography. II. Retrospective perturbation analysis. *Weed Science*, 51: 930–939.

Day, M. D., Wiley, C. J., Playford, J. and Zalucki, M. P. 2003. *Lantana*: Current Management Status and Future Prospects. *Australian Centre for International Agricultural Research Canberra*. 102:58 - 62

De Ca´ceres, M. and Wiser, S.K. 2012. Towards consistency in vegetation classification. *Journal of Vegetation Science* 23, 387–393.

Deering, D. 1975. *Measuring" forage production" of grazing units from Landsat MSS data*. Paper presented at the Proceedings of the Tenth International Symposium of Remote Sensing of the Envrionment.

DeFries, R.S., Asner, G.P. and Houghton, R., 2004. Trade-offs in land-use decisions: towards a framework for assessing multiple ecosystem responses to land-use change. *Ecosystem Land Use Change*, 2:1-9.

Delegido, J., Verrelst, J., Alonso, L.and Moreno, J. 2011. Evaluation of sentinel-2 red-edge bands for empirical estimation of green LAI and chlorophyll content. *Sensors* 11, 7063-7081.

Dhau, I. 2008. A Spatio-temporal Analysis of *L. camara* Across Contrasting Land Tenure Regimes in Zimbabwe.

Dhau, I., Adam, E., Mutanga, O., Ayisi, K., Abdel-Rahman, E. M., Odindi, J. and Masocha, M. 2017. Testing the capability of spectral resolution of the new multispectral sensors on detecting the severity of grey leaf spot disease in maize crop. *Geocarto International* 1-28.

Dlamini, W.M.D. 2010. Spatial analysis of invasive alien plant distribution patterns and processes using Bayesian network-based data mining techniques. Unpublished PhD Dissertation, University of South Africa, RSA.

Doak, D.F., Bigger, B., Harding, E.K., Marvier, M.A., O'Malley, R.E., and Thompson D. 1998. The statistical inevitability of stability ± diversity relationships in community ecology. Am. *Naturalist* 151, 264-276.

Dobhal, P.K., Kohli, R.K. and Batish, D.R. 2010. Evaluation of the impact of *L. camara* L. invasion, on four major woody shrubs, along Nayar river of Pauri Garhwal, in Uttarakhand Himalaya. *International Journal of Biodiversity and Conservation* 2(7), 155-161

Dobhal, PK, Kohli, RK. and Batish, DR. 2011. Impact of *L. camara* L. Invasion on riparian vegetation of Nayar region in Garhwal Himalayas (Uttarakhand, India). *Journal of Ecology and the Natural Environment* 3 (1), 11-22.

Dube, T. and O. Mutanga. 2015. Quantifying the variability and allocation patterns of aboveground carbon stocks across plantation forest types, structural attributes and age in sub-tropical coastal region of KwaZulu Natal, South Africa using remote sensing. *Journal of Applied Geography* 64: 55-65.

Dube, T., Mutanga O. and Ismail R. 2016. Quantifying aboveground biomass in African environments: A review of the trade-offs between sensor estimation accuracy and costs. *Tropical Ecology* 57(3):393-405

Dubula, B., Tesfamichael, S.G. and Rampedi I.T. 2016. Assessing the potential of remote sensing to discriminate invasive Asparagus laricinus from adjacent land cover types. *Cogent Geoscience* 2:11- 34

Dvorak, P., Mullerova, J., Bartalos, T., and Bruna, J. 2015. Unmanned aerial vehicles for alien plant species detection and monitoring. In the international archieves of the photogrammetry, *Remote sensing and spatial information sciences* 4,83-90

El-Kenany, E.T. and El-Darier, S.M., 2013. Suppression effects of *L. camara* L. aqueous extracts on germination efficiency of *Phalaris minor Retz*. and *Sorghum Bicolor* L. (Moench). *Journal of Taibah University for Science* 7, 64–71

Everitt, J. H., Anderson, G. L., Escobar, D. E., Davis, M. R., Spencer, N. R., and R. J. Andrascik, 1995, Use of Remote Sensing for Detecting and Mapping Leafy Spurge (Euphorbia esula). *Weed Technolog* 9(3):599–609.

Fernández, M. and Hamilton, H. 2015. Ecological niche transferability using invasive species as a case study. *PloS one* 10(3), e0119891.

Fernández, CG., Silva, B., Gawlik, J., Thies, B., Bendix, J., 2013. Bracken fern frond status classification in the Andes of southern Ecuador: combining multispectral satellite data and field spectroscopy. *International Journal of Remote Sensing* 34 (20), 7020–7037.

Fernando, G.M.T.S., Nalaka, K., Suraweera, P., and Kumari, B. 2016. Identification of Distribution of Lantana camera (Exotic Invasive Species) and its impacts on Udawalawa National Park, Sri Lanka. 214- 254.

Ficetola, G. F., Thuiller, W. and Miaud, C. 2007. Prediction and validation of the potential global distribution of a problematic alien invasive species—the American bullfrog. *Diversity and Distributions* 13(4), 476-485.

Foran, B., Smith, M. S., Burnside, D., Andrew, M., Blesing, D., Forrest, K. and Taylor, J. 2019. Australian rangeland futures: time now for systemic responses to interconnected challenges. *The Rangeland Journal* 41, 271–292.

Foxcroft, L.C., Rouget, M., Richardson, D.M. and Mac Fadyen, S. 2002. Reconstructing 50 years of Opuntia stricta invasion in the Kruger National Park, South Africa: environmental determinants and propagule pressure. *Diversity and Distributions* 10, 427–437

Funk, JL. and Vitousek, PM. 2007. Resource-use efficiency and plant invasion in low-resource systems. *Nature* 446:1079-81

Gallien, L., Douzet, R., Pratte, S., Zimmermann, N.E. and Thuiller, W. 2012. Invasive species distribution models – how violating the equilibrium assumption can create new insights. Global Ecology and Biogeography, *Global Ecol. Biogeogr* 21, 1126–1136.

Ghisalberti, E.L. 2000. *L. camara* L. (verbenecea). Fitoterapia. 71:467-48

Grice, A.C. 2006. The impacts of invasive plant species on the biodiversity of Australian rangelands. *The Rangeland Journal* 28:27–35.

Gil, A., Yu, Q., Lobo, A., Lourenço, P., Silva, L. and Calado, H., 2011. Assessing the effectiveness of high resolution satellite imagery for vegetation mapping in small islands protected areas. *J. Coast Res* 64, 1663–1667.

Gitelson, A. A., and Merzlyak, M. N. 1998. Remote sensing of chlorophyll concentration in higher plant leaves. *Advances in Space Research 22*(5), 689-692.

Goncalves, E., Herrera, I., Duarte, M., Bustamante, RO. and Lampo, M, 2014. Global Invasion of L. camara: Has the Climatic Niche Been Conserved across Continents? *PLoS ONE* 9(10): e111468.

Gooden, B., French, K. O. and Turner, P. 2009. Invasion and management of a woody plant, L. camara L., alters vegetation diversity within wet sclerophyll forest in southeastern Australia. *Forest Ecology & Management* 257 (3), 960-967.

Govere, J., Durrheim, D.N., Du Toit, N., Hunt, R.H. and Coetzee, M. 2000. Local plants as repellents against Anopheles arabiensis, in Mpumalanga Province, South Africa. 46:213-216.

Grice, A.C. 2006. The impacts of invasive plant species on the biodiversity of Australian rangelands. *The Rangeland Journal* 28, 27–35

Guisan, A and Thuiller, W. 2005. Predicting species distribution: Offering more that simple habitat models. *Ecology letters* 8: 993-1009

Hara, Y., Atkins, R.G., Yueh, S.H., Shin, R.T. and Kong, J. A. 1994. Application of Neural Networks to Radar Image Classification. *IEEE transactions on Geoscience and Remote Sensing* 32(1).

Henderson, L. 2001. Alien weeds and invasive plants. Plant Protection Research Institute Handbook, No. 12. Agricultural Research Council, Pretoria, p 300

Hernandez, P. A., Graham, C. H., Master, L. L. and Albert D. L. 2006. The effect of sample size and species characteristics on performance of different species distribution modelling methods. E*cography* 29: 773-785.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. and Jarvis, A. 2005. Very high resolution interpolated climate surfaces for global land areas. *International journal of climatology* 25(15), 1965-1978.

Hiremath, A.J. and Sundaram, B. 2005. The Fire-Lantana Cycle Hypothesis in Indian Forests. *Conservation and Society* 3: 26 – 42.

Hobbs, RJ, Huenneke, LF. 1992. Disturbance, diversity, and invasion: Implications for conservations. *Conservation Biology* 6(3): 324-337

Huang C and Gregory P. A. 2009. Applications of Remote Sensing to Alien Invasive Plant Studies. *Sensors* 9, 4869-4889.

Jarnevich, C. S. and Reynolds, L. V. 2011. Challenges of predicting the potential distribution of a slow-spreading invader: a habitat suitability map for an invasive riparian tree. *Biological Invasions* 13**,** 153-163.

Joshi, C., Leeuw, JD., Van Duren IC. and 2004. Remote sensing and GIS applications for mapping and spatial modelling of invasive species. *Proc. ISPRS, Istanbul* 23: 669-677.

Kandwal, R., Jeganathan, C., Tolpekin, V., and Kushwaha, S.P.S. 2009. Discriminating the Invasive Species, '*Lantana*' using Vegetation Indices. *J. Indian Soc. Remote Sens* 37:275–290.

Kellerman, T.S., T.W. Naude and N. Fourie. 1996. The distribution, diagnoses and estimated economic impact of plant poisonings and mycotoxicoses in South Africa. *Onderstepoort Journal of Veterinary Research* 63: 65-90.

Khan, M., Mahamood, A. and Alkhathlan, H.Z. 2015. Characterization of leaves and flowers volatile constituents of *L. camara* growing in central region of Saudi Arabia. *Arabian journal of chemistry* 22: 231-238.

Kimothi, M. M., and Dasari, A. 2010. Methodology to map the spread of an invasive plant (*L. camara*.) in forest ecosystems using Indian remote sensing satellite data, *International Journal of Remote Sensing* 31: (12) 3273-3289.

Kimothi, M. M., D. Anitha, H. B. Vasistha, P. Soni and S. K. Chandola. 2010. Remote sensing to map the invasive weed, *L. camara* in forests. *Tropical Ecology* 51: 67–74.

Kneitel, J.M. and Perrault, D. 2006. Disturbance-induced changes in community composition increase species invasion success. *Community Ecol* 7(2), 245–252.

Kohli, R. K, Batish, D. R, Singh, H. P and Dogra, K.S. 2006. Status, invasiveness and environmental threats of three tropical American invasive weeds (*Parthenium hysterophorus* L., *Ageratum conyzoides* L., *L. camara* L.) in India. *Biological Invasions* 8:1501–1510

Kozak, K. H., Graham, C. H. and Wiens, J. J. 2008. Integrating GIS-based environmental data into evolutionary biology. *Trends in Ecology & Evolution*, 23(3), 141-148.

Kumar, A. and Min, H., 2008. Some issues related with sub-pixel classification using Hyperion data. Proc. Int. Archiv. *Photogram. Remote Sens. Spat. Inf. Sci* 37, 249–254.

Kumar, S., Stohlgren, T.J. and Chong, G.W. 2006. Effects of spatial heterogeneity on native and non-native plant species richness. *Ecology* 87, 3186–3199.

Kumara, J., Millsa, R.T., Hoffmana, F. M. and Hargrove, W.W. 2011. Parallel k-Means Clustering for Quantitative Ecoregion Delineation Using Large Data Sets. *Procedia Computer Science* 4:1602–1611.

Kumbula, S.T., Mafongoya, P., Peerbhay, K.Y., Lottering, R.T. and Ismail, R. 2019. Using Sentinel-2 Multispectral Images to Map the Occurrence of the Cossid Moth (Coryphodema tristis) in Eucalyptus Nitens Plantations of Mpumalanga, South Africa. *Remote Sensing*, 11, 278

Lambert, J., Hicks, H., Childs, D. and Freckleton, R. 2017. Evaluating the potential of Unmanned Aerial Systems for mapping weeds at field scales: a case study with Alopecurus myosuroides. *Weed Research* 58, 35–45

Lass, L.W., Prather, T.S., Glenn, N.F., Weber, K.T., Mundt, J.T. and Pettingill, J. 2005. A review of remote sensing of invasive weeds and example of the early detection of spotted knapweed (Centaurea maculosa) and babysbreath (Gypsophila paniculata) with a hyperspectral sensor. *Weed Sci* 53 (2), 242–251

Le Maitrea, D.C., van Wilgena, B.W., Gelderbloma, C.M., Baileyb, C., Chapmana, R.A. and Nela, J.A. 2002. Invasive alien trees and water resources in South Africa: case studies of the costs and benefits of management. *Forest Ecology and Management* 160, 143–159

Lin, S. 2007. The distribution and role of an invasive plant species, *L. camara*, in disturbed roadside habitats in Moorea, French Polynesia.

Lu, D. and Weng, Q. 2007. A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote. Sensing* 28 (5), 823–870.

Lyons, K.G and Schwartz, M.W. 2001. Rare species loss alters ecosystem function- invasion resistance. *Ecology Letters* 4: 358-365.

Mack, R.N., and Smith, M.C., 2011. Invasive plants as catalysts for the spread of human parasites. *Neo Biota* 9: 13–29.

Mack, R.N., Simberloff, D., Londsdale, W.M., Evans, H., Clout, M. and Bazzaz, F.A. 2000. Biotic invasions: causes, epidemiology, global consequences, and control. *Ecological Applications* 10,689–710

Martin, B.W. and Foxcroft, L.C. 2002. First atlas of maps for invasive alien species within the Kruger National Park as in 2001. SANParks Report No.01/02, Alien Biota Section, Scientific Services Section, Skukuza, Kruger National Park

Martins, F., Alegria, C. and Gil, A. 2016. Mapping invasive alien Acacia dealbata Link using ASTER multispectral imagery: a case study in central-eastern of Portugal. *Forest Systems* 25:(3) 2171-9845

Masocha, M., Dube, T., Skidmore, A., Holmgren, M. and Prins, H. 2017 Assessing effect of rainfall on rate of alien shrub expansion in a southern African savanna. *African Journal of Range & Forage Science* 34:1, 39-44

Masters, R. A. and Sheley, R. 2001, Invited Synthesis Paper: Principles and practices for managing rangeland invasive plants. USDA-ARS / UNL Faculty. 1079.

Matongera, T.N., Mutanga, O., Dube T., Sibanda, M. 2017. Detection and mapping the spatial distribution of bracken fern weeds using the Landsat 8 OLI new generation sensor. *International Journal of Applied Earth Observation and Geoinformation* 57: 93–103

Matongera, TN., Mutanga, O., Dube, T., and Lottering, R.T. 2016. Detection and mapping of bracken fern weeds using multispectral remotely sensed data: a review of progress and challenges. *Geocarto International* 1–16.

Matsoukis, A. S. and Chronopoulou-Sereli, A. G. 2003. An investigation of the effects of environmental factors on *L. camara* L. subsp. camara responses to paclobutrazol and mepiquat chloride. *Journal of Horticultural Science & Biotechnology* 78 (3) 381-385.

McConnachie, AJ., Strathie, LW., Mersie, W., Gebrehiwot, L., Zewdie, K., Abdurehim, A., et al., (2011). Current and potential geographical distribution of the invasive plant Parthenium hysterophorus (Asteraceae) in eastern and southern Africa. *Weed Res* 51:71–84.

Merow, C., Bois, S. T., Allen, J. M., Xie, Y. and Silander, J. A. 2017. Climate change both facilitates and inhibits invasive plant ranges in New England. *Proceedings of the National Academy of Sciences* 114, 3276-3284

Mróz, M., and Sobieraj, A. 2004. Comparison of several vegetation indices calculated on the basis of a seasonal SPOT XS time series, and their suitability for land cover and agricultural crop identification. *Technical Sciences 7* (7), 39-66.

Mukwevho, L., Olckers, T., and Simelane, D.O. 2018. Occurrence of different *L. camara* varieties across four South African provinces and their susceptibility to a biotype of the gall-forming mite Aceria *lantanae*. *Biocontrol Science and Technology* 28:4, 377-387

Mullerova, J., Pergl, J. and Pysek, P. 2013. Remote sensing as a tool for monitoring plant invasions: testing the effects of data resolution and image classification approach on the detection of a model plant species Heracleum mantegazzianum (giant hogweed). *International Journal of Applied Earth Observation and Geo-information* 25: 55–65

Mutanga, O., Prins, H.H.T., Skidmore, A.K., Huizing, H., Grant, R., Peel, M.J.S., Biggs, H. and Van Wieren, S. 2004. Explaining Grass-Nutrient Patterns in a Savanna Rangeland of Southern Africa. *Journal of Biogeography* 31: 819–829.

Naidoo, L., Cho, M., Mathieu, R. and Asner, G. 2012. Classification of savanna tree species, in the Greater Kruger National Park region, by integrating hyperspectral and LiDAR data in a Random Forest data mining environment. ISPRS J. *Photogrammetry Remote Sens* 69, 167–179.

Nath, S.S., Mishra, G., Kar, J., Chakraborty, S. and Dey, N. 2014. A survey of image classification methods and techniques. Year: Published in: *Control, Instrumentation*, *Communication and Computational Technologies (ICCICCT), 2014 International Conference on. IEEE,* pp. 554–557

Ndlovu, P., Mutanga, O., Sibanda, M., Odindi, J., and Rushworth, I. 2018. Modelling potential distribution of bramble (rubus cuneifolius) using topographic, bioclimatic and remotely sensed data in the KwaZulu-Natal Drakensberg, South Africa. *Applied Geography* 99, 54-62

Nishii, K., Nagata, T., Wang, C.N. and Möller, M. 2012. Light as environmental regulator for germination and macrocotyledon development in Streptocarpus rexii (Gesneriaceae). *South African Journal of Botany* 81: 50–60.

Odindi, J., Adam, E., Ngubane, Z., Mutanga, O. and Slotow, R. 2014. Comparison between WorldView-2 and SPOT-5 images in mapping the bracken fern using the random forest algorithm. *Journal of Applied Remote Sensing* 8: pp. 083527

Othman, R., Latiff, N. H. M., Tukiman, I. and Hashim, K. S. H.Y. 2015. Effects of altitude and microclimate on the distribution ferns in and urban areas. *Jurnal Teknologi* 77: 125-131.

Oumar, Z. 2016. Assessing the Utility of the SPOT 6 Sensor in Detecting and Mapping L. camara for a Community Clearing Project in KwaZulu-Natal, South Africa. *South African Journal of Geomatics* 5(2): 214–226.

Parra, J. L., Graham, C. C. and D Freile, J. F. 2004. Evaluating alternative data sets for ecological niche models of birds in the Andes. *Ecography* 27(3), 350-360.

Parviainen, M., Zimmermann, N. E., Heikkinen, R. K. and Luoto, M. 2013. Using unclassified continuous remote sensing data to improve distribution models of red-listed plant species. *Biodiversity and conservation* 22(8), 1731-1754.

Pearson, R. G., Dawson, T. P. and Liu, C. 2004. Modelling species distributions in Britain: a hierarchical integration of climate and land-cover data. *Ecography* 27(3), 285-298.

Peerbhay, K., Mutanga, O., Lottering, R., Bangamwabo, V. and Ismail, R. 2016. Detecting bugweed (Solanum mauritianum) abundance in plantation forestry using multisource remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing* 121:167–176

Phillips, S. J. & Dudík, M. 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. E*cography*, 31(2), 161-175.

Phillips, S. J., Anderson, R. P. and Schapire, R. E. 2006. Maximum entropy modeling of species geographic distributions. *Ecological modelling* 190(3), 231-259.

Pimentel, D. 2007. Environmental and economic costs of vertebrate species invasions into the United States. Pages 2–8 in G.W. Witmer, W.C. Pitt, and K. A. Fager stone, editors. Managing vertebrate invasive species: proceedings of an international symposium. U.S. Department of Agriculture, Animal and Plant Health Inspection Service, Wildlife Services, National Wildlife Research Center, Fort Collins, Colorado, USA.

Prasad, A and Purohit, S. 2013. Field Study for the bioefficacy and economics of herbal- *L. camara* (L.) and fungal Beauveria bassiana (Balsamo), biopesticides against Helicoverpa armigera (Hubner) in south Rajasthan (India). *International Journal of Scientific & Engineering Research* 4(6): 1 157–61.

Priyanka, N. and Joshi, P. K. 2013. Modeling Spatial Dstribution of L. camara – A Comparative Study. *Canadian Journal of Basic and Applied Science*. 01:100-117.

Priyanka, N. and Joshi, P.K. 2013. A review of L. camara studies in India International *Journal of Scientific and Research Publications*. 3:2250-3153.

Qin, Z., Zhang, J.E., Ditommaso, A., Wang, R.L. and Liang, K.M. 2016. Predicting the potential distribution of *L. camara*. under rcp scenarios using ISI-MIP models. *Clim. Chang* 134, 193–208

Raghua, S., Osunkoyab, O.O., Perrettb, C. and Pichancourt, J. 2014. Historical demography of *L. camara* L. reveals clues about the influence of land use and weather in the management of this widespread invasive species. *Basic and Applied Ecology* 15: 565–572.

Ramaswami, G and Sukumar, R. 2014. *L. camara* L. (Verbenaceae) invasion along streams in a heterogeneous landscape. *J. Biosci* 39:717–726

Ramírez-Albores, JE, Bustamante, RO, Badano, EI. 2016. Improved Predictions of the Geographic Distribution of Invasive Plants Using Climatic Niche Models. *PLoS ONE journal.pone* 11(5).

Richardson, D., Wikson, J.R., Weyl, O.L.F. and Griffiths. C.L. 2011. South Africa: Invasions. In: Simberloff, D. and Rejmánek, M. (eds). *Encyclopaedia of Biological Invasions*. University of California Press, Berkeley and Los Angeles.

Richardson, D.M. and Rejma´nek, M. 2011. Trees and shrubs as invasive alien species – a global review. *Diversity and Distributions* 17, 788–809

Rima, P., Ng Wai-Tim., Einzmann, K., Immitzer, M., Atzberger, C., and Eckert S. Assessing the Potential of Sentinel-2 and Pléiades Data for the Detection of Prosopis and Vachellia spp. in Kenya. *remote sensing* 9(1): 47

Rocchini, D., Andreo, V., Förster, M., Garzon-Lopez, C. X., Gutierrez, A. P., Gillespie, T. W., Hauffe, H. C., He, K. S., Kleinschmit, B. and Mairota, P. 2015. Potential of remote sensing to predict species invasions: A modelling perspective. *Progress in Physical Geography* 39(3), 283-309.

Rodgers, J.C. III and Parker, K.C. 2003. Distribution of alien plant species in relation to human disturbance on the Georgia Sea Islands. *Diversity and Distributions* 9, 385–398

Rouget, M., Richardson, D.M., Nel, J.L., Le Maitre, D.C., Egoh, B. and Mgidi, T. 2004. Mapping the potential ranges of major plant invaders in South Africa, Lesotho and Swaziland using climatic suitability. *Bioiversity and Distributions*, (*Diversity Distrib*.) 10, 475–484.

Rouse, Jr., J. W., Haas, R. H., Schell, J. A. and Deering, D. W. 1973. Monitoring vegetation systems in the Great Plains with ERTS. In S. C. Freden, E. P. Mercanti, & M. Becker (Eds.), Third Earth Resources Technology Satellite-1 Symposium. Technical presentations, section A, l, 309 – 317.

Royimani, L., Mutanga, O., Odindi, J., Dube, T. and Matongera, T.N. 2019. Advancements in satellite remote sensing for mapping and monitoring of alien invasive plant species (AIPs). *Physics and Chemistry of the Earth* 112, 237–245

Saatchi, S., Buermann, W., Ter Steege, H., Mori, S. and Smith, T. B. 2008. Modeling distribution of Amazonian tree species and diversity using remote sensing measurements. *Remote Sensing of Environment* 112(5), 2000-2017.

Sahu, P. K. and Singh, J. S. 2008. Structural attributes of lantana-invaded forest plots in Achanakmar–Amarkantak Biosphere Reserve, Central India. *Current Science Association* 94, (4). 494-500.

Shackleton, R.T., Witt, A.B.R., Aool, W and Pratt, C.F 2017. Distribution of the invasive alien weed, *L. camara*, and its ecological and livelihood impacts in eastern Africa, *African Journal of Range & Forage Science* 34: (1), 1-11.

Shackleton, S., Saskia, A., McHardy, T. and Shackleton, C. 2002. Use of marula products for domestic and commercial purposes: Synthesis of key findings from three sites in Southern Africa. Project No. ZF0140/R7795. 6-18.

Sharma, G.P., Raghubansh, A.S. 2007. Effect of *L. camara* cover on local depletion of tree population in the Vindhyan tropical dry deciduous forest of India. *Applied Ecology and Environmental Research* 5(1): 109-121

Sharma, G.P., Raghubanshi, A.S. and Singh, J.S., 2005. *Lantana* invasion: An overview. *Weed Biology and Management* 5: 157–165.

Sharma, O.P., Sharma, S., Pattabhi, V., Mahato, S.B. and Sharma, P.D. 2007. A Review of the Hepatotoxic Plant *L. camara*. *Critical Reviews in Toxicology* 37:4, 313-352,

Shoko, C., Mutanga, O. and Dube, T. 2016. Progress in the remote sensing of C3 and C4 grass species aboveground biomass over time and space. *ISPRS Journal of Photogrammetry and Remote Sensing* 120: 13–24

Sibanda, M., Mutanga, O. and Rouget, M. 2015. Examining the potential of Sentinel-2 MSI spectral resolution in quantifying above ground biomass across different fertilizer treatments. *ISPRS Journal of Photogrammetry and Remote Sensing*, 110, 55-65.

Strand, H., R. Höft, J. Strittholt, L. Miles, N. Horning, E. Fosnight, and W. Turner, editors. 2007. Sourcebook on remote sensing and biodiversity indicators. CBD Technical Series 32. Secretariat of the Convention on Biological Diversity, Montreal, Canada. [online] URL: http://www.cbd.int/doc/ publications/cbd-ts-32.pdf.

Tamado, T., Ohlander, L., and Milberg, P. 2002. Interference by the weed Parthenium hysterophorus L. with grain sorghum: influence of weed density and duration of competition. *International Journal of Pest Manage* 48:183–188

Taylor, S, and Kumar, L. 2014. Impacts of climate change on invasive L. camara L. distribution in South Africa. *African Journal of Environmental science and technology* 8(6), 391-400

Taylor, S., Kumar, L. and Reid, N. 2011. Accuracy comparison of Quickbird, Landsat TM and SPOT 5 imagery for *L. camara* mapping. *Journal of Spatial Science* 56: (2), 2, 241–252.

Taylor, S., Kumar, L., Reid, N. and. Lewis, C.R.G. 2012. Optimal band selection from hyperspectral data for L. camara discrimination. *International Journal of Remote Sensing* 33: 5418–5437.

Taylor, S., Kumar, L., Reid, N., Kriticos, D. J. 2012. Climate Change and the Potential Distribution of an Invasive Shrub, *L. camara* L. *PLoS ONE* 4: 101-137.

Thamaga K.H. and Dube T. 2018. Remote sensing of invasive water hyacinth (Eichhornia crassipes): A review on applications and challenges. *Remote Sensing Applications: Society and Environment* 10, 36–46

Thamaga, K.H. and Dube, T. 2018. Testing two methods for mapping water hyacinth (*Eichhornia crassipes*) in the Greater Letaba river system, South Africa: discrimination and mapping potential of the polar-orbiting Sentinel-2 MSI and Landsat 8 OLI sensors, *International Journal of Remote Sensing* 39:22, 8041-8059.

Tilman, D., Lehman, C.L and Bristow, C.E. 1998. Diversity±stability relationships: statistical inevitabilit or ecological con-sequence.Am. *Naturalist* 151, 277

Tollman, S. M. 2009. Agincourt health and socio-demographic surveillance system South Africa. School of Public Health University of the Witwatersrand MRC/WITS rural public health and health transitions research unit (Agincourt).1-2

Underwood, E., Ustin, S., DiPietro, D. 2003. Mapping nonnative plants using hyperspectral imagery. *Remote Sensing of Environment* 86 (2):150-161

Underwood, E.C., Ustin, S.L. and Ramirez, C.M. 2007. A Comparison of Spatial and Spectral Image Resolution for Mapping Invasive Plants in Coastal California. *Environ Manage* 39:63–83

Urban, A.J., Simelane, D.O., Retief, E., Heystek, F., Williams, H.E and Madire, L.G. 2011. The invasive '*L. camara* L.' hybrid complex (Verbenaceae): a review of research into its identity and biological control in South Africa. *African Entomology* 19(2): 315–348.

Ustin, S.L., DiPietro, D., Olmstead, K., Underwood, E., and Scheer, G.J. 2014. Hyperspectral Remote Sensing for Invasive Species Detection and Mapping. *ACS National Meeting Book of Abstracts* · DOI: 10.1109/IGARSS.2002.1026212 · Source: IEEE Xplore

Van Wilgen, B.W., Forsyth, G.G., Le Maitre, D.C., Wannenburgh, A., Kotzé, I., van den Berg, L. and Henderson, L. 2012. An Assessment of the Effectiveness of a Large, National-scale Invasive Alien Plant Control Strategy in South Africa. *Biological Conservation*, 148:28

Vardien, W., Richardson, D.M., Foxcroft, L.C., Thompson, G.D., Wilson, J.R.U and Le Roux, J.J. 2012. Invasion dynamics of *L. camara* L. (sensu lato) in South Africa. *South African Journal of Botany* 81: 81–94.

Wakie, T., Evangelista, P., Jarnevich, C. and Laituri, M. 2014. Mapping current and potential distribution of non-native Prosopis juliflora in the Afar region of Ethiopia. *PloS One* 9(11e112854)

Wang, A., Goslee S C., Miller D A., Sanderson M A. and Gonet J M. 2017. Topographic variables improve climaticmodels of forage species abundance in the northeastern United States. *Applied Vegetation Science* 20:84–93

West, A M., Kumar, S., Brown, C S., Thomas, J., Bromberg S.J. 2016. Field validation of an invasive species Maxent model. Ecological Informatics 36, 126–134.

Wisz, M. S., Hijmans, R.J., Li, J., Peterson, A. T., Graham, C. H. and Guisan, A. 2008. Effects of sample size on the performance of species distribution models. *Diversity and Distributions*, (*Diversity Distrib*.) 14, 763–773

Wortman, S. E., A. S. Davis, B. J. Schutte, J. L. Lindquist, J. Cardina, J. Felix, C. L. Sprague, J. A. Dille, A. H. M. Ramirez, G. Reicks, and S. A. Clay. 2012. Local conditions, not regional gradients, drive demographic variation of giant ragweed (Ambrosia trifida) and common sunflower (Helianthus annuus) across northern U.S. maize belt. Weed Science 60: 440–450.

Xie, Y., Sha, Z. and Yu, M., 2008. Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology*, 1(1):9-23.

Xue, J. and Su, B. 2017. Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of Sensors* 1–17, 1353691. https://doi.org/10.1155/2017/1353691

Zhang, J. and Foody, G.M. 1998. A fuzzy classification of sub-urban land cover from remotely sensed imagery. *International Journal of Remote Sensing* 19:2721-2738.

Zhu, Li., Osbert, J. Sun., Weiguo, Sang., Zhenyu, Li. and Keping, M. 2007. Predicting the spatial distribution of an invasive plant species (*Eupatorium adenophorum*) in China. Landscape *Ecology* 22:1143–1154