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

by

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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,

3. I have not used work previously produced by another student or any other person to hand in as my own,

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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.


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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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 of 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 km²) 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.
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.


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.

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 hectares (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 WorldView-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

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

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 neural 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 et al., 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:

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](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

<table>
<thead>
<tr>
<th>Band no</th>
<th>Band name</th>
<th>Band width (µm)</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Blue</td>
<td>0.490</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>Green</td>
<td>0.560</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>Red</td>
<td>0.665</td>
<td>10</td>
</tr>
<tr>
<td>5</td>
<td>Vegetation red edge</td>
<td>0.705</td>
<td>20</td>
</tr>
<tr>
<td>6</td>
<td>Vegetation red edge</td>
<td>0.740</td>
<td>20</td>
</tr>
<tr>
<td>7</td>
<td>Vegetation red edge</td>
<td>0.783</td>
<td>20</td>
</tr>
<tr>
<td>8</td>
<td>Near infrared (NIR)</td>
<td>0.842</td>
<td>20</td>
</tr>
<tr>
<td>8a</td>
<td>Vegetation red edge</td>
<td>0.865</td>
<td>10</td>
</tr>
<tr>
<td>11</td>
<td>Shortwave infrared (SWIR)</td>
<td>1.610</td>
<td>20</td>
</tr>
<tr>
<td>12</td>
<td>Shortwave infrared (SWIR)</td>
<td>2.190</td>
<td>20</td>
</tr>
</tbody>
</table>
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 \textit{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 \textit{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 \textit{et al}., 1996).

Table 3.2: Selected vegetation indices used in this study

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

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 \textit{et al}.,
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)

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Name</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Temperature variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bio01</td>
<td>mean annual temperature</td>
<td>°C</td>
</tr>
<tr>
<td>Bio02</td>
<td>mean diurnal range in temperature</td>
<td>°C</td>
</tr>
<tr>
<td>Bio03</td>
<td>Isothermality (bio 02/bio 07) X100</td>
<td>°C</td>
</tr>
<tr>
<td>Bio04</td>
<td>temperature seasonality</td>
<td>°C</td>
</tr>
<tr>
<td>Bio05</td>
<td>maximum temperature warmest month</td>
<td>°C</td>
</tr>
<tr>
<td>Bio06</td>
<td>minimum temperature coolest month</td>
<td>°C</td>
</tr>
<tr>
<td>Bio07</td>
<td>annual temperature range</td>
<td>°C</td>
</tr>
<tr>
<td>Bio10</td>
<td>mean temperature warmest quarter</td>
<td>°C</td>
</tr>
<tr>
<td>Bio11</td>
<td>mean temperature coolest quarter</td>
<td>°C</td>
</tr>
<tr>
<td><strong>Moisture variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bio12</td>
<td>mean annual rainfall</td>
<td>mm</td>
</tr>
<tr>
<td>Bio13</td>
<td>rainfall wettest month</td>
<td>mm</td>
</tr>
<tr>
<td>Bio14</td>
<td>rainfall driest month</td>
<td>mm</td>
</tr>
<tr>
<td>Bio15</td>
<td>rainfall seasonality (coefficient of variation)</td>
<td>mm</td>
</tr>
<tr>
<td>Bio16</td>
<td>rainfall wettest quarter</td>
<td>mm</td>
</tr>
<tr>
<td>Bio17</td>
<td>rainfall driest quarter</td>
<td>mm</td>
</tr>
</tbody>
</table>

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

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

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

<table>
<thead>
<tr>
<th>MODEL SCENARIOS</th>
<th>AUC</th>
<th>TSS</th>
<th>KAPPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODEL 1</td>
<td>0.924</td>
<td>0.667</td>
<td>0.338</td>
</tr>
<tr>
<td>MODEL 2</td>
<td>0.906</td>
<td>0.621</td>
<td>0.328</td>
</tr>
<tr>
<td>MODEL 3</td>
<td>0.925</td>
<td>0.751</td>
<td>0.397</td>
</tr>
<tr>
<td>MODEL 4</td>
<td>0.854</td>
<td>0.549</td>
<td>0.295</td>
</tr>
<tr>
<td>MODEL 5</td>
<td>0.952</td>
<td>0.773</td>
<td>0.401</td>
</tr>
<tr>
<td>MODEL 6</td>
<td>0.928</td>
<td>0.698</td>
<td>0.367</td>
</tr>
<tr>
<td>MODEL 7</td>
<td>0.955</td>
<td>0.765</td>
<td>0.387</td>
</tr>
</tbody>
</table>

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.
3.3.2 Spatial distribution of \textit{L. camara}

Figure 3.2. shows the predicted potential habitats suitable for \textit{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 \textit{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 Dudik, (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 the 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.
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