UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

MODELLING THE SPATIAL DISTRIBUTION OF *LANTANA CAMARA* IN THE INKOMATI CATCHMENT IN MPUMALANGA, SOUTH AFRICA

By

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A research report submitted to the to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science.

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12 June 2023 in Johannesburg

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Abstract

Lantana Camara is a highly problematic invasive species, extensively studied for its spatial distribution. The present study was conducted to investigate *Lantana Camara*'s spatial patterns across the topographic variations within the Inkomati catchment, located in Mpumalanga, South Africa, using the Random Forest and Maxent algorithms with Sentinel-2 data within Google Earth. *Lantana Camara* covered 34.86% of the study area, with a user's accuracy of 91% and producer's accuracy of 84%. Elevation strongly influenced the species' spatial distribution, while the Topographic Wetness Index had minimal impact. MaxEnt vulnerability maps revealed higher vulnerability to *Lantana Camara* in the central western part of the study area than the eastern part. The model using topographic variables achieved the highest accuracy (AUC = 0.88), surpassing the predictive model with Sentinel-2 bands (AUC = 0.81). The study suggests that the Sentinel-2 Red Edge and NIR bands, combined with Random Forest, offer accurate insights into *Lantana Camara* distribution, aiding in identifying regions vulnerable to its invasion.

Keywords: *Lantana Camara*; MaxEnt; satellite data; species distribution; topographic variable

Dedication

I dedicate my work to God Almighty, my creator, continuous supporter, and source of comprehension, awareness, and knowledge. Christ has been my source of strength throughout the whole program, and I can only soar on His wings.

My dissertation is also dedicated to my most ardent supporters, who are no longer with us on this planet, but I know they are watching over me and cheering me on. To my grandma (Nomathemba Mtyobile), who loved me unconditionally and taught me the value of hard work, and to my aunt (Nombuyiselo Mtyobile), who supported me financially and emotionally throughout my life. Finally, I am thankful to my father (Denis Moyo) for bringing me into this world and for safeguarding me.

Acknowledgements

"For I know the plans I have for you," affirms the Lord, "plans to prosper you and not to harm you, plans to give you hope and a future." (Jeremiah chapter 29:11, NIV)

I would like to express my sincere appreciation to the University of the Witwatersrand for providing me with the opportunity to pursue my education. I am particularly grateful to the Department of Geography and the School of Geographical, Archaeological, and Environmental Science for their support. This research would not have been possible without their assistance. I would also like to extend my gratitude to the Gauteng City Region Academy for financing my degree.

The data utilized for modeling in the research project was collected by Dr. Cletah Shoko, my supervisor. The data collection coincided with the period when the Sentinel-2 imagery was obtained. I am deeply indebted to my supervisor for her unwavering support throughout my research. Her exceptional professional expertise, dedication, encouragement, and patience in supervising my work have been remarkable. It has been a pleasure to work with her.

Lastly, I would like to thank my family for their unending love and prayers, especially my mother, Nontobeko Mtyobila, Xoliswa Mtyobile, and Simangele Mtyobile. I am grateful to have you in my life, and I pray that the good Lord blesses you abundantly.

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List of Abbreviations

AUC – Area Under Curve

DEM – Digital Elevation Model

GIS– Geographic Information Systems

GPS – Global Positioning System

IAPs – Invasive Alien Plant Species

IWMA – Inkomati Water Management Area

MaxEnt – Maximum Entropy

RF – Random Forest

RS – Remote Sensing

SDM – Species Distribution Model

TPI – Topographic Position Index

TSS – True Skills Statistic

CHAPTER ONE: GENERAL INTRODUCTION

1.1. Background

Invasive Alien Species (IAPs) are weeds relocated from their natural environment to a new one (Rai and Singh, 2020). When established, IAPs have the capability to swiftly spread across large areas (Ricciardi and Cohen, 2007). Biological conservationists, ecologists, and managers of natural resources are now interested in invasive species because of their fast expansion, risk to biodiversity, and harm to ecosystems. In grasslands, invasions may change the nutrient cycle, hydrology, and carbon sequestration processes (Pimentel *et al.,* 2005; Polley *et al.,*1997). IAPs are homogenizing the globe's fauna and flora (Mooney and Hobbs, 2000), and they are recognized as a major contributor to the loss of biodiversity worldwide (Wilcove and Chen, 1998).

IAPs are a worldwide problem, and they cause severe economic losses with annual costs in the billions of dollars (Goncalves *et al.,* 2014; Pimentel *et al.,* 2005). For instance, Australia on its own loses roughly 2.2 million USD each year (Cusack *et al.,* 2009) whereas the United States loses an estimated 120 billion USD per year (Ayele, 2007). The economic costs associated with livestock poisoning by *Lantana Camara* in South Africa are projected to be R 1 728 900 each year (Heystek, 2006). Plant invasions pose a distinct challenge to biodiversity, which is already threatened by environmental damage induced by human population expansion (Pejchar and Mooney 2009).

Knowledge on temporal and spatial distribution, together with abundance, is needed to reduce the spread of IAPs (Peerbhay *et al.,* 2016a). Historically, aerial images and field surveys have been employed to obtain information about IAPs (Zuberi *et al.,* 2014; Crossman and Kochergen, 2002). However, several studies have emphasized that such techniques are not sustainable since they are costly, time consuming, and labour-intensive, particularly for large-scale applications (Shariq and Hughes, 2020). Conversely, satellite remote sensing has grown in recognition as a feasible substitute in IAPs mapping (Aitkenhead and Aalders, 2011; Gómez-Casero *et al.,* 2010). Contrasting to conventional methods, remotely sensed data and methods from satellites may be used across vast and remote geographic areas (Dorigo *et al.,* 2012).

Similar to this, the frequent coverage provided by satellite remote sensing methods enables the identification of plant phenology, that is required to detect the spread of IAPs (Zuberi *et al.,* 2014; Flood, 2013).

Various studies have investigated methods to enhance the mapping and detection of IAPs (Peerbhay *et al.,* 2016c; Lass *et al.,* 2005). Huang and Asner (2009) detected IAPs based on functional and structural properties at different canopy levels, and offered an outline of spectral, temporal as well as spatial sensor resolutions. The study makes use of a cutting-edge image fusion technique recently released. It combines passive and active energies that were simultaneously collected by a (LiDAR) system, which is a scanning-wavefront light detection and ranging system, and an imaging spectrometer. This method detects the structural and functional features of IAPs at various canopy heights. Bradley (2014) examined the importance of spectral, structural, and phenological properties in detecting IAPs, while Peerbhay *et al.* (2016c) investigated the use of remotely sensed data for the best detection of structural and functional characteristics of IAPs in commercial forests.

1.2. Problem statement

Lantana Camara is an invasive species that alters ecosystems by changing water and nutrient cycling, resulting in unfavourable conditions for indigenous species (Bouda *et al.,* 2001; Ghayal and Dhumal 2011). It can also harm livelihoods by intruding on agricultural land and reducing access or mobility, leading to income losses and increased vulnerability (Wang *et al.,* 2017). This noxious plant species threatens the ecosystem, resulting in the loss of biodiversity and displacement of species richness in forest fragments. To implement effective management methods, accurate information on the spatial distribution of the species is required (Bhagwat *et al.,* 2012). Traditional approaches, such as field surveys, are time-consuming, labour-intensive, and expensive. Therefore, there is a need for more efficient methods to detect and map *Lantana Camara* (Taylor *et al.,* 2011; Wakie *et al.,* 2014; Thamaga and Dube,2018).

Remote sensing technology is being used more and more to monitor the invasive *Lantana Camara* (Dube *et al.*, 2016: Dube and Mutanga, 2015). Using a variety of satellite datasets, the species has been successfully mapped and modelled. For instance, Dhau (2008) utilized information from Aster and Landsat TM to map and track the *Lantana Camara* invasion throughout three various land tenure systems in Zimbabwe. However, there are limitations to detecting small and isolated patches with intermediate spatial resolution sensors like the Landsat (8 OLI and 7 ETM) and SPOT-5 (Zhang and Foody, 1998). It may be possible to map *Lantana Camara* with greater accuracy thanks to Sentinel-2's distinctive spatial, spectral, and temporal features (Addabbo *et al.*, 2016).

Spatial Distribution Models (SDMs) are useful techniques for identifying areas vulnerable to invasive alien plant (IAP) invasion. SDMs correlate a species' distribution with environmental factors using modern Geographical Information Systems (GIS), RS, and predictive algorithms (Martins *et al.,* 2016). Previous studies have successfully employed SDMs to identify and detect locations sensitive to *Lantana Camara* invasion (Ramrez-Albores *et al.,* 2016; Adhikari *et al.,* 2015; Zhu *et al.,* 2007). For instance, Zhu *et al.,* (2007) employed SDMs to effectively identify and predict locations sensitive to *Lantana Camara* invasion. However, the most important environmental determinants contributing to *Lantana Camara* invasion have not been thoroughly investigated in the savanna ecosystems in South Africa.

1.3. Study aim

To explore *Lantana Camara* spatial patterns across the topographical variations of the Inkomati catchment, in Mpumalanga, South Africa,

1.4. Study objectives

- To map the recent *Lantana Camara* spatial distribution in the Inkomati catchment.
- To establish key topographic variables and their influence on the *Lantana Camara* spatial distribution and invasion.
- To model areas vulnerable to the invasion of *Lantana Camara* in the Inkomati catchment.

1.5. Key research questions

- What is the recent spatial distribution of *Lantana Camara* in Inkomati catchment?
- Which areas across the topographical gradient of the catchment are most exposed to theinvasion of *Lantana Camara*?

1.6. Structure of the report

CHAPTER ONE: General introduction. This chapter covers the background to the study, the gap in knowledge, study aim, specific objectives, research questions and the structure of the report.

CHAPTER TWO: Review of literature. This chapter includes the background to the literature review, an overview of *Lantana Camara* invasive species, the invasion of *Lantana Camara* in South Africa, remote sensing, and approaches to the spatial monitoring of *Lantana Camara* and other IAPs, the integration of environmental variables in monitoring invasive species and species distribution models in monitoring invasive species and conclusion.

CHAPTER THREE: Methodological approach. This chapter encompasses the description of the study area, *Lantana Camara* land use and land cover field data collection, image acquisition and pre-processing of Sentinel-2 satellite imagery, topographic data used to model the spatial distribution of *Lantana Camara*, image classification for the spatial distribution of *Lantana Camara*, modelling the spatial distribution of *Lantana Camara* and evaluation of MaxEnt's accuracy in modelling the spatial distribution of *Lantana Camara*.

CHAPTER FOUR: Results. This chapter presents the study findings, the recent spatial distribution of *Lantana Camara* and other land cover types, random forest and variable importance, random forest accuracy assessment results, influence of topographical variables in *Lantana Camara* spatial distribution, the recent and future spatial distribution of *Lantana*

Camara and other land cover types and MaxEnt's accuracy in modelling the spatial distribution of *Lantana Camara*.

CHAPTER FIVE: Discussion. This chapter comprises of the findings in mapping the recent spatial distribution of *Lantana Camara* in the Inkomati catchment, establishing key topographic variables and their influence on the spatial distribution of *Lantana Camara*, and lastly, modelling the future spatial distribution of *Lantana Camara* in the Inkomati catchment. Finally, conclusion and recommendations.

CHAPTER TWO: REVIEW OF LITERATURE

2.1. Introduction

One of the greatest environmental challenges of today is the invasion of natural habitats by infamous IAPs. Biological invasions are normally a natural procedure, but human intervention has sped up the process. *Lantana Camara* contributes a large amount to ecosystem change on rangelands worldwide. With the use of RS methods, *Lantana Camara* has been discovered, mapped, and monitored in rangeland habitats. First, knowledge on the effects of *Lantana Camara* on rangelands is presented, followed by an analysis of various features supplied by RS data for *Lantana Camara* mapping. A summary of prior methodologies used to map *Lantana Camara* is also offered, as well as their limitations. The influence of topographic variables on species distribution is addressed, and lastly, recommendations for future directions are provided. The geographical coverage of the published studies is not restricted to South African research but extends all the way across the world.

2.2. An overview of *Lantana Camara* invasive species

Lantana Camara, a member of the Verbenaceae family, is an herbaceous plant or shrub with over 150 species (Baars *et al.,* 1999). It is commonly found in open areas with little or no shade and has replaced much of the native flora in agricultural areas, meadows, wastelands, beaches, marshes, and forests that are recovering from fires or deforestation (Dvorak, *et al.,* 2015). *Lantana Camara* is an evergreen bushy species that can attain heights of up to two meters with the aid of neighbouring flora. Figure 1 shows *Lantana Camara* during the summer season in Mpumalanga, South Africa. (Sharma, *et al.,* 2005). *Lantana Camara* prefers tropical and subtropical climates and is well-suited to locations in South and Central America. In contrast, locations with moderate climates, such as the Southern Mediterranean, Northern New Zealand and Europe are less suitable for the species (Goncalves *et al.,* 2014).

Figure 1: Image showing the characteristics of Lantana Camara

According to Day *et al.* (2003), *Lantana Camara* is capable of significantly altering fire regimes in natural settings. Research conducted bythe School for Field Studies (SFS) at the Centre for Rainforest Studies in North Queensland, Australia, has revealed that *Lantana Camara* has the potential to exacerbate the risk of fires in dry rainforests by modifying fuel loads (Berry *et al.*, 2011). Although *Lantana Camara* is less likely to ignite than native rainforest species, it creates a continuous layer of ladder fuels, potentially allowing fire to reach the forest canopy. As a result, authors recommend purposeful removal of this species in fire-prone environments to reduce fuel loads (Humphries and Stanton 1992; Berry *et al.*, 2011).

Surprisingly, the range of the *Lantana Camara* species varies according to abiotic and biotic factors (Richardson and Pysek, 2012). These changes have diverse effects on plant species because they restrict, disrupt, or create favourable environments for certain plant species (Guisan and Thuiller, 2005). The spatial distribution of invasive alien plants is influenced by environmental factors such as topography and climate (Guisan and Thuiller, 2005).

In addition to the quantity and quality of soil nutrients and light, an area's physical characteristics, such as its slope, aspect, and elevation, can have a significant impact on the microclimate (Wang *et al.*, 2017). Precipitation and temperature are also important factors in determining the establishment and distribution of IAPs (Zhu *et al.*, 2007). Pearson *et al.* (2004) found that the connection between *Lantana Camara* and its habitat can result in differences in its distribution across various landscape scales. Therefore, to understand the potential niche and

IAPs' spatial distribution like *Lantana Camara*, it is fundamental to identify the environmental variables that limit or facilitate their growth. Unfortunately, this information is often missing for most species (Negi *et al.*, 2019). Therefore, using topographic variables to understand the prevalence and spatial distribution of *Lantana Camara* can improve the management of this species, specifically in semi-arid savanna habitats.

Prior research has shown that invasive species such as *Lantana Camara* can enhance their invasion by altering ecosystems such as water and nutrient cycling, among other things, producing unfavourable circumstances for native species (Osunkoya and Perrett, 2011; Kohli *et al.,* 2006). Moreover, by invading fertile land and decreasing access or movement, species such as *Lantana Camara* may impair livelihoods and increase vulnerability (Guisan and Thuiller, 2005). The presence of *Lantana Camara*, a poisonous plant species, can have negative impacts on rural communities by reducing natural resources and damaging rangelands, leading to income losses and increased vulnerability (Wang *et al.,* 2017; Kruse *et al.,* 2000). The plant is highly resilient, able to withstand adverse environmental conditions such as flooding, extreme heat, and droughts, and poses a threat to both local and international ecology by causing loss of biodiversity and displacement of species in forest fragments. Ongoing discussions about foreign IAPs have reignited debates over the methods necessary to manage and reduce the spread of *Lantana Camara* (Shackleton *et al.*, 2017; Priyanka, 2013; Taylor and Kumar 2013; Bhagwat *et al.,* 2012).

Lantana Camara is native to tropical areas of Central and South America, but it has been widely used as an ornamental plant in various regions of the world, including South Africa (Priyanka and Joshi, 2013). Despite originally being found only in Mexico to Brazil, the planthas now spread to over 60 countries globally, leading to significant economic losses in some of those nations (Ghisalberti, 2000). In the 17th century, *Lantana Camara* was introduced to Europe from Brazil and subsequently spread to other parts of the world, including Africa, America, Oceania, and Asia (Binggeli, 2003). Although only a few African countries (Angola,Gabon, Tanzania, and Zambia) were predicted to have suitable climatic conditions for *Lantana Camara* in 2070, sections of South Africa are already severely impacted by the species (Vardien *et al.*, 2011).

2.3. The Invasion of *Lantana Camara* in South Africa

Lantana Camara first appeared in South Africa in 1858, when four species were found in the Cape Town Botanical Gardens, but their origin was unknown (Simelane *et al.*, 2021). The plant was introduced as an ornamental in KwaZulu Natal from Mauritius in 1883 and later from Europe in 1885, but there are no further records of its importation to South Africa (Eckert *et al.*, 2020; Morton, 1994). However, the current variety of cultivars suggests that there may have been additional unreported imports or significant genetic diversity in the original introduction (Vardien and Richardson, 2012; Cilliers and Neser, 1991). The plant quickly spread throughout the country as an ornamental, aided by frugivorous birds that dispersed its seeds. By 1946, *Lantana Camara* was recognized as a harmful plant in agricultural ecosystems requiring management in KwaZulu-Natal (Simelane *et al.*, 2021; Morton, 1994).

Lantana Camara has become naturalized in most sections of South Africa, excluding the driest and severely frozen regions (Taylor *et al.*, 2012; Cilliers and Neser, 1991). *Lantana Camara* highest-density populations are found in the eastern sections of the country, particularly in the Eastern Cape, Mpumalanga, and KwaZulu-Natal provinces where it invades temperate and moist subtropical environments (Wessels, 2006). *Lantana Camara* belongs to a set of Invasive Alien Plants (IAPs), which are classified into nine different groups based on their distribution patterns and the environmental factors that contribute to them. Some of the other species in this group include *Acacia mearnsii De Wild., Acacia melanoxylon R. Br., Ricinus communis L., and Solanum mauritianum Scop.,* which share similar distribution patterns across South Africa (Richardson *et al.,* 2004). Although it is occasionally grown as an ornamental plant in gardens, it is primarily found in riparian zones and near residential gardens (Henderson, 2001, Henderson, 2007). The plant has not become naturalized in the Northern Cape and Free State provinces, and populations in the Western Cape are less numerous and dense than in the warmer and wetter provinces, such as Mpumalanga and KwaZulu Natal (Meek *et al.,* 2010; Alston and Richardson, 2006).

Despite its prevalence in an extensive range of landscape and flora types, the occurrence of *Lantana Camara* in South Africa is a cause for concern (Richardson *et al.,* 2007). This invasive species is found in seven of the country's nine terrestrial biomes and is not limited to any biome border (Richardson *et al.,* 2004). It is commonly found in the Savanna and Indian Ocean Coastal Belt biomes and has invaded two-thirds of South Africa's ecoregions. *Lantana Camara*'s ability to thrive across diverse ecological communities highlights its broad ecological tolerance. *Lantana Camara* prefers disturbed environments such as roadsides, degraded ground, pastures, bushveld, and riparian areas (Meek *et al.*, 2010; Richardson *et al.,* 2004; Baars and Neser, 1999; Van Wyk and Van Wyk, 1997).

2.4. Remote Sensing of *Lantana Camara* and other IAPs

The traditional techniques of visual interpretation and field surveys have been commonly used for mapping invasive IAPs. However, these methods have been criticized for their negative impacts on the ecosystem and their impracticality for global implementations (Niphadkar 2016). These methods are time-consuming, expensive, demanding in terms of fieldwork, and require massive amounts of additional data. Moreover, these traditional methods have been found to be inadequate for detecting and mapping the spatial distribution of IAPs, especially on a regional scale (Dube *et al.,* 2016).

In recent years, remote sensing has emerged as a viable alternative for mapping invasive alien plant species (IAPs) worldwide. A variety of satellite sensors have been used to collect data on IAPs over the past few decades, as shown in Table 1. Remote sensing technology has been recognized as a critical tool for mapping the distribution of IAPs due to its ability to provide high-quality spatial and temporal data that can be used at different spatial scales (Brewer *et al.*, 2022). It is also faster and more efficient compared to traditional methods, as noted in Carreiras *et al.* (2012). Remote sensing and GIS technologies can present data inputs that can predict areas vulnerable to the different IAPs invasions, and they can offer potentially valuable tools to detect, map, and monitor IAPs, as noted in Martins *et al.* (2016). Various types of remote sensing data, including multispectral and hyperspectral satellites, unmanned aerial vehicles or airborne data (Iqbal *et al.*, 2023; Niphadkar 2016; Taylor *et al.*, 2012), and aerial images (Tharushi *et al.*, 2018; Oumar, 2016; Sundaram *et al.*, 2012), have been used to detect invasive species, as reported in Joshi *et al.* (2004).

Table 1: A list of satellite remote sensing sensors often used to monitor Lantana Camara and other IAPs in South Africa.

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

Remote sensing is a useful tool in studying various ecosystems, including complex terrains, due to its benefits such as multispectral data, cost-effectiveness, multi-temporal coverage, and synoptic views (Ozesmi and Bauer, 2002). It provides different sensor systems, such as satellite imaging, ground-based spectrometer measurements, and aerial images. These sensors improve the collection of information on various targets of the surface of the earth, such as land cover, land usage, as well as environmental risks associated with IAPs (Thamaga and Dube, 2018; Matongera *et al.,* 2016). The usage of remote sensing in studying IAPs, including *Lantana Camara and Bug weed*, has grown in recent years, with some successful studies demonstrating moderate spatial and spectral resolution sensors' effectiveness in acquiring data with a spatial resolution of 10-100m in fewer than 20 bands (Priyanka *et al.*, 2019; Negi *et al.*, 2019; Kandwal *et al.*, 2009). Data sources such as ASTER (Advanced Space-borne Thematic Emission and Reflection Radiometer), SPOT (Satellite Pour l'Observation de la Terre), and Landsat ETM+ (Enhanced Thematic Mapper Plus) or LTM (Landsat Thematic Mapper) have been utilized by researchers (Raphela and duffy, 2023; Huang and Gregory, 2009).

The employment of images with high spatial resolution is a simple and direct remote sensing technique for mapping and monitoring IAPs, as it allows for the identification of IAPs based on their unique spatial arrangements (Beck *et al.,* 2008). Peerbhay *et al.* (2016) utilized this technique in South Africa to detect *Bug weed* in KwaZulu-Natal's plantation woods by combining WorldView-2 with LiDAR and an AISA Eagle aerial hyperspectral dataset. The ensamble of LiDAR and AISA resulted in a classification accuracy of 78 %, while LiDARand WorldView-2 achieved 74 %. On the other hand, WorldView-2, AISA, and LiDAR achieved classification accuracies of 63 %, 68 %, and 64 %, respectively.

Similarly, in the mapping of the invasive *Prosopis Glandulosa* in semi-arid South African habitats, Adam *et al.* (2017) successfully identified the species using high-resolution WorldView-2 images at a 2-meter resolution. The images allowed for discrimination of the *Prosopis Glandulosa* among coexisting native acacia species, with an overall classification accuracy of 86 %. In another study, Evritt *et al.* (2018) monitored *Eurasian Euphorbia Asula and Asian Tamarix Chinensis* using aerial images obtained during their flowering seasons in the United States. The study found that infected areas had a higher visible-wavelength (400-700 nm) reflectance due to the brightly coloured inflorescences. Similar findings are expected when mapping *Lantana Camara* using the same procedure due to its brightly coloured inflorescences.

Oumar (2016) employed SPOT 6 as well as vegetation indicators like Normalized Difference Vegetation Indices and Simple Ratio to map *Lantana Camara* in Kwazulu-Natal rangelands. The ensamble of SPOT 6 standard bands and the two vegetation indices allowed for the classification of *Lantana Camara*, resulting in an overall accuracy of 75 %. However, according to Huang and Gregory (2009), the use of moderate spatial and spectral resolution imagery for mapping and monitoring IAPs in the presence of native flora has not been widely utilized, making detection difficult. They propose that such data might be valuable in discovering big patches of IAPs that are time dependent. For example, Joshi *et al.* (2004) attempted to map *Lantana Camara* at the species level using 30 m Landsat TM and SPOT data with a spatial resolution of 20 m, but the results were insufficient.

Recent improvements in remote sensing technology have brought about new imaging options, such as Worldview, RapidEye, and Sentinel, among others. These advanced images offer enhanced spatial and spectral resolutions, making them highly useful for mapping land use and land cover (Odindi *et al.*, 2014). For example, Sibanda *et al.* (2016) explained that, Sentinel-2 is a multispectral dataset with a high spatial resolution and a temporal resolution of six days, which can be adjusted to optimize image acquisition angles, making it a vital data source for large-scale mapping, especially in resource-constrained areas. Sentinel-2's spectral properties make it suitable for accurately mapping invasive species, as demonstrated by Rima *et al.* (2017), who used the sensor in ensamble with Pleiades to detect invasive alien plant species in Kenya. The study found that Sentinel-2 identified more invasive species than the Pleiades sensor. Despite its effectiveness in detecting and mapping invasive species, there has been limited research on the use of Sentinel-2 to identify and map *Lantana Camara* (Rajah *et al.*, 2019).

High spatial resolution datasets, for example aerial images and unmanned aerial vehicles (UAVs), have the potential to provide detailed information on the distribution as well as extent of invasive species (Alvarez-Taboada *et al.*, 2017). However, these datasets also have several limitations that can hinder their effectiveness in mapping invasive species. For example, high spatial resolution datasets may be limited by their ability to capture only a small area at a time, which can make it difficult to map invasive species across large areas (Kattenborn *et al.*, 2020). Additionally, these datasets may not provide information on the invasive species spectral signatures, making it difficult to recognise them from other types of vegetation. Finally, high spatial resolution datasets may also be affected by factors such as cloud cover, atmospheric conditions, and topography, which can further limit their accuracy in mapping invasive species. Overall, while high spatial resolution datasets, such as aerial images and unmanned aerial vehicles (UAVs), can be useful in mapping invasive species, they must be used in conjunction with other types of data and careful analysis to ensure their effectiveness (Lu and He, 2017).

Moreover, sensors with pixel size bigger than Sentinel-2, such as those on Landsat or MODIS, may have limitations in mapping *Lantana Camara* (Ngadze *et al.*, 2020). This is because *Lantana Camara* is a small shrub that can grow in patches within larger areas of vegetation, and the larger pixel sizes of these sensors may not be able to capture these small-scale variations. This can result in misclassification or underestimation of the extent of *Lantana Camara* invasions (Rajah *et al.*, 2019). In addition, these sensors may not be able to distinguish *Lantana Camara* from other types of vegetation with similar spectral characteristics, making it difficult to accurately map its distribution. Furthermore, these sensors typically have lower spatial resolution, which can limit the level of detail that can be captured in the imagery. Overall, while sensors with larger pixel sizes may be useful for mapping larger-scale vegetation patterns, they may not be as effective in mapping the distribution of small-scale invasive species like *Lantana Camara* (Muthoka *et al.*, 2021).

Approaches to remote sensing characterization of invasion over time and space. Although remote sensing is presently one of the frequently used mapping techniques, most vegetation has a similar spectral signature, distinguishing among various plants may be difficult. However, the addition of various classification algorithms improves the capability to recognise different plant types (IAPs included) and other land cover classifications (Xie *et al.,* 2008). In most cases, images are classified using either supervised or unsupervised classification methods (Strand *et al.,* 2007; Lass *et al.,* 2005). Image classification methods are classified based on a variety of factors, including sensor data and the type of the training dataset (Royimani *et al.,* 2019; Nath *et al.,* 2014). Minimum and distance Maximum Likelihood (ML) classifiers are examples of supervised classification. The Maximum Likelihood approach is a common supervised classification algorithm used to analyse satellite images based on statistical distribution patterns (Thamaga and Dube, 2018; Hara *et al.*, 1994). The classifier is trained using known instances, and the necessary statistics or parameters for each class are determined. Yet, because human input is necessary to designate training regions for diverse terrains and extract their properties, automatic operation of supervised classifiers becomes difficult (Hara *et al.*, 1994).

Unsupervised classification techniques, such as the Migrating Means clustering approach (also known as ISODATA) and Random Forest (RF), are commonly used for categorizing landscapes based on information extracted from measured data (Abdullah *et al.*, 2019). ISODATA has traditionally been the most prevalent unsupervised classification method for analysing images obtained by infrared or optical sensors, and it has been widely employed in conjunction with supervised classification methods to reduce the workload of image analysts (Gil *et al.,* 2011). Unlike supervised classifiers, unsupervised classifiers do not require predefined training areas to function and use algorithms to group measured feature vectors into distinct clusters, which are then assigned as new classes. This makes them well-suited for various applications, especially those that require real-time processing (De Caceres and Wiser, 2012).

According to Kobylin *et al.* (2020) the two types of classifiers that are used in classification methods are parametric and non-parametric. Maximum Likelihood (ML), Spectral Angle Mapper (SAM), and Minimum Distance to Mean (MDM) are a few examples of parametric classifiers that are frequently used to reduce redundancy in remotely sensed data and are advised for species discrimination in IAP (Lu and Weng, 2007). Although these algorithms are widely used and have produced good results, they still have some drawbacks, such as poor performance, especially in mixed terrain, and the presumption that the data used to train the model in the classification process accurately represents the feature or surface (Campbell and Wynne, 2011). The output of parametric classifiers is provided at the pixel level, which decreases classification accuracy (Kumar and Min, 2008).

Non-parametric classifiers, such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), can be used to identify single pixels as endmembers as well as mixtures of unpolluted materials and recover biophysical characteristics in various plants (Kale *et al.*, 2017). Masocha *et al.* (2014) successfully mapped the distribution of *Lantana Camara* with an acceptable accuracy of 83 % using SVM and NN classifiers in conjunction with a GIS expert system that included topography and habitat location data. Fernando and other people. (2008) achieved 92 % accuracy when determining the spatial distribution of *Lantana Camara* by combining the Normalized Difference Vegetation Index (NDVI) and supervised maximum likelihood classification. In a research project by Samarajeewa *et al.* (2018) Convolutional Neural Networks (CNN) were used on aerial images to detect the spread of *Lantana Camara*, with 967 flower species classified achieving an accuracy of 52 % and *Lantana Camara* achieving an accuracy of 94.6 %. These studies show that it is possible to predict the spread of *Lantana Camara* with high accuracy by combining non-parametric classifiers with environmental and remote sensing data.

2.5. The integration of environmental variables in monitoring invasive species

Environmental variables can influence plant species in several ways, either by restricting or enhancing their growth or by providing resources (Sharma *et al.,* 2005). These variables include elevation, light intensity, soil pH, slope, rainfall, relative humidity, soil temperature, Topographic Wetness Index, and Topographic Position Index. Research shows that rainfall can affect the spread of *Lantana Camara* in Southern Africa, as the plant spreads more quickly during wet seasons (Masocha *et al.,* 2017). In poor-resource habitats, IAPs tend to outperform native species, but this is not always the case. *Lantana Camara* has a low mortality rate in low soil moisture, poor soil nutrients, and strong light, making moister areas more vulnerable to invasion than drier ones (Funk and Vitousek, 2007).

The impact of disturbance, topography, and environmental gradients on the spatial distribution of IAPs has not received as much attention as it should. However, earlier research by McConnachie *et al.* (2011) as well as Tamado *et al.* (2002), have observed that elevation significantly affects the distribution of IAPs like *Lantana Camara*. Othman and others. (2015) noted that topsoil characteristics and microclimate vary regionally depending on elevation. In order to model the distribution of *Lantana Camara* in the Indian Himalayas, Priyanka (2013) used ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) imagery to extract topographic variables such as elevation, slope, aspect, and terrain ruggedness from a DEM (Digital Elevation Model). These observations were supported by Priyanka's (2013) research, which revealed that *Lantana Camara* thrives at lower elevations, which results in a decline in other species and an increase in *Lantana Camara* invasions. In South Africa, Ndlovu *et al.* (2018) have also noted comparable patterns and mapped the potential occurrence and spread of Rubus Cuneifolius using remotely sensed data along with top- climatic data. In their study, Ndlovu *et al.* (2018) modelled the distribution of *Lantana Camara* in Kruger National Park, South Africa, using topographic variables such as elevation, slope, and aspect that were extracted from Landsat 8 imagery, including the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI). The study found that elevation was a key indicator of the distribution of the species. Finally, the research by Adeola (2017) used both Landsat 8 and Sentinel-2A imagery to extract vegetation indices and topographic variables, including elevation, slope, aspect, and terrain roughness, to predict the occurrence of *Lantana Camara* in a region of Nigeria. They discovered that topographic factors like elevation play a crucial role in the spread and distribution of *Lantana Camara*.

Various factors have been identified as significant contributors to the spread and proliferation of invasive species, including bodies of water, natural disturbances, severe weather events, and human activities like land use (Ramaswami and Sukumar, 2014; Foxcroft and Richardson, 2003). The occurrence of unutilized resources in both time and space, like fresh water and nutrients, is believed to create an environment conducive to biological invasions, which can be induced by anthropogenic disruptions or environmental unpredictability. Fluctuations in resource availability, especially in cases where resources are heterogeneous in time or space, have been observed to encourage invasion (Catford *et al.,* 2012). Ecological heterogeneity, particularly on a larger scale, is a determining factor in the number of invasive species present in an ecosystem. Topographic variables such as periodic disturbances impact the spatiotemporal distribution of resources, making some habitats more vulnerable to invasion. Riparian environments, where invasive species often outnumber adjacent areas, are especially vulnerable to *Lantana Camara* invasion due to various processes like loss of existing vegetation and sedimentation caused by flooding. According to Kumar *et al.* (2006), invasive species richness is correlated with the number of landscape borders.

Huiyu *et al.* (2020) investigated the influence of global climatic suitability and regional environmental variables on the distribution of *Spartina alterniflora* using species distribution models (SDMs). Using the MaxEnt approach, they created a combined regional environmental niche (CREN) model by combining the global climate niche (GCN) model with the regional environmental niche (REN) model. The CREN model outperformed the GCN model in terms of AUC, TSS, specificity, and sensitivity, as well as reduced overfitting. When the overall impacts are taken into account, the anticipated appropriate area decreases from 66.90 % to 18.53 %. Elevation and global climatic suitability were shown to have substantial interactions and to be the most influential factors in the global sensitivity analysis. The likelihood of presence rose with global climatic suitability and soil salinity while decreasing with elevation, soil organic carbon, and sand percentage. Well-drained soil had the highest probability of presence, while poorly drained soil had the lowest.

2.6. Species Distribution Models in monitoring invasive species

Species distribution models (SDMs) are statistical and machine learning tools utilized for predicting the spatial distribution of a species using environmental variables (Naimi *et al.,* 2014). SDMs determine the factors that limit a species' distribution and use this information to estimate the likelihood of the species' occurrence. SDMs are useful for mapping the potential distribution of invasive species and identifying areas where the environmental conditions are conducive to their growth and survival (Ryo *et al.,* 2021). This information may be used to predict the spread of invasive species and prioritize management efforts. SDMs can also identify areas where invasive species are unlikely to survive, useful for identifying potential refugia or areas where native species may persist in the face of invasive species encroachment (Duan *et al.,* 2014). Overall, SDMs are an effective tool for mapping invasive species, predicting their potential distribution under current and future environmental conditions, and guiding management efforts to prevent further spread of these harmful species (Naimi *et al.*, 2011).

The choice of environmental predictor variables affects the correlative models' (SDMs') ability to accurately and realistically predict plant species distributions variables (Jamevich *et al.*, 2017; Mod *et al.*, 2016). The importance of selecting Eco physiologically significant variables, such as water, temperature, soil nutrients, disturbances, biotic interactions, and light has been highlighted in earlier research (Kemppinen *et al.*, 2019; Mainali *et al.*, 2015; Fischer *et al.*, 2013). However, the list of predictors used in published plant SDM studies varies considerably, and there is no thorough review of useful and accessible predictors used in practice. Therefore, explicit consideration of all pertinent eco-physiological variables is essential for capturing significant species' environmental needs (Mod *et al.*, 2016). Additionally, experts have been looking for a way to detect the geographic distribution of ecological entities like populations, ecosystems, and species. SDMs are one well-liked technique that makes use of geo-located observations of occurrence and environmental factors that support a species' survival and expansion (Singh *et al.*, 2020). Based on response functions that describe the environmental factors connected to an organism's ecological niche and are derived from statistics or theory, this relationship is established (Guisan and Thuiller, 2005). SDMs can detect the probability of occurrence in areas where information on species distribution was previously unavailable using GIS (Williams *et al.*, 2009).

A variety of ecological issues can now be addressed by SDMs thanks to modern developments in statistical and geospatial modelling techniques and increased species data availability (Mainali *et al.*, 2015; Strubbe and Matthysen, 2009). Managing rare and endangered species is one of them, as is detecting how species will react to climate change and human habitat destruction, as well as spotting the geographic distribution of biological invasions (Ryo *et al.*, 2021). SDMs are being used more frequently to detect invasion outbreaks, prioritize locations for early detection, and prevent the establishment of non-native species as a result of globalization and significant changes in land use (Naimi *et al.*, 2014; Lippitt *et al.*, 2008).

Since the ecological assumptions underlying SDMs do not apply to invasive species distribution models (iSDMs), they face unique challenges (Vaclavik and Meentenmeyer, 2009). The primary difficulty is that invasive species are out of balance with their environment, and their potential dispersion restrictions are frequently underestimated (Wisz *et al.*, 2013). Many SDMs assume that species occur wherever favourable environmental conditions exist, and that dispersion is not a limiting factor (Zurell, 2017). Invasive species, on the other hand, may be missing from some regions owing to stochastic events, geographical boundaries, or dispersion limits, rather than poor habitat quality (Araujo and Pearson, 2005). More than biotic interactions or abiotic variables, dispersal limitations play a crucial role in invasion spread; nevertheless, few research have investigated the benefits of adding dispersal limits in iSDMs (Elith *et al.*, 2011; Soberon and Peterson, 2005).

The lack of absence data is the second challenge in developing and evaluating iSDMs, and it is often considered unavailable or ignored due to difficulty interpreting absences in suitable habitats (Jimenez-Valverde *et al.,* 2008). To address this challenge, a diversity of presence-only profile methods have been introduced and tested for a variety of native taxa, but they can predict potential rather than actual distribution of invasion (Chefaoui and Lobo, 2008). The absence component is crucial in evaluating distribution predictions, and generating pseudo-absence data can introduce errors (Lutolf *et al.,* 2006). To overcome this, approaches for utilizing heuristically calculated pseudo-absences outside of the organism's ecological domain have been developed (Engler *et al.*, 2004). When dispersal parameters are available and the purpose is to anticipate an invader's actual spread, incorporating information on absence at favourable places might be valuable. Nevertheless, without absence data, the assessment of distribution forecasts is constrained (Vaclavik, 2011).

Finally, the pseudo-absence approach has a limitation in that it relies on using pseudo-absence data for both model calibration and evaluation. This approach assesses the fit of the model to the training data rather than the actual predictive ability of the model (Chefaoui and Lobo, 2008). There hasn't been much research done to put the assumptions of employing presence-only and pseudo-absence data in iSDMs with true-absence data to the test. This data is required to increase knowledge of SDMs for biological invasions (Zaniewski *et al.,* 2002). Authors argue that testing the assumptions of employing presence-only and pseudo-absence data with comprehensive true-absence data is necessary to increase knowledge of SDMs for biological invasions (Amiri *et al.*, 2022; Senay *et al.*, 2013; Engler *et al.,* 2004). Locations where a species is known to be missing are referred to as true-absence data. Researchers can enhance the accuracy of their SDMs and boost their confidence in their prediction capacity by including true-absence data into model calibration and assessment (Vaclavik, 2011).

Correlative species distribution modelling (CSDM) is a widely used approach in ecology and biogeography, encompassing various names such as habitat suitability, (bio) climatic envelope modelling and ecological niche (Mouquet *et al.,* 2015; Araujo and Guisan 2006). CSDM has gained popularity over the years and is now among the most favoured tools for studying the impact of various threats to biodiversity and supporting conservation decisions (Franklin 2009). Despite the fact that there are several case studies on species distributions for conservation and risk assessment, there are ongoing discussions on technical and theoretical matters, such as modelling techniques, spatial autocorrelation handling, model selection and evaluation, and most significantly, variable selection (Elith and Leathwick 2009; Guisan *et al.,* 2006). Whilst SDMs predict species distributions by statistically linking environmental variables to species presence-only (presence/absence) data, the appropriate selection of environmental variables is crucial (Guisan and Zimmermann 2000). Williams *et al.* (2009) used a suite of SDMs, including GLMs (Generalised Liner Models), random forests, artificial neural networks, and MaxEnt, to determine populations of scarce plant species with substantially specialized habitat requirements. Barbert-Massin *et al.* (2012)developed an improved approach to predict the distribution of rare and endangered species. Barbert-Massin *et al.* (2012) used ENFA (Ecological Niche Factor Analysis) to simulate pseudo-absences from occurrence and absence data, resulting in more accurate predictions. The researchers suggested that incorporating ENFA weighted pseudo-absences into SDMs could potentially enhance the models' ability to explain species distribution patterns. Raes *et al.* (2009) used SDMs to assess endemicity patterns and botanical richness in Flora Malesiana in Borneo, guiding conservation efforts. Esselman and Allan (2011) applied SDMs in data-limitedfreshwater settings to enhance conservation planning, in developing countries, while Brotons (2014) used long-term monitoring data to map habitat suitability for bird species. Additionally,SDMs have potential in palaeobotany to provide a quantitative ecological perspective and assess past organism distributions and range determinants (Svenning *et al.*, 2017).

Taylor and Kumar (2014) used the *Lantana Camara* invasion in Fiji as an example to examine the effectiveness of SDMs in managing invasive plants in small island environments. They created a *Lantana Camara* niche model with phenological data and geographic distribution records using the CLIMEX SDM program. The model estimated the spread of *Lantana Camara* under historical climate conditions and forecasted future climate scenarios using the CSIRO Mk3.0 World Climate Model. The findings indicated that a sizable portion of Fiji was suitable for *Lantana Camara*, but suitability was anticipated to decline under projected changes in climate. The study showed that SDMs are useful in developing low-cost invasive species management strategies, and the resulting species distribution maps can be used on other islands in the South Pacific.

Likewise, Pagny *et al.*, (2020) conducted a study in Côte d'Ivoire to model the ecological niche of *Lantana Camara* across the country. Using the HadGEM2-ES climate model, 89 occurrence locations and 19 bioclimatic variables were collected to simulate the possible spread of the *Lantana Camara* in the RCP 8.5 scenario. 75 % of the data was used for model calibrationand 25 % for testing. The results showed that areas suitable for the invasion of *Lantana Camara* were characterized by low temperatures and heavy rainfall. Currently, about 20 %of the national territory, equivalent to 65,782.40 km², was suitable for the species invasion, with some protected areas having a high probability of presence. By 2050, due to projected high temperatures and low precipitation, the suitable area for *Lantana Camara* invasion is expected to increase to 24 % of the national territory, equivalent to 78,036.05 km², with arate of change of 18.6. Control strategies must be implemented in areas identified as most vulnerable to the invasion to maintain ecosystem functioning and sustainability of ecosystem services.

2.7. Conclusion

The present study conducted an effective review of the literature on the use of remote sensing to study IAPs in ecosystems. The literature suggests that traditional field surveys for detecting, mapping, and understanding the distribution of *Lantana Camara* have proven to be challenging in many parts of the world. Remote sensing techniques have been found to be more effective in detecting and mapping *Lantana Camara*. However, most research has concentrated on the species' spatial distribution, and there is a lack of understanding of the underlying mechanisms responsible for its invasive capacity in multiple environments. To better comprehend the spatial distribution of *Lantana Camara*, future research should include topographic variables and analyse the components contributing to its distribution.

CHAPTER THREE: METHODOLOGICAL APPROACH

3.1. Introduction

This chapter examines the research methodology, which details the techniques used to collect data and the analytical processes. The chapter gives a thorough description of the study area. This chapter examines the Sentinel-2 remote sensing satellite images and describes how, among other land cover categories, the spatial distribution of *Lantana Camara* was mapped. Maximum Entropy (MaxEnt) with the assistance of topographic derivatives was utilized to study important environmental variables impacting the spatial distribution of *Lantana Camara* and the areas vulnerable to *Lantana Camara* invasion. In addition, it is explained in detail how the *Lantana Camara* spatial distribution in the Inkomati catchment was modelled using MaxEnt.

3.2. Description of the study area

The study was conducted in the Inkomati Water Management Area (IWMA), located in the north-eastern region of the Mpumalanga Province, in South Africa (as shown in Figure 2). The IWMA spans an area of 28,757 km2 and comprises three major rivers: the Komati, the Crocodile, and the Sabie (Mahlathi, 2018). The Komati River originates in South Africa, traverses through Swaziland, and then returns to South Africa, where it meets the Crocodile River near the Mozambique border (Hassan and Mahlathi, 2020). The most significant topographical feature in the IWMA is the Great Escarpment, which divides the water management area into the Plateau region in the west (with an elevation of over 2,000 m above sea level) and the Lowveld in the east (Chibwe *et al.*, 2012).

The climate in the study area is highly diverse and influenced by the terrain, ranging from temperate Highveld in the west to sub-tropical in the eastern Lowveld (McLoughlin *et al.*, 2021). The average temperature throughout the year is 17°C, with January being the hottest month with an average of 21°C, and June being the coldest month with an average minimum temperature of 11.5°C, according to Hassan and Mahlathi, 2020. Frost is usually observed from

June to early August, except in the extreme east where there is no frost. The region experiences most of its rainfall during the summer months (October to April), with an average annual precipitation of 767 mm. The amount of rainfall varies across the area, ranging from 400 mm to 1000 mm in most regions, and up to 1500 mm in hilly areas along the cliff (DWA, 2016).

The IWMA has an estimated mean annual runoff (MAR) of 3 539 million m3/year, with the majority of surface runoff coming from the Komati, Crocodile, and Sabie sub-catchments due to their steep terrain and heavy rainfall (DWAF, 2004). There are no natural lakes in the catchment area, but isolated wetlands and small pan areas can be found in the southwestern border of the water management area. The reduction of natural drainage is primarily due to large commercial plantations and invasive alien plants covering approximately 132 000 ha (Raheem, 2013). Afforestation and invasive alien vegetation are estimated to have reduced runoff by 53 million m3 and 38 million m3, respectively. According to DWAF (2004), alien vegetation absorbs 91 million m3/year of water in the IWMA, with 7 million m3/year in Komati West, 0 million m3/year in Lower Komati, 57 million m3/year in Crocodile, and 24 million m3/year in Sabie, and 3 million m3/year in Sand.

Four quaternary catchments which are: the Injaka Dam, the Blyde River/Graskop, the Crocodile, and the Sabie located in the study area were the subject of the study. The renowned Kruger National Park is located right next to the northern boundary of the water management area. While the Crocodile River serves as the park's southern boundary, the Sabie River, which flowsthrough the park, is one of South Africa's most ecologically significant rivers (Wangusi *et al.*,2013).

The IWMA is experiencing water scarcity due to various reasons, including regular water restrictions, growing demands from black farmers, international agreements, and concerns about water quality and ecological preservation. According to several sources, including the DWA (2007, 2012a) and Woodhouse (2012), there is a rising water deficit in the basin. The over-allocation of three out of four sub-catchments (Komati, Sand, and Crocodile) is causing a water yield deficit, and reserve and international criteria are not being met, as noted by Schreiner (2012).

The IWMA relies heavily on tourism, commercial irrigation, forestry, and mining for economic growth. However, it is important to note that despite accounting for only 3 % of the area, commercial irrigation consumes 51 % of the total water usage. This intensive use of landand water resources has caused significant depletion and degradation of the natural capital in the region. Currently, the IWMA faces a water deficit of around 12 % of its totalrequirements due to excessive agricultural water extraction and contamination from chemicalssuch as fertilizers and herbicides that end up in the rivers. Additionally, land degradation and changes in land use have been increasing in the area. This information is supported by variousstudies and reports, including those by LeMarie *et al.* (2006), Soppe *et al.* (2006), Sengo *et al.* (2005), the Department of Water Affairs and Forestry (2004), and Van der Zaag and Vaz (2003).

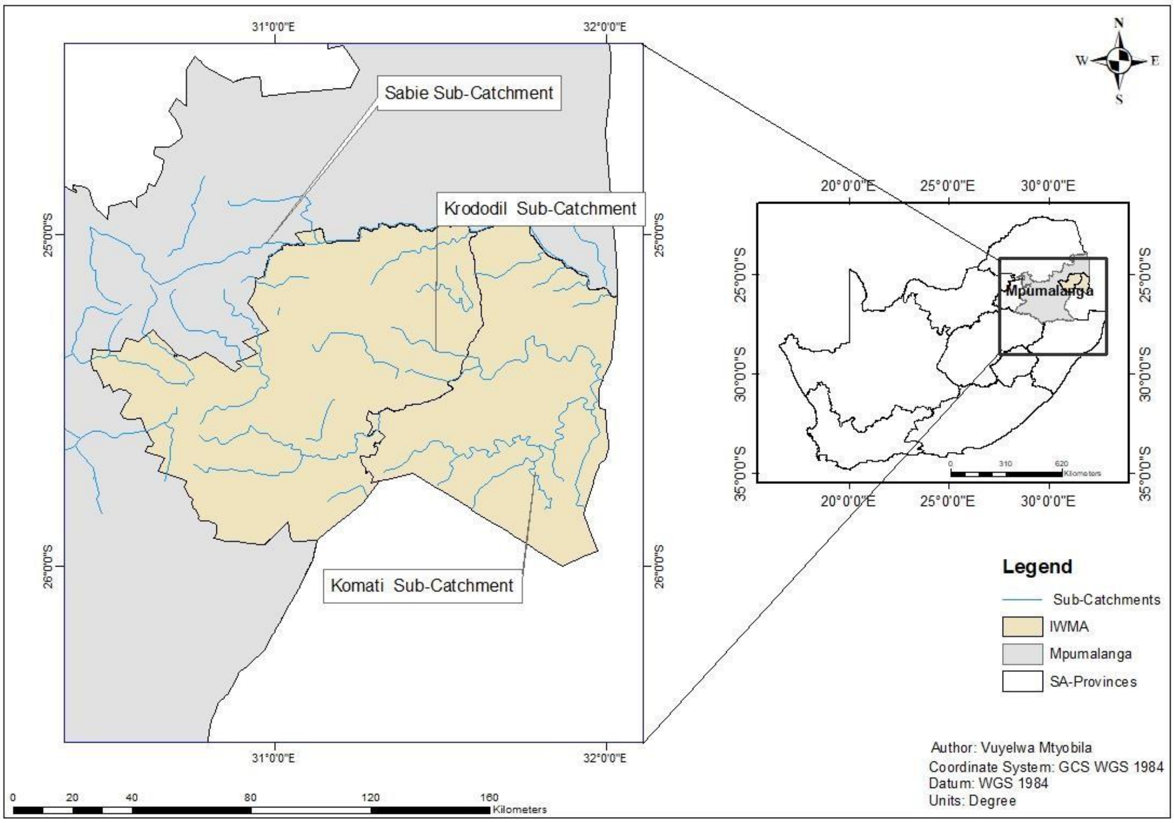

Figure 2: Map of the Inkomati Catchment in Mpumalanga, South Africa

3.3. *Field data collection*

In this study, previously gathered field data on *Lantana Camara*, land use and land cover types were utilized. To accurately record the location points of *Lantana Camara*, a handheld Garmin eTrexGlobal Positioning System (GPS) receiver was utilized with sub-meter precision in mid-December 2020. The study consisted of five classes, namely waterbody, *Lantana Camara*, cashnuts, banana, and sugarcane plantations, with 284, 225, 80, 170, and 122 samples for each class, respectively. 70 % of the sampling points were used for model training, while 30 % were used for model validation, following the approach used in previous studies (Maxwell *et al.*, 2018; Watts *et al.*, 2012). GPS coordinates were captured using Microsoft Excel Version 4.0 and presented in a table format. Then, they were overlaid on the study area shapefile in the ArcGIS 10.6 software environment. The measured GPS points for *Lantana Camara* were converted to comma-separated values (CSV) to ensure compatibility withMaxEnt for the modelling of potentially vulnerable areas.

3.4. Sentinel-2 satellite imagery image acquisition and pre-processing.

Sentinel-2 imagery, which is freely available and consists of the two satellites Sentinel-2A and Sentinel-2B, is a multispectral sensor that was launched on June 23, 2015 (Paul and Kumar, 2019). An aggressive invasive species like *Lantana Camara* can now be detected, mapped, and monitored thanks to this sensor. Sentinel-2 data demonstrate the necessity and viability of employing broadband multispectral sensors to characterize and profile invasive species, a previously challenging task. The satellite takes pictures every five days, covering 13 spectral bands (443-2190 nm) with various spatial resolutions and a swath width of 290 km; see Table 2 for more information. The study did not include bands 1, 9, or 10 because of their 60-meter-wide coarse spatial resolution. The study used all available Sentinel-2A and -B MSI Level-1C images with less than 10 % cloud cover and performed cloud masking based on the flags of the Sentinel-2 QA band, which provides cloud state information. Using the Sen2Cor tool inthe Sentinel Application Platform (SNAP) version 5.0.8, the images were atmospherically corrected in Google Earth Engine (GEE) and were applied at 10 m and 20 m spatial resolutions.

Table 2: Spectral characteristics of Sentinel-2 datasets

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1- Coastal aerosol	0.443	60
Band 2- Blue	0.490	10
Band 3- Green	0.560	10
Band 4- Red	0.665	10
Band 5-Vegetation Red Edge	0.705	20
Band 6- Vegetation Red Edge	0.740	20
Band 7- Vegetation Red Edge	0.783	20
Band 8- NIR	0.842	10
Band 8A- Vegetation Red Edge	0.865	20
Band 9- Water Vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

3.5. Topographic data utilised to model areas vulnerable to *Lantana Camara* invasion.

The Advanced Space-born Thermal Emission and Reflection Radiometer (ASTER), (https://asterweb.jpl.nasa.gov/gdem.asp), which covers 99 % of the earth, provided a freedigital elevation model (DEM) with a 30m spatial resolution. The DEM gives the terrain a three-dimensional representation. The topographic variables Topographic Wetness Index (TWI), Topographic Position Index (TPI), and elevation were extracted from the DEM using the spatial analyst tool in ArcGIS. TWI, a soil moisture index, has been used successfully in earlier studies to analyse vegetation patterns and forecast their distribution (Sorensen and Seibert, 2007). It affects the growth and composition of vegetation. The TWI was derived usingthe following equation 1:

$$TWI = \ln \alpha \tan \beta$$

α and $tan\beta$ represent the local upslope area and the slope, respectively. TWI indicates the likelihood of a wet area. It is determined by slope and contributing area. Locations with higher TWI values are more likely to be wet than areas with lower values (Lindemayer *et al.*, 2016; Davidson *et al.*, 1998).

Tip is a useful tool for classifying the landforms found in a particular location and for understanding the biophysical processes that are occurring on the landscape. This information is important when predicting the suitability of habitats and the distribution of species in the area (Seif, 2014). TPI is calculated as the difference between the elevation of a cell in a DEM and the average elevation of the surrounding cells. The following equation 2 shows the calculation of TPI:

$$TPI = M_0 - \sum_{n=1} M_n/n \, TPI = M0 - \sum n = 1. Mn/n$$

M0 is the DEM elevation point being evaluated, *Mn* is the pixel grid elevation, and *n* is the summation of the nearby points. A value close to zero indicates a flat or nearly continuous slope, while a large positive value indicates the central pixel is located on a hill or ridge. Conversely, a large negative value suggests that the central pixel is in a valley or gulley (Weiss 2001). Slope and aspect were derived from the DEM using the QGIS terrain analysis plugin. Soil moisture, soil type, precipitation, and sun angle are influenced by terrain variables, hence the distribution of vegetation. These topographic variables have an impact on hydrological processes and solar radiation, causing changes in soil moisture and plant function as well as structure (Guo *et al.*, 2020).

3.6. Image classification for the spatial distribution of *Lantana Camara*

Many de-correlated decision trees are combined in the Random Forest (RF) algorithm, an ensemble learning technique that enhances classification and regression of trees, to classify images (Oumar, 2016; Breiman, 2001). A random subset of samples from the first two-thirds of the dataset are bagged and subjected to a random selection process in the algorithm (Odindi *et al.*, 2016). The RF model was implemented in Google Earth Engine to create a classification map, and the outcome was a Sentinel-2 map that visualizes the distribution of *Lantana Camara* in the Inkomati catchment.

Binary n-trees are built using bootstrap samples and replacement data taken from the sample dataset to build the Random Forest algorithm. The ensemble of trees is then used to classify each waveband. The final classification is determined by the class that received the greatest number of tree votes. The classification process is based on a class's maximum number of votes from the collection of trees. This technique is frequently applied in image classification to increase precision and decrease overfitting (Odindi *et al.*, 2016; Lee *et al.*, 2014; Adjorlolo *et al.*, 2012). Out-of-bag (OOB) samples are samples that are not part of the bootstrap sample (Lee *et al.*, 2015; Adelabu *et al.*, 2013). The accuracy of the classification model is evaluated using these samples, which make up roughly one-third of the sample dataset. According to numerous studies (Adjorlolo *et al.*, 2012; Prasad *et al.*, 2006).

To evaluate the accuracy of the image classification, Sentinel-2 MSI data was employed, and confusion matrices were used to calculate the Overall Accuracy (OA), User Accuracy (UA), and Producer Accuracy (PA). 70 % of the training data was used to generate the *Lantana Camara* maps, while the remaining 30 % was utilized to evaluate classification accuracy. Additionally, the RF method was used to create a confusion matrix, and user and producer accuracies were computed to assess the accuracy of the *Lantana Camara* maps.

3.7. Modelling areas vulnerable to the *Lantana Camara* invasion

Areas vulnerable to the invasion of *Lantana Camara* were modelled using the Maximum entropy (MaxEnt), which can be downloaded for free from (http://biodiversityinformatics.amnh.org/open_source/MaxEnt/). MaxEnt is a stand-alone Java program created for modelling species distributions that makes use of occurrence records (locations where the species has been found) and environmental variables for a nearby study area (Phillips and Dudk, 2008; Phillips *et al.*, 2006). MaxEnt is an SDM that is helpful in locating the distribution of invasive species. It is a correlative technique that has been acknowledged as one of the top SDMs for present-only data analysis (Ficetola *et al.*, 2007). For MaxEnt to build models, there must be only current data and a small number of locations. It performs better than other present-only models because of its sensitivity to spatial errors associated with low data (Phillips *et al.*, 2006).

MaxEnt can also handle categorical and continuous data. But because it uses a regularization technique to account for data with low occurrence, it is vulnerable to overfitting (Merow *et al.*, 2017; Phillips *et al.*, 2006). MaxEnt has been successful in accurately modelling and forecasting the distribution of comparable invasive species. It was used to estimate the geographic spread of *Lantana Camara* under current conditions (Choudhury *et al.*, 2016; Qin *et al.*, 2016; Roger *et al.*, 2015; Adhikari *et al.*, 2015; Pawar *et al.*, 2007). The field dataset was divided into two portions: 20 % for model testing and 80 % for model development. Four MaxEnt model types—linear, quadratic, hinge, and threshold—were looked at, and the model was cross-checked using a 25 % test sample chosen at random from the presence locations. The presence data were carefully examined throughout the area, and the species wasconsistently present, so the best alternative was to draw random background points within thesame climatic zone (Elith *et al.*, 2010; Phillips *et al.*, 2009).

A jack-knife test was used to assess the importance of the predictor variables in explaining the spatial distribution of the species and their distinctive contributions. This statistical method can estimate parameters and correct divergence without making any assumptions about the probability of the distribution because it was used to assess the effects of topographical variables on the distribution of the species. Sentinel-2 bands, elevation, slope, TPI, and TWI were among the variables used in the MaxEnt model to model the distribution of the species. The MaxEnt output for each scenario was converted into a presence distribution using a 10th percentile presence threshold (Radosavljevic and Anderson 2014). The distribution of *Lantana Camara* in the study area was predicted by the model, which also established the relationship between *Lantana Camara* and the environment.

3.8. Evaluation of MaxEnt's accuracy in modelling areas vulnerable to the *Lantana Camara* invasion

An important step in determining a model's accuracy and dependability is to evaluate the model's performance. In this regard, the accuracy and effectiveness of the model were assessed using the Area Under Curve (AUC) and True Skill Static (TSS). The TSS is a threshold-dependent measure of accuracy, whereas the AUC is a threshold-independent measure (Allouche *et al.*, 2006). The AUC evaluates the congruence between the species' observed presence and the classifier's predicted distribution, demonstrating whether the relative importance of presence versus absence was correctly arranged. An AUC value of 0.5 indicates that the model's predictions are no better than random, a value below 0.5 is worse than random, a value of 0.5-0.7 indicates poor performance, a value of 0.7-0.9 indicates moderate performance, and a value of 0.9 represents high performance (Shabani *et al.*, 2016).

Kappa has been used in earlier studies to evaluate model performance, but it has drawn criticism for being susceptible to prevalence (Ndlovu *et al.*, 2018; Mouton *et al.*,2010; Allouche*et al.*, 2006) TSS has thus been presented as an alternative accuracy measure that corrects this dependence while maintaining the benefits of Kappa. When it is mentioned that the Kappa statistic is susceptible to prevalence, it means that the measure is influenced by the proportion of agreement by chance alone, which is also known as the prevalence of the outcome being observed. In other words, if the prevalence of a particular category is high or low, it can affect the Kappa value. TSS combines sensitivity and specificity,with sensitivity representing the percentage of true positives and specificity representing the percentage of false positives. TSS values range from -1 to 1, with values closer to 1 indicatingbetter model performance and those closer to -1 indicating poor and random model performance (Mouton *et al.* ,2010). TSS can be used to find errors that a model has made in commission and omission (Allouche *et al.*, 2006). Further, with background samples as absence data, the error matrix was used to calculate the specificity, Kappa, sensitivity, and TSSvalues. The 10th percentile was used to gauge the precision of the classification.

CHAPTER FOUR: RESULTS

4.1. Introduction

This study aimed to investigate the spatial patterns of *Lantana Camara* across topographical variations in the Inkomati catchment of Mpumalanga, South Africa. To achieve this goal, the study was organized around three specific objectives. The first objective was to map the recent spatial distribution of *Lantana Camara* in the Inkomati catchment by utilizing Sentinel-2 images and the Random Forest classification algorithm in Google Earth Engine. The second objective was to identify the key topographic variables and their impact on the spatial distribution and invasion of *Lantana Camara* using MaxEnt and DEM models. The third and final objective was to model the areas vulnerable to *Lantana Camara* invasion in the Inkomati catchment by using MaxEnt and models based on topographic variables and Sentinel-2 bands.

4.2. The recent spatial distribution of *Lantana Camara* and other land use land cover types

Figure 3 illustrates the distribution of *Lantana Camara* and other land use land cover types, including Waterbody, Cashnuts, Sugarcane, and Banana plantations. The majority of *Lantana Camara* is concentrated in the northeast region of the study area. Additionally, *Lantana Camara* was found to be in closer proximity to waterbodies, as well as sugarcane and banana plantations.

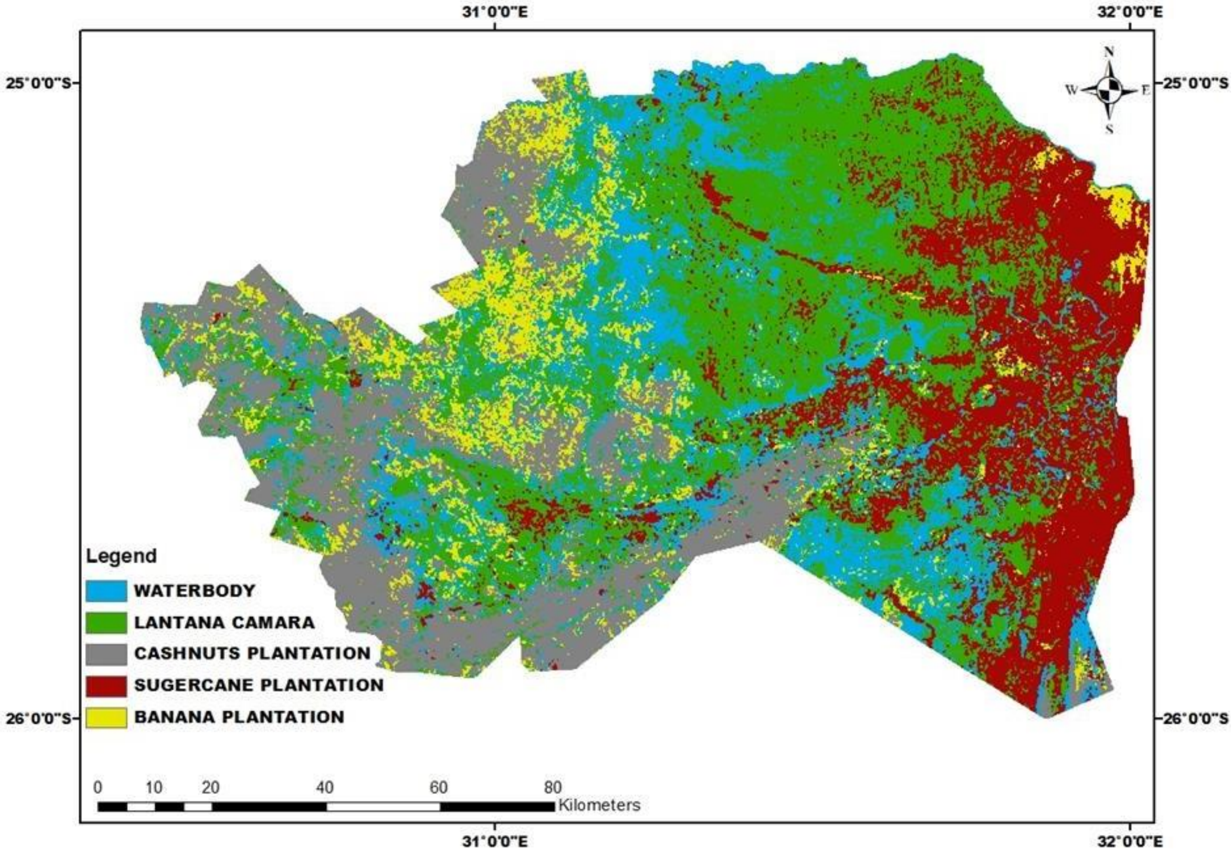

Figure 3: Distribution of Lantana Camara and other land cover types across the study area

The percentage areal coverage of each land use land cover class is depicted in Figure 4. The graph displays that *Lantana Camara* covers the highest percentage of the study area at 34.86 %, followed by sugarcane plantation at 21.44 %. In contrast, banana plantation has the least coverage at 11.64 %.

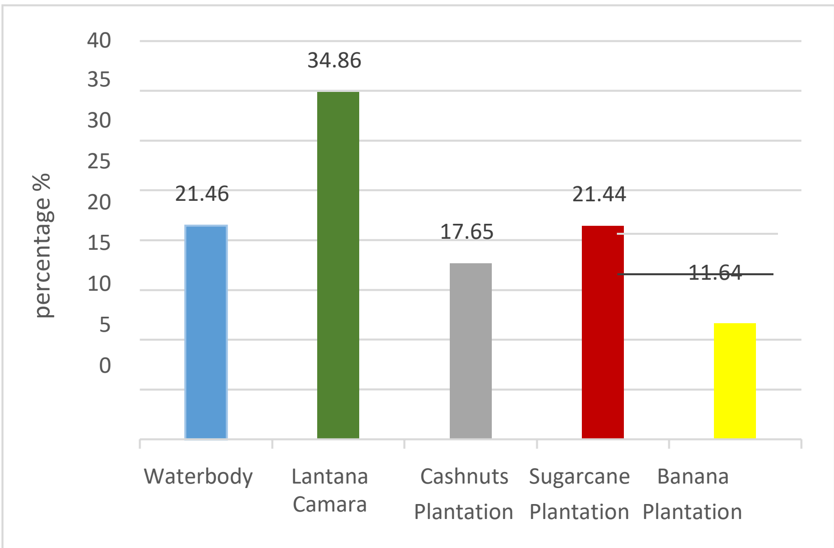

Figure 4: Areal coverage of each class as a percentage

4.2.1. Random Forest classification algorithm and Sentinel-2 bands variable importance

Figure 5 presents the random forest bands variable importance, which includes all mtry values used in the classification. The variable importance scores highlight key variables that have a significant impact on the model's performance. The bar graph displaying the variable importance shows that Band 8a (Vegetation Red Edge) and Band 11 (Shortwave Infrared) had the highest importance scores of 450 and 498, respectively, indicating their crucial role in the model. In contrast, Band 4 (Red) had the lowest importance score of 340, indicating its lesser significance in the classification.

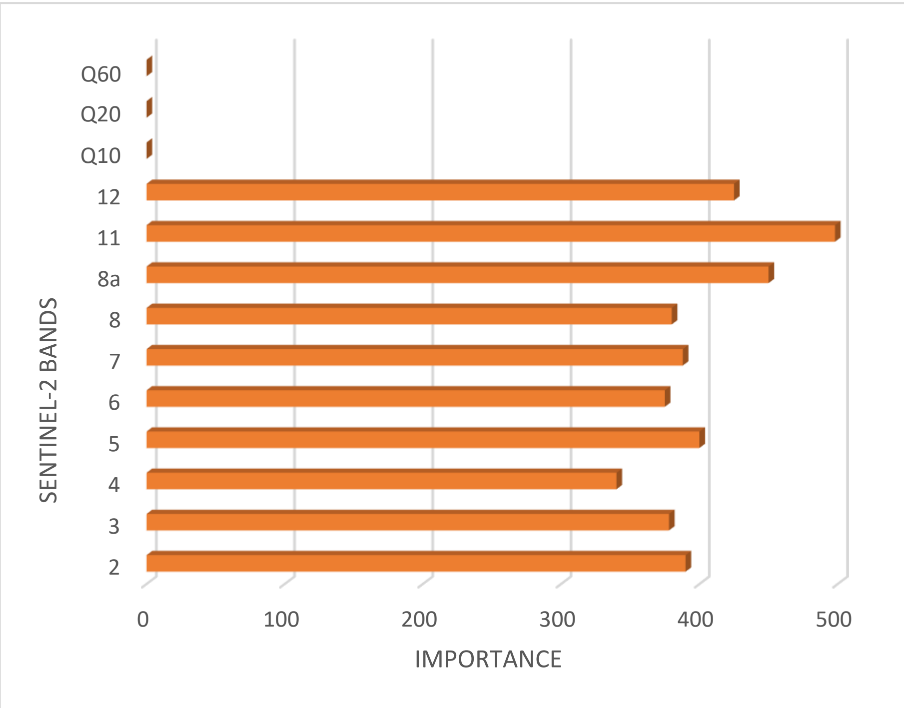

Figure 5: Random Forest Bands Variable Importance

4.2.2. Random Forest classification algorithm accuracy assessment results

Table 3 displays the confusion matrix that illustrates the classification of *Lantana Camara* and other land cover types using the Random Forest classification algorithm on the independent 30 % test dataset. The model was able to classify *Lantana Camara* and other land cover types with an overall accuracy of 84 % and a k statistic of 0.78. The user's accuracy for *Lantana Camara* was 91 %, while the producer's accuracy was 84 %.

Table 3: Confusion Matrix with omission and commission errors

Class Name	Waterbody	*Lantana Camara*	Cashnuts	Sugarcane	Banana	**Total**	**User's Accuracy**
Waterbody	33	6	2	2	1	44	**75**
Lantana Camara	2	41	0	1	1	45	**91**
Cashnuts	0	0	3	0	1	4	**75**
Sugarcane	6	2	0	21	0	29	**72**
Banana	1	0	0	1	34	36	**94**
Total	42	49	5	25	37	**158**	
Producer's Accuracy	**78**	**84**	**60**	**84**	**92**		
Overall Accuracy				**84 %**			
Kappa				**0.78**			

4.3. Influence of topographical variables on the spatial distribution of *Lantana Camara*

The topographical derivatives map in Figure 6 illustrates the elevation, slope, TPI, and TWI variables utilized in the MaxEnt model to predict vulnerable areas for *Lantana Camara* invasion. These derivatives were also analysed to determine their influence on the spatial distribution of the *Lantana Camara*. The maps use an orange-to-blue colour gradient to depict the lowest and highest values of each derivative, respectively. Low elevation areas are indicated by dark orange colour while high elevation locations are depicted in blue. The southwestern part of the study area has high elevation areas while the eastern part has low elevation areas. Similarly, gentle slope areas are shown in orange while steep slope areas are in blue. The eastern side of the map displays gentle slope areas, while thesouthwestern side has steep slope areas. Additionally, low TPI locations are shown in orange,and high TPI areas are shown in blue. High TPI areas are in the eastern part of the study area,while low TPI areas are primarily found in the southwestern region. Therefore, the maps for slope and elevation depict comparable patterns, where high elevation and steep slope, occur in the same locations. However, TPI presents contrasting patterns with elevation and slope. Lastly, the TWI map highlights high TWI areas, shown in blue, primarily located in waterbodies, while low TWI areas, shown in orange, are presented in areas without waterbodies.

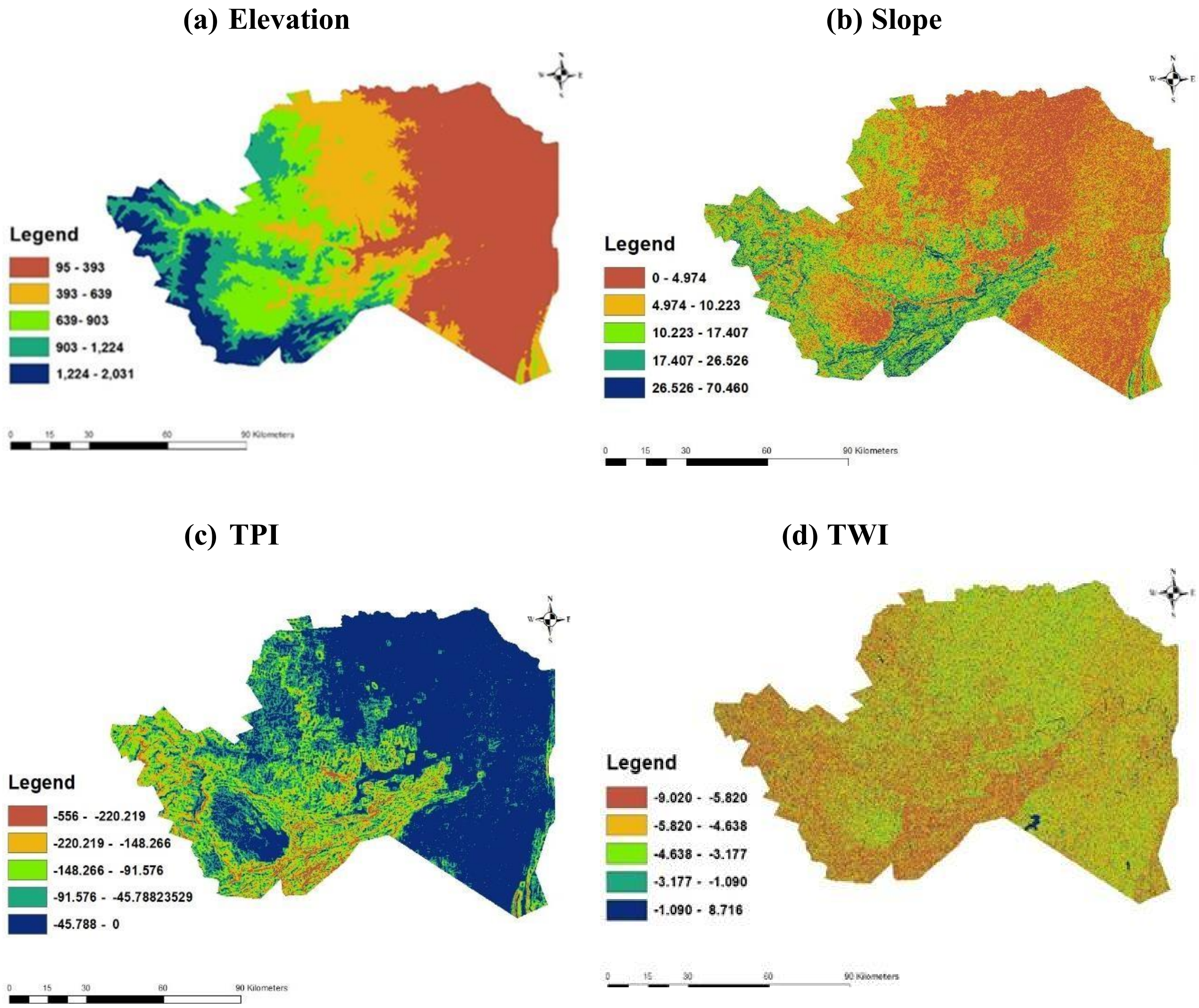

Figure 6: Topographic variables for the study area derived from the DEM.

4.4. Areas vulnerable to the *Lantana Camara* invasion in the Inkomati catchment

Figure 7 (a) illustrates a vulnerability map of *Lantana Camara* obtained using topographic variables (elevation, slope, TPI, and TWI), where the red areas are identified as highly vulnerable to invasion compared to other areas. The map indicates that there is low *Lantana Camara* invasion, as the red areas are fewer compared to other colours. The areas with high invasion risks are mostly located on the central westernmost part of the study area, while the areas with low invasion risks are situated on the easternmost part of the study area. The areas with low elevation, gentle slope, low TPI, and low TWI are vulnerable to high invasion risks, whereas the areas with high elevation, steep slope, high TPI, and high TWI experience low invasion. Overall, the maps in Figures 6 and 7 (a) coincide in that the central western part of the study area is the most vulnerable to *Lantana Camara* invasion.

Figure 7 (b) presents a vulnerability map of *Lantana Camara* using Sentinel-2 bands 2,3,4,5,6,7,8,11,12. The map indicates a significant invasion of *Lantana Camara* as yellow areas dominate over others. The invasion risks are high in almost all parts of the map except for the southwestern and north-western areas. The areas with high invasion risks have low elevation, gentle slope, high TPI, and low TWI. On the other hand, low invasion is found in areas that are more elevated, have a steep slope, low TPI, and high TWI, which differs from the other map. Therefore, the two maps (vulnerability maps derived using topographic variables and Sentinel-2 bands) appear to disagree on the places that are most vulnerable to the invasion of *Lantana Camara*.

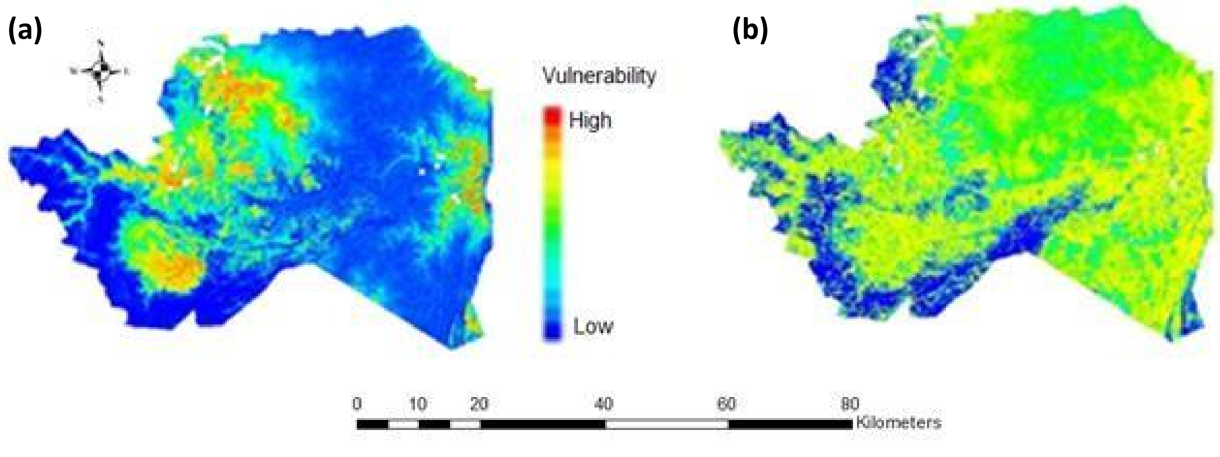

Figure 7: Vulnerability maps derived from (a) topographic variables and (b)Sentinel-2 bands using MaxEnt.

The vulnerability map created from topographic variables (a) and the recent distribution map (c) seem to be contradictory. The recent distribution map indicates a significant concentration of *Lantana Camara* in the north-eastern part of the study area. However, the vulnerability map based on topographic variables indicates that the areas with a high risk of *Lantana Camara* invasion are primarily situated in the westernmost part of the study area. In contrast, the recent distribution map (c) aligns with the vulnerability map generated from Sentinel-2 bands (b), where *Lantana Camara* is strongly concentrated in the north-eastern part of the research region, while areas with a high risk of *Lantana Camara* invasion are mainly located on the eastern side of the study area, see Figure 8.

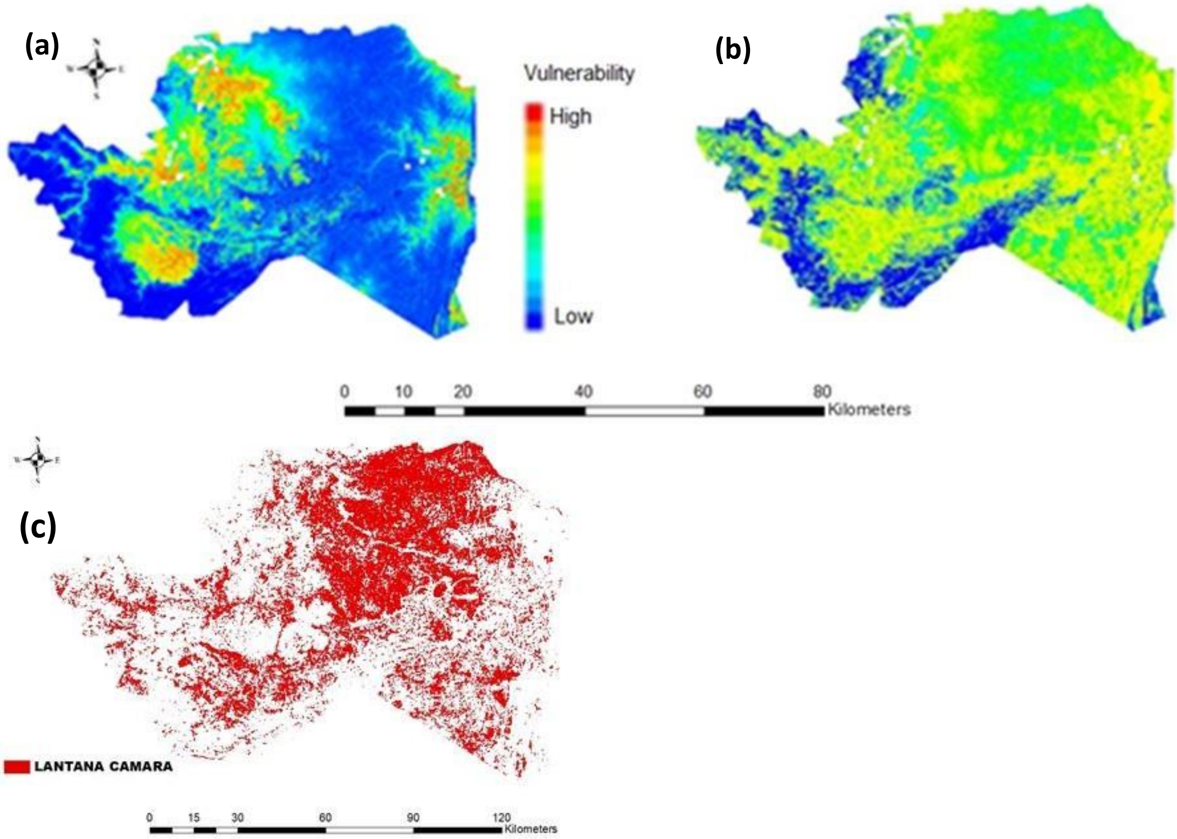

Figure 8: Vulnerability maps using (a) Topographic variables and (b) Sentinel-2 bands, as well as (c) the recent spatialdistribution map of Lantana Camara

4.4.1. MaxEnt's accuracy in modelling areas vulnerable to *Lantana Camara* invasion in the Inkomati catchment

To assess the importance of predictor variables that explain the invasion of *Lantana Camara*, a jack-knife test was conducted to determine their unique contributions. Two model settings were employed: Model 1 used topographic variables, and Model 2 used Sentinel-2 bands. Table 4 displays the AUC values obtained from the different models, which are threshold independent. Model 1 achieved the highest predictive accuracy, using topographic variables to model areas vulnerable to *Lantana Camara* invasion, with an AUC of 0.882. Conversely, Model 2 used Sentinel-2 bands to model areas vulnerable to *Lantana Camara* invasion and had the lowest accuracy, with an AUC of 0.810.

Table 4: Model scenarios used to model Lantana Camara as well as evaluation results.

Model Setting	Variables	Number of variables	AUC
Model 1	Topographic variables: Elevation, TWI, Slope, TPI	4	0.882
Model 2	Sentinel-2 bands: 2,3,4,5,6,7,8,11,12	9	0.810

The jack-knife test of variable importance was conducted to determine the most important variables in predicting areas vulnerable to *Lantana Camara* invasion. According to Figure 9 (a), elevation was found to be the most important variable in predicting areas vulnerable to *Lantana Camara* invasion. This was evident from its high gain when used alone and the highest mean decrease in accuracy when omitted from the model. Additionally, it contained the most unique information compared to other topographic variables. Conversely, the Topographic Wetness Index (TWI) was rated as the least influential topographic variable. Figure 9(b) revealed that the Vegetation Red Edge bands (6 and 7) and the Near Infrared band (8) were the most important variables while the red band (4) was the least important in predicting areas vulnerable to *Lantana Camara* invasion.

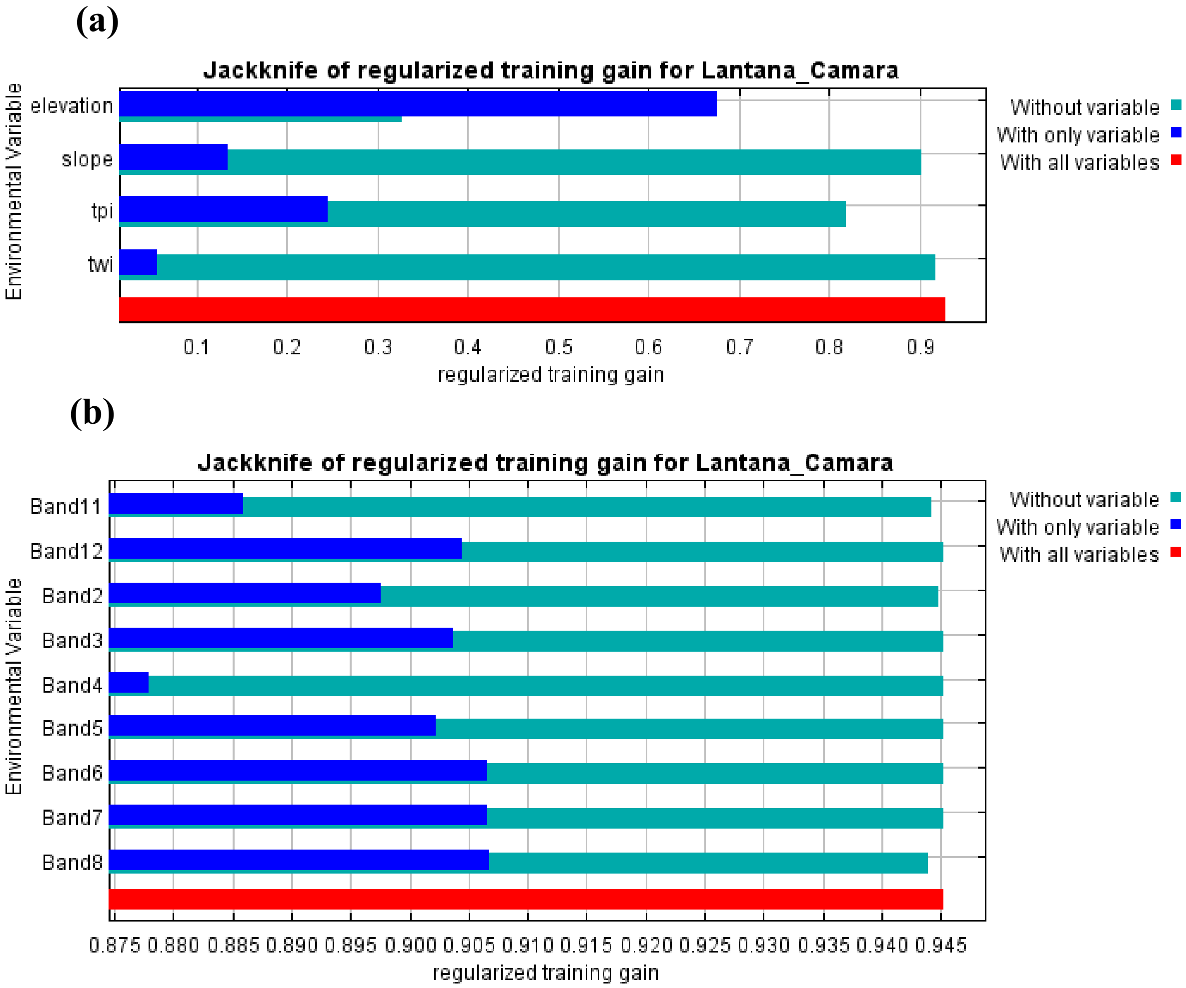

Figure 9: Variable importance Jacknife test showing (a) topographic variables and (b) bands.

CHAPTER FIVE: DISCUSSION

5.1. Mapping the recent spatial distribution of *Lantana Camara* in the Inkomati catchment

The aim of this study was to map the recent distribution of *Lantana Camara* in the Inkomati catchment in Mpumalanga, South Africa, using the Random Forest classification algorithm and Sentinel-2 data. The results showed a high overall accuracy of 84.63 % and a Kappa valueof 0.78, indicating the potential of RF in mapping invasive species with remote sensing data. The RF algorithm's ability to handle large datasets, multispectral data, and multicollinear datasets makes it robust in identifying *Lantana Camara* (Gil *et al.,* 2011). The RF technique uses bagging to generate an ensemble of trees as base classifiers, which are trained on multipledata subsets and randomly resampled without replacement to improve classifier stability and classification accuracy (Rodriguez-Galiano and Chica-Rivas, 2014; Rodriguez-Galiano *et al.,* 2012; Briem *et al.,* 2002). Another advantage of the RF ensemble is that the tree classifiers grow without being pruned, resulting in high variance and minimal bias, and low generalization errors (Berhane *et al.,* 2018). The present study's findings demonstrated high classification accuracy for specific vegetation classes, aligning with previous research that showed the RF technique to be effective in mapping invasive species like *Lantana Camara* studies (e.g., Chan *et al.,* 2012; Peters *et al.,* 2011; Watts *et al.,* 2009).

Several studies, including Dixon and Candade (2008), Pal and Mather (2004), and Song *et al.* (2012), have reported that non-parametric algorithms like RF perform better than parametric techniques such as maximum likelihood in invasive plant mapping. In this study, Sentinel-2 data with high spectral and moderate to high spatial resolution were used, and a classification accuracy of 84.63 % was achieved using the RF algorithm. The data obtained from Sentinel-2 had a high spectral resolution and moderate to high spatial resolution, including 13spectral bands. Some of the bands had undergone pan-sharpening, which is the process of combining high-resolution panchromatic bands (Band 8) with lower-resolution multispectral bands (Bands 2-7 and 8a) to create a single, high-resolution multispectral image (Dehkordi, 2017). While a classification accuracy of 70 % or more is generally considered optimal inland cover mapping (Thomlinson *et al.*, 1999), Odindi *et al.* (2016) noted that the 68 % accuracy they achieved in classifying *Lantana Camara*, a plant with unclear spectral features (which vary as it develops, and these changes can lead to confusion with other species in termsof their spectral patterns) was still useful for initial screening. Adelabu *et al.* (2013) also reported achieving over 70 % overall classification accuracy with 10 % allocation and3 % quantity disagreement scores in differentiating between five tree species, both invasive and indigenous.

Earlier research has shown that the primary challenges in determining the spatial distribution of *Lantana Camara* are spatial and spectral resolution, as noted in studies by Tarugara *et al.* (2022), Khare *et al.* (2019), and Kimothi and Dasari (2010). To produce accurate and reliable data on the spatial distribution of *Lantana Camara*, both fine spectral and high spatialresolution capabilities are essential, which Sentinel-2 satellite imagery has proven to provide (Rajah *et al.*, 2018). Prior research primarily utilized medium spatial resolution sensors such as Landsat 7 and SPOT 5, which had insufficient spatial and spectral resolution and posed significant difficulties in mapping the distribution of *Lantana Camara* (Roymani *et al.*, 2019; Khare *et al.*, 2018; Thamaga and Dube 2018). However, high-resolution sensors like Sentinel-2 and SPOT 6, with spatial resolutions of less than 20 meters, can detect the invasive *Lantana Camara* on a regional scale (Laso *et al.*, 2019).

Dube *et al.* (2014) used data from both Sentinel-2 and Landsat 8 to distinguish *Lantana Camara* from other types of land cover. The study showed that both Sentinel-2 MSI data and Landsat 8 are effective in detecting and mapping *Lantana Camara* invasions on the landscape. The classification outcomes revealed that variables based on Landsat 8 and Sentinel-2 MSI had significant potential for distinguishing *Lantana Camara* from other land cover types with reasonable accuracy, with the maximum kappa statistics between 0.6 and 0.75 indicating good classification (Dube et al 2014). The spatial resolution of Sentinel-2, which is 10 meters, helps to address the spectral mixing or mixed pixel problem, as noted in studies by Immitzer *et al.* (2016) and Mallinis *et al.* (2018). Due to its unique spectral configuration and advanced geospatial data, Sentinel-2 can distinguish *Lantana Camara* from other land cover types effectively, as evidenced by studies by Shoko *et al.* (2016) and Sibanda *et al.* (2019). Finally, when mapping the spatial distribution of *Lantana Camara*, both Random Forest and Sentinel-2 achieved high accuracies and optimal performance.

There could be several factors that could explain why the majority of *Lantana Camara* is concentrated in the northeast region of the study area. Here are some possible explanations: *Lantana Camara* is known to thrive in warm, dry environments with plenty of sunlight. If one side of the study area has more of these environmental conditions compared to the other side, it could explain why the plant is distributed unevenly (Negi *et al.*, 2019). *Lantana Camara* prefers well-drained soils with a slightly acidic pH. If the soil on one side of the study area meets these requirements better than the other side, it could explain why the plant is found there and not in other areas (Mandal and Joshi, 2014). *Lantana Camara* is often introduced tonew areas through human activities, such as gardening or agriculture. If humans have been more active on one side of the study area compared to the other side, it could explain why theplant is distributed unevenly (Richardson and Pysek, 2012). *Lantana Camara* can compete with other plant species for resources such as light, water, and nutrients. If other plants are more abundant on one side of the study area, it could limit the growth and distribution of *Lantana Camara* in that area (Mandal and Joshi, 2015). *Lantana Camara* can produce large amounts of seeds that are dispersed by animals, water, or wind. If the distribution of the plant is influenced by the movement of these dispersal agents, it could explain why the plant is foundin certain areas and not in others (Kohli *et al.*, 2006). Additionally, the topography of the studyarea could play a role in the plant's distribution. For example, areas with more slopes or changesin elevation may be less favourable for *Lantana Camara* growth (Thapa *et al.*, 2018). Naturaldisturbances such as fires, floods, or landslides could create favourable conditions for *Lantana Camara* growth and distribution in certain areas. Conversely, areas that are less disturbed maybe less favourable for the plant (Sukopp and Starfinger, 1999).

There have been several studies that have examined the factors that influence the distribution of *Lantana Camara*. Singh *et al.* (2008) found that *Lantana Camara* was more abundant in areas with warmer temperatures and higher levels of solar radiation. The study also found that the plant was more likely to occur in areas with lower annual rainfall. DiTommaso *et al.* (2005) found that *Lantana Camara* was more likely to occur in areas with sandy soils that had a low pH. The study also found that the plant was more abundant in areas with low levels of nitrogen and phosphorus. Rathour *et al.* (2017) found that human activity, such as deforestation and agriculture, was a key factor in the spread of *Lantana Camara* in the Western Ghats region of India. Wang *et al.* (2012) found that *Lantana Camara* had a negative impact on the growth and survival of native plant species in a forest in China. Ospina-Torres *et al.* (2019) found that *Lantana Camara* seeds were dispersed by several animal species, including birds and bats, and that seed dispersal was an important factor in the spread of the plant in Colombia. Overall, these studies suggest that the distribution of *Lantana Camara* is influenced by an ensamble of environmental factors, soil type, human activity, competition with other plants, and seed dispersal. However, it is important to note that the specific factors that influence the distribution of the plant may vary depending on the location and context of the study.

5.2. Establishing key topographic factors and their influence on the spatial distribution and invasion of *Lantana Camara* in the Inkomati catchment

The aim of this research was to establish which topographic variables are significant in determining the distribution of *Lantana Camara* across elevation, slope, TWI, and TPI. The results indicated that different topographic variables have varying influence on the spatial distribution of *Lantana Camara*, with some variables having a stronger influence than others. Elevation was found to be the most important topographic variable when used as an independent dataset to model the distribution of *Lantana Camara*, as it had the largest gain. In a MaxEnt species distribution model, 'gain' refers to the increase in information or decrease in uncertainty achieved by including a particular environmental variable in the model (Phillips and Dudik, 2008). In summary, the gain represents the amount of new information that a variable contributes to the model's ability to predict the species' distribution (Warren *et al.*, 2010).

The most significant topographic variable in predicting the spatial distribution of *Lantana Camara* is elevation, which is believed to influence the distribution of the species due to variations in temperature and soil conditions along an elevation gradient. Temperature and precipitation patterns are crucial factors affecting the distribution of *Lantana Camara*, and elevation can influence these factors. Additionally, soil properties, such as nutrient content, moisture levels, and pH, can be affected by elevation, which, in turn, can influence the growth and survival of the species (Phillips and Dudik, 2008). Studies by Ndlovu *et al.* (2018) and

Adeola (2017) have found that elevation is a significant factor in explaining the likelihood of occurrence of *Lantana Camara*. Adeola (2017) further asserts that elevation plays a crucial role in the distribution of plant species and soil conditions. Priyanka's (2013) research also supports the importance of elevation gradients in predicting the distribution of *Lantana Camara*, as the species is known to thrive at lower altitudes. This finding aligns with the presentstudy's results, indicating that *Lantana Camara* grows best at low elevations.

There could be several reasons why the Topographic Wetness Index (TWI) was found to have the least influence on the spatial distribution of *Lantana Camara* in the study. One possible explanation is that TWI may not be a significant variable in the areas where the species is found, as it is primarily used to measure the wetness of soil and may not be as relevant in drier regions. Additionally, other factors, such as soil nutrient content or temperature, may have a stronger influence on the growth and survival of the species in these areas.

Several studies have explored the relationship between TWI and the distribution of *Lantana Camara*, with mixed findings. In a study conducted in the Kumaon region of India, Singh *et al.* (2019) found that TWI had a significant influence on the distribution of *Lantana Camara*. They observed that the species occurred more frequently on sites with a higher TWI value, which suggests that soil moisture plays a crucial role in the growth and survival of the species. Supporting this idea, research by Vila *et al.* (2010) found that *Lantana Camara* is adaptable to a range of soil types and moisture levels, which may explain why TWI was found to have a weaker influence on its distribution compared to other topographic variables. Similarly, a study by Chauhan *et al.* (2010) found that temperature and precipitation patterns were significant drivers of the species' distribution, whereas soil moisture was not found to be as important.

However, other studies have found little to no relationship between TWI and the distribution of *Lantana Camara*. In a study conducted in the Western Ghats region of India, Krishnakumar *et al.* (2018) found that TWI was not a significant predictor of the species' distribution. The authors observed that the species occurred across a wide range of TWI values, which suggests that soil moisture is not a limiting factor for the growth and survival of the species in the region. Similarly, a study conducted in the Tarai region of Nepal by Devkota *et al.* (2017) found that TWI was not a significant predictor of the distribution of *Lantana Camara*. The authors found that the species occurred across a wide range of TWI values, which suggests that soil moisture is not a limiting factor for the species in the region. The results of the research conducted by Devkota *et al.* (2017) and Krishnakumar *et al.* (2018) concur with the findings of the present study. Overall, the relationship between TWI and the distribution of *Lantana Camara* appears to vary depending on the region and local environmental conditions. While some studies have found a significant relationship between TWI and the species' distribution, others have found little to no relationship. Further research is needed to better understand the role of TWI in the growth and survival of *Lantana Camara*.

5.3. Modelling areas vulnerable to *Lantana Camara* invasion in the Inkomati catchment

The objective of the study was to utilize MaxEnt to predict areas vulnerable to *Lantana Camara* invasion within the Inkomati Catchment. The findings indicate that the central-western section of the study area is more vulnerable to *Lantana Camara* invasion than other parts. Areas with low elevation, a gentle slope, low TPI and low TWI within the area have high invasion risks while the areas that are more elevated, have a steep slope, a high TPI and high TWI have low invasion taking place. This may be related to the influence of elevation on the spatial distribution of *Lantana Camara*. Temperature, precipitation, and soil properties are all influenced by elevation, which can affect the distribution and survival of the species. Elevation can have a significant influence on temperature, rainfall, and soil properties (Munson *et al.*, 2011). The higher the elevation, the cooler the temperature tends to be, as the atmosphere thins and there is less heat trapped close to the earth's surface. This is known as the lapse rate. As a result, mountainous areas are often cooler than nearby lowlands (Ab Lah *et al.*, 2021). Rainfall patterns can also be affected by elevation. Mountains can cause moist air to rise and cool, leading to condensation and precipitation. This can result in more rainfall on the windward side of a mountain range, while the leeward side may be drier (Chambers *et al.*, 2007). Additionally, higher elevations may experience more snowfall, which can affect soil moisture levels and contribute to the formation of glaciers and permafrost. Soil properties can also be influenced by elevation. Higher elevations generally have thinner soils due to the presence of rocks and steeper slopes that prevent the accumulation of organic matter (Yang *et al.*, 2018). Additionally, soil pH may be lower in high-elevation areas due to increased precipitation, which can leach minerals from the soil. However, there may be variations in soil properties depending on the local geology and climate, so it is important to consider specific factors when studying the relationship between elevation and soil (Buytaert *et al.*, 2011). In a study by Rodgers *et al.* (2003), the level of alien plant invasion was compared between two tourist islands and two protected National Wildlife Refuge Islands in the United States. It was found that locations with high levels of damage had significantly greater alien plant cover in both ecosystems and islands. Another study by Lin (2005) focused on *Lantana Camara* cover on main roadsides in Moorea, French Polynesia, in relation to environmental factors. The study found that *Lantana Camara* covered 1.99 % of the roadside area, with the greatest presence being in areas with agricultural disturbance and associated with the roadside habitat type.

Additionally, Muniappan *et al.* (2004) found that *Lantana Camara* was more abundant in disturbed habitats at lower elevations in the Pacific Island of Guam. Bhowmik *et al.* (2015) found that *Lantana Camara* was more likely to occur in areas with high levels of disturbance and lower elevations in the Chittagong Hill Tracts of Bangladesh. Chandra *et al.*, 2006 found that *Lantana Camara* was more abundant in disturbed habitats such as roadsides, wastelands, and forest edges at lower elevations in the Western Himalayan region of India. Ntuli *et al.*, (2007) found that *Lantana Camara* was more abundant in disturbed habitats such as roadsides and clearings at lower elevations in the Makhonjwas Mountains of South Africa.

Lantana Camara is known to be a highly invasive species, and it often thrives in disturbed habitats such as areas that have been cleared or degraded by human activities like agriculture, logging, and grazing. Several studies have found that *Lantana Camara* tends to occur at lower elevations, where disturbance is more common. For example, a study published in the journal Biological Invasions (Rathour *et al.*, 2016) found that *Lantana Camara* was more abundant in disturbed habitats at lower elevations in the Western Ghats region of India. Similarly, a study published in the journal Weed Research (Rasool *et al.*, 2017) found that *Lantana Camara* was more likely to occur in areas with higher levels of human disturbance and lower elevations in the Himalayan foothills of India. Therefore, when modelling areas vulnerable to *Lantana Camara* invasion, it is important to consider both disturbance and elevation as important factors that can influence the distribution of the plant. Disturbance can increase the availability of resources that *Lantana Camara* needs to grow and reproduce, while lower elevations may provide more favourable environmental conditions for the plant.

Therefore, the present study area (IWMA) is in the eastern part of South Africa, covering parts of Mpumalanga and Limpopo provinces. The area is characterized by a range of habitats, including grasslands, savannas, forests, and wetlands, and is home to a diverse array of plant and animal species. Based on the studies discussed earlier, we can infer that *Lantana Camara* is more likely to occur in disturbed habitats such as roadsides, clearings, and forest edges, which are more common at lower elevations in the study area. Therefore, areas that have experienced high levels of human disturbance, such as agricultural lands, urban areas, and transportation corridors, may be at a higher risk of invasion by *Lantana Camara*. Additionally, the environmental conditions at lower elevations, such as higher temperatures and lower rainfall, may also provide more favourable conditions for the growth and spread of *Lantana Camara* in the study area. These factors should be taken into consideration when assessing the potential risk of invasion by *Lantana Camara* in the region and when developing strategies for managing and controlling this invasive species.

The use of bands 6, 7, (Vegetation Red Edge) and 8 (Near Infrared) in isolation produced the maximum gain but resulted in poor model performance when excluded while modelling invasive *Lantana Camara*. Additionally, Sentinel-2 Bands 6, 7, and 8 were identified as significant variables in modelling *Lantana Camara* invasion. The presence of red edge bands is critical for Sentinel-2 to produce an accurate green canopy and chlorophyll, according to Delegido *et al.* (2011), and this is significant for *Lantana Camara* prediction. The red edge is crucial for distinguishing small vegetation changes and features, as well as variations in specific areas of the electromagnetic spectrum (Zhu *et al.,* 2007). Vegetation red edge bands are important for vegetation mapping and distinction (Dhau *et al.*, 2017). Moreover, in a studyon *Lantana Camara*'s spatial distribution in South African savanna ecosystems, Maluleke (2019) found that Band 5 (vegetation red edge) derived from Sentinel-2 was a critical variablein modelling invasive *Lantana Camara*.

The study utilized two sets of variables and models to predict areas vulnerable to *Lantana*

Camara invasion. Model 1, which employed topographic variables, produced the most accurate predictions with an AUC of 0.882. Model 2, which used Sentinel-2 bands, yielded lower accuracies with an AUC of 0.810. Previous studies have found that models based on topographic variables perform better than those based solely on Sentinel-2 variables (Dube *et al.* 2022; Malahlela *et al.* 2022; Ndlovu *et al.* 2022; Parra *et al.,* 2004). For instance, Dube *et al.* (2022) used MaxEnt, Sentinel-2 derived variables and environmental variables to model the distribution of *Lantana Camara*, and the model incorporating environmental variables achieved the highest accuracy. Similarly, Parra *et al.* (2004) utilized climatic, topographic (elevation), and remote sensing data (Normalized Difference Vegetation Index) to predict the distribution of six bird species in the Ecuadorian Andes, South America. Models including climate variables performed better than those relying only on remote sensing data. Elevation-based models are effective at predicting most areas of invasion but tend to have a high over-prediction error. On the other hand, combining different data sets generally improves the models' performance, albeit not significantly (Saatchi *et al.*, 2008; Parra *et al.*, 2004). Additionally, both models in the present study were successful in predicting areas that are vulnerable to *Lantana Camara* invasion, this is because topographic variables can help to identify areas with suitable soil and moisture conditions, while Sentinel-2 bands can help to distinguish *Lantana Camara* from other vegetation types. The use of topographic variables and Sentinel-2 bands can provide a comprehensive and accurate representation of the spatial distribution of *Lantana Camara*, which can be useful for invasive species management and conservation planning. The use of topographic variables and Sentinel-2 bands can provide a comprehensive and accurate representation of the spatial distribution of *Lantana Camara*, which can be useful for invasive species management and conservation planning.

The models developed in the study had AUC values above 0.80, this indicates that both models (model derived from topographic data and another derived from Sentinel-2 bands) were successful in predicting areas that are vulnerable to *Lantana Camara* invasion. An AUC value above 0.8 is a good classifier. A study by Zhang *et al.* (2019) used Sentinel-2 satellite imagery to map the spatial distribution of invasive Spartina alterniflora in the Yangtze River estuary in China. The authors used supervised classification techniques and several vegetation indices derived from Sentinel-2 bands to classify different land cover types, including invasive*Spartina* and obtained an AUC of 0.87. Another study by Zhao *et al.* (2018) used remote sensing data from Landsat and the Shuttle Radar Topography Mission (SRTM) to investigate the spatial patterns and drivers of invasive *Amaranthus retroflexus* in the Loess Plateau of China. The authors used maximum entropy modelling (MaxEnt) to analyze the relationships between invasive plant distribution and environmental variables, such as topography and climate and obtained an AUC of 0.89. Finally, A study by Singh and Kushwaha (2013) used MaxEnt modelling to analyse the distribution patterns of *Lantana Camara* in the Rajaji National Park in India. The authors used environmental variables, such as topography, climate,and soil, to predict the potential habitat suitability of *Lantana Camara* in the study area and obtained an AUC of 0.93. Overall, remote sensing and machine learning models, such as MaxEnt, have become popular tools for predicting and mapping the spatial distribution of invasive species. These models often incorporate multiple data sources, including satellite imagery, topographic data, and environmental variables, to improve prediction accuracy and understand the drivers of invasion.

CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

Lantana Camara is an IAPs found across the subtropical and tropical areas (Day 2009). Due to its high-water consumption, the growth of this deadly weed into ecosystems can cause significant disruption to indigenous flora. Before suitable management techniques can be adopted, the geographical extent of an IAP must be determined. For mapping the spatial distribution and arrangement of *Lantana Camara*, precise methodologies capable of depicting species information are required. *Lantana Camara* has been mapped extensively, however most of these studies have focused on regional scale mapping, with little effort on the local scale. It is important to highlight, however, that most of the areas impacted by *Lantana Camara* on a small scale are mostly utilized for subsistence agricultural production.

The study aimed to investigate the spatial patterns of *Lantana Camara* across the topography of the Inkomati catchment of Mpumalanga, South Africa. The findings highlighted the effectiveness of using multispectral remote sensing satellite imagery in accurately detecting, mapping, and assessing changes in *Lantana Camara*. Sentinel-2, with its improved spectral and spatial resolution, was found to be a practical and suitable primary data source for regional applications, especially in areas with limited resources. The newly launched high-resolution Sentinel-2 multispectral sensor was found to be capable of detecting and mapping *Lantana Camara* at both local and regional scales. The study used the Random Forest classifier to track the spatial distribution of *Lantana Camara*, and the results showed that the weed is highly concentrated in the north-eastern part of the study area. The Random Forest classifier was found to be an efficient method for mapping the spatial distribution of *Lantana Camara*, yielding high accuracy.

Findings of the study when explaining and modelling areas vulnerable to *Lantana Camara* invasion found that topographic and remotely sensed variables have a significant impact on the invasion of *Lantana Camara*. Both models showed predictions that were better than random, with varying strengths depending on the variables used. However, the model that used a combination of topographic variables produced the highest AUC score. While other topographic variables also play a role in *Lantana Camara* invasion, elevation was found to be the primary variable that influences *Lantana Camara* invasion. These findings provide a basis for identifying areas that require management and control interventions for *Lantana Camara*

The study shows that areas with low elevation, a gentle slope, high TPI, and low TWI are more vulnerable to the invasion of *Lantana Camara* than other areas. The models developed in the study had excellent performance with AUC scores exceeding 0.80. The model that used topographic variables had the highest accuracy and performed the best. Furthermore, the results indicate that elevation is the most critical variable in the invasion of *Lantana Camara* compared to the other variables utilised in this study.

6.2. Recommendations

The growth of invasive alien plants (IAPs) in South Africa is a significant issue, and the findings of this study could aid in the development of conservation strategies and the preparation of conservation areas to combat the spread of IAPs. This information is crucial for environmentalists, policymakers, and landscape architects to identify areas prone to *Lantana Camara* invasion and establish early response mechanisms. The study provides valuable insights into the spatial distribution of *Lantana Camara* and demonstrates the effectiveness of SDMs in identifying the factors that contribute to its spread in sensitive locations. However, while this study provides useful information, future research is needed to gain a deeper understanding of the invasion. This study therefore recommends the following:

• Conducting research to identify locations at risk of IAPs invasion by permitting broad differentiation between uninvaded and invaded areas, as well as the integration of various variables such as climatic and soil data for improved invasion modelling.

• Particularly near rivers or in countries with a shortage of water like South Africa, it is important to establish how much water *Lantana Camara* uses as well as how much it loses over time. The data gathered can aid in determining which areas are most affected by the species, making it easier to prioritize eradication efforts.

• Long-term monitoring and seasonal modelling of *Lantana Camara* on a larger scale are necessary to determine the rate of invasion and the required number of control strategies.

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