Spatial modelling of invasive species distribution in water-limited environments using remotely sensed data and climatic scenarios in the Heuningnes catchment, South Africa

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ABSTRACT

The occurrence and spread of Invasive Alien Plants (IAPs) is a threat to global water resources and natural ecosystems due to high water use rates. With the current climate change projections and their ability to survive extreme environmental conditions, these species pose a huge threat to grazing resources, water availability and ecosystems in general. Routine monitoring and understanding their distribution and potential vulnerable areas is fundamental as it provides the requisite baseline information to guide clearing efforts and other related management and rehabilitation initiatives. It is therefore, imperative to detect, map and monitor the distribution of these species to provide baseline information, which can be useful to guide clearing efforts and mitigating unintended impacts and any further proliferation. The aim of the study was, therefore, to detect and model the distribution of IAPs, using multisource data that is remote sensing, bioclimatic and environmental data to assess how the projected climate changes and variability will affect their distribution in Heuningnes catchment in the Western Cape, South Africa. Heuningnes catchment is part of the Cape Floristic Region in the Western Cape, which is one of the key global biodiversity hotspots. To achieve this, firstly, the ability of two multispectral satellite datasets (i.e. Landsat 8 OLI and Sentinel 2 MSI) to detect and map the current distribution of IAPs was assessed. The results showed that both the two sensors have the ability to detect and map IAPs within the catchment, although Sentinel 2 obtained slightly higher accuracies in terms of the overall accuracy assessment methods. For example, IAPs were mapped with an accuracy of 71% from Sentinel 2 and 65% for Landsat 8 data. However, the McNemar's statistical test results showed no significant difference in the overall classification between the two sensors (*p*-value = 0.53). Secondly, the current and future potential distribution of IAPs were modelled using three different Species Distribution Models (SDMs) namely the Boosted Regression Trees (BRT), Maxent, Random Forest (RF) and their ensemble which combined all the three models. Two Representative Concentration Pathways (RCPs) climate projections were used for best-case (RCP 2.6) and worse-case (RCP 8.5) atmospheric carbon concentration to assess the anticipated potential distribution of IAPs. All the SDMs produced the highest IAPs predictive results. Specifically, RF yielded an Area Under Curve (AUC) value of 0.94 and True Skill Statistics (TSS) value of 0.84, Maxent an AUC value of 0.92 and TSS value of 0.82 and BRT an AUC value of 0.89 and TSS value of 0.70. Further, the overall results indicated that currently, IAPs cover approximately 9% of the catchment area and are likely to increase to 11% under the influence of climate change. In addition, the mean diurnal range, maximum temperature of the warmest quarter and precipitation of the warmest quarter were the most important climatic variables in predicting the future potential distribution of IAPs. The findings of this study highlight the relevance of spatially explicit multisource data in determining the occurrence, spread and areas at risk of infestation to provide baseline information useful in the eradication and rehabilitation frameworks for the affected areas.

Keywords: Biodiversity hotspots; Cape Floristic region; ecosystem restoration; satellite data; species distribution modelling; water scarcity.

PREFACE

This research study was conducted in the Department of Earth Sciences, Faculty of Natural Sciences, University of the Western Cape in South Africa from February 2019 to October 2020 under the supervision of Professor Timothy Dube.

Full name: Bhongolethu Mtengwana Signature: ………… Date: 28 October 2020

As the candidate's supervisor, I certify the aforementioned statement and have approved this thesis for submission.

Full name: Prof. Timothy Dube Signature: ………… Date: 28 October 2020

DECLARATION

I declare that the thesis entitled "**Spatial modelling of invasive species distribution in water-limited environments using remotely sensed data and climatic scenarios in the Heuningnes catchment, South Africa**" is my own work that it has not been submitted before for any degree or examination in any other university. All the sources I have used or quoted have been indicated and acknowledged by means of complete references.

Full name : Bhongolethu Mtengwana Date : 28 October 2020

Signature : …………………

PUBLICATIONS AND MANUSCRIPTS

The following manuscripts have been submitted and published in international peer-reviewed journals and presented in both local and international conferences. The co-authors played a role in reviewing and improving the manuscript with my contribution being the largest.

1. **Mtengwana, B.,** Dube, T., Mkunyana, Y. P. and Mazvimavi, D. Use of multispectral satellite datasets to improve ecological understanding of the distribution of Invasive Alien Plants (IAPs) in a water-limited catchment, South Africa. *African Journal of Ecology*. 2020;00:1-8. https://doi.org/10.1111/aje.12751.
2. **Mtengwana, B.,** Dube, T., Mudereri, B., Shoko, C. and Mazvimavi, D. Modelling the current and future potential distribution of invasive alien plants (IAPs) in the Heuningnes catchment, South Africa under projected climatic scenarios using species distribution models. *GIScience & Remote Sensing.* [Accepted with minor comments]

The research work was presented at the following local and international conferences:

1. 20th WaterNET/WARFSA/GWP-SA Symposium, October 2019, Johannesburg, South Africa
2. 12th GSN SAEON Indibano, September 2019, Cape St. Francis, South Africa

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"It is with great pleasure to honour myself for the perseverance and hard work that I have put through the sleepless nights. Once again, I have proved myself to be greater than what I thought I can achieve." Bhongolethu Mtengwana

DEDICATIONS

This dissertation is dedicated to my:

Mother, Miss N. Mtengwana,
Brother, Sive Mtengwana,
Daughter, Imolathe, and the
Mtengwana family.

"I have done it because I could through passion, perseverance and support."

~ Bhongolethu Mtengwana

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Chapter One

1.1 Introduction

Invasive Alien Plants (IAPs) are plant species occurring in a non-native environments spreading across large geographic ranges posing negative impacts in newly found environments (Preston et al., 2018). These species propagate across the landscape with or without the anthropogenic or natural interference (Asner et al., 2008a, Asner et al., 2008b). The success of IAPs is characterised by the ability to outgrow and replace native species, change disturbance regimes and fundamental ecosystem processes (Asner et al., 2008a). The lack of strong natural preventive mechanisms for IAPs results in successful competition with natural indigenous species resulting rapid spread (Enright, 2000; Rawlins et al., 2011). As such, IAPs will increase and continue to spread even with no new further introductions because of naturalisation (Wilson et al., 2013).

Historically, the spread of IAPs has strongly been globally linked to anthropogenic influences such as disturbances, species movement and plantations for particular benefits although such a process may be natural (Sharma et al., 2005; Parker et al., 2017). For example, the lack of adequate forest resources in South Africa has led to the introduction of alien tree plant species for several benefits such timber and stabilization of sand dunes (King, 1943, Midgley et al., 1997, Bennett and Kruger, 2015). As a result, a significant number of alien plant species have currently established in South Africa (Bennet and Kruger, 2015). These plant species then became invasive, spreading uncontrollably beyond the established areas with the associated negative impacts to natural ecosystems that include threat to economic losses, biodiversity and water resources amongst other impacts (Le Maitre et al., 2002, Le Maitre et al., 2020, Van Wilgen et al., 2001). The impacts of IAPs on water resources may create conservation challenges in regions like South Africa that are ecologically diverse and partly semi-arid due to frequent occurrences of droughts and disturbed rainfall patterns (Bennet and Kruger, 2015). The dense stands of these species where natural vegetation is displaced, result in reduction of surface water runoff, decline in groundwater reserves and increased evapotranspiration (van Wilgen et al., 2008, Van Wilgen et al., 2001). This is of great concern in regions like Southern Africa where the annual rainfall is on average below the global average (990 mm), considering their affinity for water resources and ability to outcompete other plant species (Malisawa and Rautenbach, 2012, Matchaya et al., 2019, Nhamo et al., 2019, Sun et al., 2019). For instance, the southwestern regions of South Africa are susceptible to high concentrations of biological plant invasions and are identified as some of the highly invaded areas (Ntshidi et al., 2018, Kotze et al., 2010). It has also been reported that the majority of these invasions occur in the wetter regions of the country like the Western Cape (Van Wilgen et al., 2001). Recently, South Africa has been strongly affected by water shortages that have been a result of global climatic variability. Therefore, the impacts of IAPs on water resources in invaded regions will result in severe water losses, thereby threatening water security with the worsening climate conditions.

Biological invasions occurring across a wide range of bioclimatic conditions respond significantly to regional and global climate change (Huang and Asner 2009). The spatial distribution of IAPs is, therefore, influenced by climatic conditions. Projected future climate conditions characterised by a declining rainfall and an increase in temperatures may result in further spread and new establishment of IAPs in previously unaffected areas. This is because global climate change can alter species range limits that might promote the expansion of IAPs, thereby further exacerbating their impacts, a great concern for conservation management (Haeuser et al., 2017). Similarly, other environmental changes such as land use and topography can also mediate the rate and spatial pattern of alien plants promoting the process of invasions (Higgins et al., 2004; Huang and Asner, 2009). Some habitats such as those that are fertile, with high availability of water are substantially vulnerable to alien plant invasions (Arianoutsou et al., 2013, Pysek et al., 2010). This makes the wetter regions in South Africa very vulnerable to the impacts due by their spread. It is thus essential to understand the extent of invasion and environmental factors that drive the spread of IAPs to determine their distribution shifts under future climatic conditions (Guan et al., 2020). Understanding how these species respond to particular environments is key in identifying factors influencing their distribution and thus effective management to mitigate the spread through informed decisions. Therefore, an understanding of these factors can be enhanced through early and routine detection, modelling and mapping of their spatial distribution.

To achieve this, there is an increasing need to develop and implement robust approaches to facilitate the management of IAPs. These approaches should be able to frequently monitor their ongoing spread to provide guidance in clearing endeavours and reduce their impacts effectively (Hulme et al., 2009). Currently, the advanced development of technological tools and instruments such as remote sensors and species distribution models (SDMs) are some innovative approaches and techniques that can be advantageous to achieve this task. Remote sensing remains a vital tool for frequently detecting and mapping of the spatial distribution IAPs in order to mitigate and rehabilitate the invaded landscapes (Mutanga, et al., 2018). The improved sensor characteristics also facilitate accurate detection and discrimination of these species from other land cover types. The derived maps showing invaded areas are important for decision making to manage species occurrence and spread as well as scaling their impacts (Shaw, 2005; Bradley, 2013). Similarly, SDMs have been increasingly used to determine the ecological response of alien plant species in order to understand their invasion process (Guisan and Thuiller, 2005, Booth, 2018). The underlying principle behind SDMs is to relate the occurrence of species to environmental variables to obtain ecological and evolutionary insights (Elith and Leathwick, 2009, Higgins et al., 1999). Unlike remote sensing, which only uses spectral characteristics to detect the spatial distribution of these species, these models use statistical approaches to model the probability occurrence based on a set of bioclimatic, environmental and topographic variables. The assumption behind the statistical approach for predicting species distribution is that the response of the current species distribution is influenced by a set of environmental factors (Higgins et al., 1999). However, integrating remotely sensed data with other spatial datasets in SDMs yields high classification results, thus more accurate predicted distribution of species (Rozenstein and Karnieli, 2011). Therefore, adopting this approach has a great potential and positive impact in management strategies, through understanding of the magnitude and extent of alien plant invasions to justify eradication and control (Le Maitre et al., 2002).

The abundance of invasive species continues to grow regardless of the growing efforts of eradication and management (Müllerová, Pergl and Pyšek, 2013). Once IAPs become established, eradication is often difficult and expensive with the possibility of previously cleared invaded areas resulting in secondary invasions (Denslow, 2007, Ogden and Rejmanek, 2005). The early detection of invasive species for management efforts is often difficult to achieve and the management of invaded areas demands significant efforts and resources (Muthukrishman et al., 2018). To avoid the associated negative impacts, strategic management of IAPs is required (Terblanche et al., 2016). Thus, predicting invasion risk areas will help to justify and prioritize control (lodge et al., 2006). This can be achieved by using and implementing knowledge sound approaches such as remote sensing techniques and Species Distribution Models (SDMs) to understand the occurrence and evolution of these species. Therefore, detecting the current and potential distribution of future invasions will greatly contribute in active monitoring and management of IAPs to reduce the impacts they pose on water resources to meet current and future demands.

1.2 Aim and objectives

The aim of this study was to detect and model the distribution of alien invasive plants using satellite remote sensing, environmental and climatic data.

The specific objectives are:

1. To compare the performance of Landsat 8 and Sentinel 2 multispectral data in detecting and mapping invasive alien plants in the Heuningnes Catchment, Western Cape province of South Africa.
2. To predict the potential distribution of IAPs in the catchment using multisource data for best-case (RCP2.6) and worse-case (RCP8.5) climatic projection scenarios.

1.3 Research questions

- How does varying sensor characteristics affect the detection and mapping of IAPs at catchment scale?
- What is the influence of remote sensing data in prediction distribution of IAPs using SDMs?
- Which environmental and climatic factors influence the distribution of IAPs in the Heuningnes catchment in the Western Cape, South Africa?
- How will the distribution of IAPs change with projected changes of climatic conditions?

1.4 Conceptual framework

This study utilises the application of Geographic Information System (GIS), remote sensing and Species Distribution Models (SDMs) in detecting, modelling and mapping the distribution of IAPs.

Figure 1.1 shows the conceptual framework of the study in determining the current distribution of IAPs and the suitable areas based on current and future climatic conditions. The outputs of the study are likely to be informative in managing the spread of IAPs. The first objective is focused at comparing the ability of Landsat 8 and Sentinel 2 in detecting the spatial distribution of IAPs and discriminating these plant species from other land cover types, particularly vegetation types. The two new generation multispectral satellite data sets vary in spatial and spectral resolution with Sentinel 2 having improved characteristics compared to Landsat 8. Therefore, it is critical to identify a better platform for accurate detection and mapping of these species and determine to what extent these sensors vary in detecting and discriminating IAPs. The output results will be two classified satellite images, which show the current extent and distribution patterns of IAPs. Further, the satellite image, which discriminated IAPs better than the other, will then be incorporated in objective two, which is to model and determine the suitable areas for IAPs distribution under best-case and worse-case climate projections. Multisource data namely bioclimatic, environmental and the incorporation of remote sensing data were used for modelling the current and future suitable areas of IAPs for both best-case and worse-case climate scenarios. Remote sensing satellite data was incorporated to improve the discrimination ability, thus improving the model predictions and providing reliable estimates by using multiple strong predictive SDMs. The important predictor variables, which largely facilitate and contribute to the spread of IAPs, were also determined.

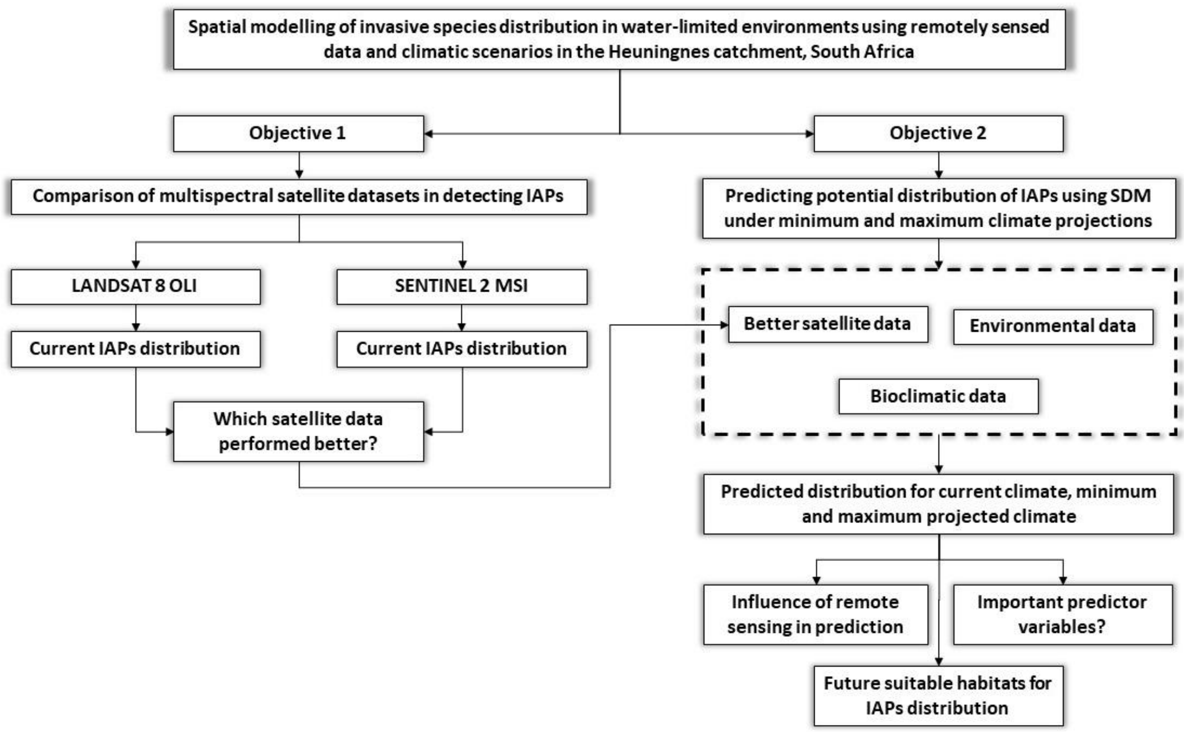

Figure 1.1: Conceptual framework of the study.

1.5 Significance of the study

Timeous information on the distribution IAPs is needed in order to inform management practices in clearing IAPs. The study provides spatially explicit framework for IAPs detection and mapping. It also provides an explicit approach for the development of proactive management strategies to help mitigate the spread and impacts of these species. Further, this study also provides a baseline information on the spatial distribution of IAPs in Heuningnes catchment. Such information is useful for the identification of priority areas for targeted clearing of IAPs in line with the global and local biodiversity conservation initiatives. This will thus contribute into making informed decisions on effective management approaches and proactive monitoring for the spread of IAPs to prevent further spread in future.

1.6 Study area description

1.6.1 Location

The Heuningnes catchment is located within the Overberg region in the Western Cape Province in South Africa (Figure 1.2). It lies between the latitudes 34°19` S  and 34°50` S and longitudes of 19°35` E and 20°18` E, covering a relatively small area of approximately 1 938 km² (Bickerton, 1984). This catchment forms the southernmost part of the African continent and divides the Indian Ocean and Atlantic Ocean. The catchment has five quaternary catchments (G50B, G50C, G50D, G50E and G50F) with three inland towns Bredasdorp, Napier, Elim and three coastal towns Cape Agulhas, Struisbaai and Molshoop.

The elevation ranges in catchment varies from sea levels up to approximately 837 m above sea level (Figure 1.2) (Mazvimavi et al., 2018). The lower part of the catchment is relatively flat and gentle with the southwestern areas characterised by mostly coastal lowlands at less than 60 m. The upper part in the northeast of the catchment is mountainous with gradual and steeper slopes.

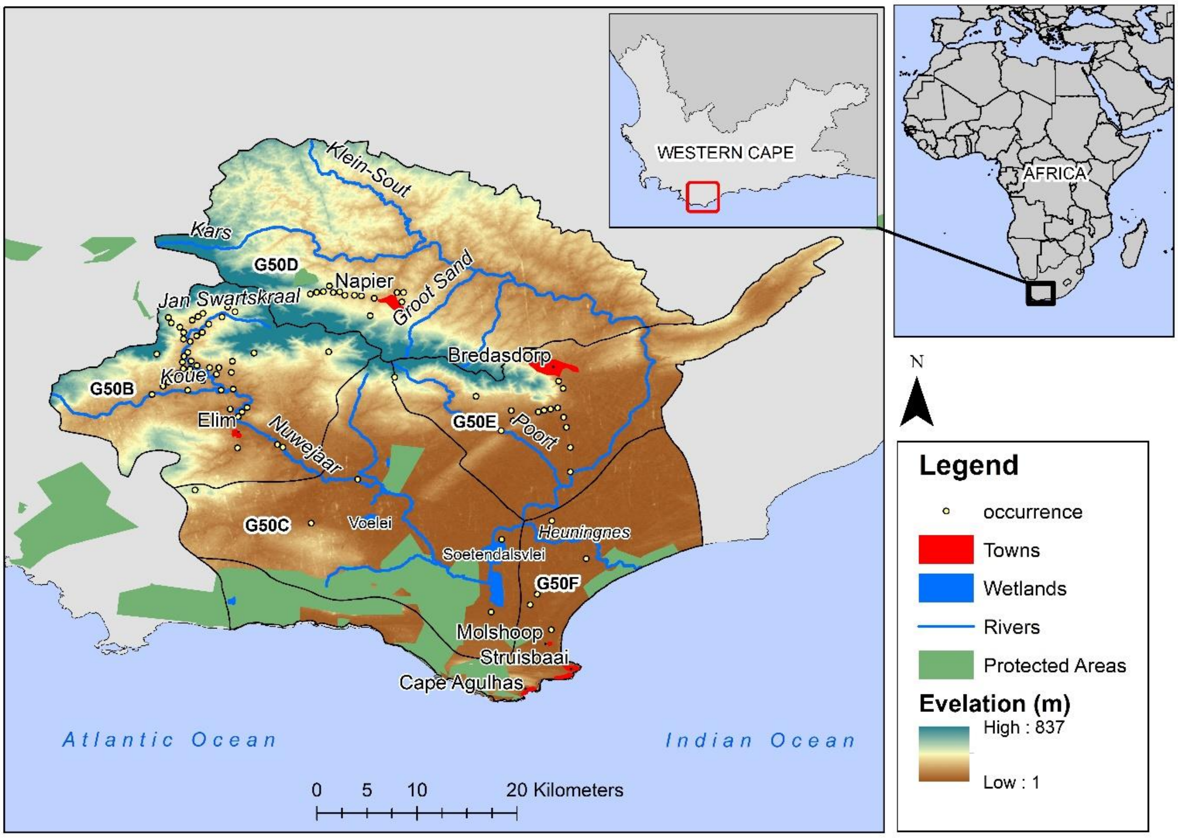

Figure 1.2. The location of Heuningnes catchment showing situated in Cape Agulhas, Western Cape, in South Africa.

The catchment lies within a Mediterranean climate region characterised by hot dry summers (November to March) and wet cold winter seasons (May to August) caused by orographic effects due to the presence of mountains (Midgely et al., 2003). The mean maximum temperatures in summer can reach up to 27 °C with mean minimum temperatures below 10 °C (Mkunyana et al., 2018). The average annual rainfall in the catchment is 500 mm/year (Kraaij et al., 2009) but varies from 400 mm/year in the lowlands to 675 mm/year in the mountains, which form the headwaters. Most of the rainfall occurs during winter and the annual average A-pan evaporation rate is 1445 mm/year. The cold fronts experienced in this area are associated with westerly winds and the moisture during the year is transported from the Indian Ocean onto the southern mountains and coastal plains of the region (Midgeley et al., 2003).

1.6.2 Hydrology

The catchment has a complex hydrological system characterised by several tributaries, wetlands and pans (Figure 1.2). The Kars River and the Nuwejaar River, which passes through the Soetendalsvlei, are the main tributaries of the Heuningnes River. The Kars River runs 75 km to its confluence to Soetendalsvlei while the Nuwejaar River runs 55 km from its primary source to Soetendalsvlei (Marnewick et al., 2015). The pans and wide floodplains dominate on the southwestern part of the catchment that is low lying. The Soetendalsvlei is the largest lake in the catchment with about 3 km wide and 8 km long and drains into the Heuningnes River that joins the Indian Ocean. Other pans include the Voevlei (4 km by 1.7 km), Soutpan (1.3 km by 1.9 km), Longpan (1 km by 0.5 km), and Roundepan (0.6 km by 0.4 km). The major lakes are found on the low-lying areas located on the south and east of the catchment (Mkunyana et al., 2018).

1.6.3 Geology

The geology is dominated by the Bredasdorp, Bokkeveld and Table Mountain Group. The Bredasdorp beds which consist of calcite sand dunes underlie the majority of the low-lying areas that are located south and lower east of the catchment where the major lakes are found (Mkunyana et al., 2018). The Table Mountain Group quartzite and sandstones dominate the Kars River upper catchment while the Bredasdorpberge shale dominates in the southern parts and the Bokkeveld shale occurs in the undulating northern parts. The Malmesbury and the Peninsula Granite, which intruded the Malmesbury group and exposed because of uplift and erosion dominates the upper catchment of the Nuwejaars River. The soils in the catchment comprise of mainly material derived from sandstone with uncommon occurrence of calcareous soils (Midgeley et al., 2003). The coastal platforms are associated with the duplex soils, where sands overlie heavier subsoils (Midgeley et al., 2003).

1.6.4 Land cover, biodiversity and conservation

The major land uses are dryland crop cultivation (wheat, barley, canola), livestock production (cattle and sheep), vineyards, and growing of indigenous flowers (Mazvimavi, 2018; Mkunyana et al., 2018). The land cover of the plain is mostly characterised by farmlands, and shrubs. The build-up area is not very extensive, making the large proportion of the area largely natural (Apedo, 2015). This catchment is species and endemic-rich as it forms part of the Cape Floristic Region which is rich in biodiversity. The established plant endemics are often within a restricted range (Midgeley et al., 2003). The *sclerophyllous* shrub, fynbos is the main indigenous vegetation, with species belonging to *Proteaceae, Ericaceae, Restionaceae* and *Irididaceae* families (Munica and Rutherford, 2006; Privett, 2002; Bek et al., 2013; Midgeley et al., 2003; Tylor, 1978). There are five protected areas within the study area namely the De Mond nature reserve, Heuningnes private nature reserve, Andrewsfield private nature reserve, Agulhas national park and Heuningberg nature reserve.

1.6.5 Management of the established IAPs

The National Invasive Alien Plant Survey done by Kotzé et al. (2010) and work by Le Maitre et al. (2000) showed that the Cape Agulhas area of the Western Cape Province of South Africa had the greatest proportion of over 60% of the land area being affected by IAPs. The Heuningnes catchment, which is situated in this region, is one of the severely affected catchments by IAPs. *Eucalyptus*, *Pinus* and *Acacia* (*Acacia longifolia*, *A. cyclops* and *A. saligna*) are the most dominant species in the Heuningnes catchment (Nowell, 2011). These IAPs threaten the ecosystem and protected areas, with frequent fires and clearing activities taking place to control the spread of these species. Previous studies in this catchment found that these IAPs mostly occurred along riparian zones and hillslopes and were rapidly spreading (Mazvimavi, 2018; Mkunyana, 2018). The landowners in this catchment formed a forum to coordinate and implement clearing of IAPs on a continuous basis. Therefore, both the Working for Water Programme and landowners require information about changes on an annual basis of areas with IAPs, in order to identify areas for prioritised clearing. Due to this demand for information about the spatial distribution of IAPs, the Heuningnes catchment was selected for the study presented in this dissertation.

1.7 Thesis outline

General outline of the structure

This dissertation is comprised of five chapters which include two standalone manuscript articles (chapter two and three) that are based on each objective. These two standalone manuscripts have been presented as published in scientific journals to retain their original content with minor changes. However, repetition of some content or overlaps may occur due to coherence of each standalone manuscript to the overall aim of the study. But this has been reduced to minimum.

1.7.1 Chapter One

This chapter provides an overall overview about the background of the research conducted on the subject. It also presents research questions, as well as outlines the main aim and objectives of the study.

1.7.2 Chapter Two

Accurately detecting the distribution of IAPs is important in understand their current spatial distribution. This chapter is based on objective one of the dissertation which is to detect the abundance and distribution of IAPs by assessing the ability of the two multispectral satellite datasets namely Landsat 8 and Sentinel 2 in discriminating these species from other land cover types. Both satellite datasets are readily available for earth observation application such as land cover monitoring with Sentinel 2 having higher spatial and spectral resolution than Landsat 8. Having Landsat 8 providing long historical data at a coarser resolution, the recently launched Sentinel 2 provides an opportunity for species detection at improved resolution that can be advantageous for small-scale mapping and eradication and clearing initiatives.

1.7.3 Chapter Three

The spread of IAPs is likely to expand rapidly in the future due to projected climatic changes that can will great negative impact on water resources as a result of expected reduction in rainfall. This chapter is based on objective two, which focuses on the prediction of areas within the Heuningnes catchment that are favourable to the growth of IAPs using multisource data. Further, the chapter provides detail on the key factors that largely contribute to the spread of IAPs in the catchment. The combined use of SDMs with remote sensing data in modelling the spatial distribution of IAPs is investigated. Having identified a better sensor with suitable spectral and spatial from the previous chapter, Sentinel 2 data was used to improve model predictions.

1.7.4 Chapter Four

This chapter provides a detailed synthesis of the main findings of the study. The chapter also further includes major conclusions and recommendations drawn from the dissertation.

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Chapter Two

Use of multispectral satellite datasets to improve ecological understanding of the distribution of Invasive Alien Plants (IAPs) in a water-limited catchment, South Africa

Abstract

Invasive Alien Plants (IAPs) pose major threats to biodiversity, ecosystem functioning and services. The availability of moderate resolution satellite data (e.g. Sentinel 2 Multispectral Instrument and Landsat 8 Operational Land Imager) offers an opportunity to map and monitor the occurrence and spatial distribution of IAPs. The use of two multispectral remote sensing datasets to map and monitor IAPs in the Heuningnes catchment, South Africa, was therefore investigated using the maximum likelihood classification algorithm. It was possible to identify areas infested with IAPs using remote sensing data. Specifically, IAPs were mapped with a higher overall accuracy of 71% using Sentinel 2 MSI as compared to using Landsat 8 OLI, which produced 63% accuracy. However, both sensors showed similar patterns in the spatial distribution of IAPs within the hillslopes and riparian zones of the catchment. This work demonstrates the utility of the two multispectral datasets in mapping and monitoring the occurrence and distribution of IAPs, which contributes to improved ecological modelling and thus to improved management of invasions and biodiversity in the catchment.

Keywords: Agroecosystems; catchment scale; fynbos-dominated ecosystems; satellite data; water scarcity.

This chapter is based on the following manuscript:

Mtengwana, B., Dube, T., Mkunyana, Y.P., Mazvimavi, D. 2020. The use of multispectral satellite data to improve ecological understanding of the distribution of Invasive Alien Plants (IAPs) in a water-limited catchment, South Africa. *African Journal of Ecology*. 2020;00:1-8. https://doi.org/10.1111/aje.12751.

The research work was also presented at both international conferences:

- 20th WaterNET/WARFSA/GWP-SA Symposium, October 2019, Johannesburg, South Africa
- 20th SAEON Indibano, September 2019, St. Francis, South Africa

2.1 Introduction

The spreading of invasive alien species is a global problem. A review by Turbelin et al (2017) established that in terms of the number of occurrences of alien species, the USA, New Zealand, Australia and South Africa were the leading countries. However, small island states such as the Reunion, French Polynesia, and Fiji were highly affected with number of alien species ranging from 914 to 6890 species per 100,000 km^2. Alien species out-compete and cause a decline in the number of indigenous species. Terrestrial alien plants also increase the frequency and intensity of fires (Pyšek et. al., 2012; van Wilgen and Richardson, 2012). Initially, Invasive Alien Plants (IAPs) were introduced in different countries for economic development and to curb environmental problems. For example, *Prosopis* was introduced in Sudan to curb desertification. In South Africa they were introduced during the 19th century for the supply of timber (*e.g. Eucalyptus, Pines*), fodder (*e.g. Acacias, Prosopis*) and stabilization of dunes (*Acacia*) (Bennet and Kruger, 2015). However, these species have become problematic and expand at unprecedented rates. For example, in South Africa, the condensed area covered by the different IAPs is currently equivalent to 8% of the country's total land area and 16% of the Western Cape Province (Le Maitre et al., 2000).

South Africa is predominantly semi-arid to arid, with an average annual rainfall of approximately 464 mm/year of which 8% forms surface runoff. Mountainous areas, which cover 8% of South Africa's land area generate over 50% of the surface runoff and are considered to be strategic water source areas for the whole country (Nel et. al., 2013). However, the spread of IAPs into these mountainous areas is a major threat to the availability of water resources. Le Maitre et al. (2000) estimated that the presence of IAPs causes 7% decrease in the available water due to the increase of transpiration losses. The most problematic IAPs in South Africa are the *Australian Acacia, Eucalyptus* and *Pinus* genera (Chamier et al., 2012, Dzikiti et al. 2013a,b, and Meijninger and Jarmain, 2014). Studies done in the Cape Agulhas showed that IAPs were consuming water equivalent to the long-term average runoff (Mazvimavi, 2018, Mkunyana, et. al 2018). Due to the considerable adverse effects of IAPs on water resources, the South African government launched the Working for Water Programme in 1996 focusing on clearing IAPs (Le Maitre et. al., 2000). Landowners such as those in the Cape Agulhas are also involved in clearing programmes. The effectiveness of clearing programmes depends on knowledge about the spatial distribution of IAPs. This requires routine monitoring since the spatial distribution of IAPs often rapidly increases over a year in some locations. National surveys of the spatial distribution have been undertaken, e.g. Southern African Plant Invaders Atlas (Henderson, 1998, Versfeld *et al.*, 1998), National Invasive Alien Plant Survey (Kotzé et al., 2010). However, such surveys undertaken after a lengthy period e.g. 10 years, do not provide information necessary for implementing effective clearing on an annual basis. The availability of remote sensing data offers the opportunity to monitor the changes in the spatial distribution of IAPs on an annual basis and thus assist in identifying areas to be targeted for routine clearing.

Data from Landsat 8 OLI (LT8), which has a spatial resolution of 30 m and a 16-day revisit time, and Sentinel 2 MSI (S2), with the spatial resolution of 10 to 20 m and a 5-days revisit time, offer an opportunity to establish the spatial distribution of IAPs at time intervals suitable for developing routine clearing programmes. For example, a study by Dube *et al.* (2017a) showed that the spatial distribution of IAPs could be established using Landsat 7 data. The study presented in this paper, thus, has the objective of evaluating the feasibility of determining the spatial distribution of IAPs in the Heuningnes catchment, South Africa both using LT8 and S2 satellite data. The study used the datasets from the two satellites in order to identify which data source would be more appropriate for accurately mapping the distribution of IAPs in the catchment.

2.2 Materials and methods

2.2.1 Field data collection

This study required ground data on the occurrence of IAPs in order to assist in the classification and validation of land cover types from satellite images. Therefore, ground data were collected during August 2018 that coincided with flowering period of most IAPs in the catchment. A plot size of 30 m × 30 m was used to collect GPS locational data on individual species within the plot. This was solely informed by other works in literature that have compared the two satellite sensors in vegetation mapping or other-related types of works (Abdullah et al., 2019, Clark, 2017, Forkuor et al., 2018). Species locations were recorded, using the eTrex 10 Garmin GPS with an error margin of 3.65 m (Garmin, 2019). Three hundred and sixty-five ground truth points representing different land cover types were identified and recorded. The minimum distance between the GPS points was at least 100 meters to avoid over sampling and adequately capture the species distribution. The observed vegetation classes included cultivated lands, natural shrubs (fynbos), alien shrubs and invasive tree species namely *Acacia cyclops, A. longifolia, A. saligna, Eucalyptus, Hakea* and *Pines.* Figure 2.1 shows typical IAPs co-occurring within the Heuningnes catchment.

Figure 2.1. Typical examples of IAPs co-occurring in the Heuningnes catchment.

2.2.2 Satellite data acquisition

The LT8 and S2 satellite datasets with varying spatial and spectral resolution were acquired to assess their capabilities in discriminating IAPs (Table 2.1). The LT8 image was obtained from the online USGS earth observation database (http:/earthexplorer.usgs.gov). The S2 images were obtained from the European Space Agency Copernicus hub.

Table 2.1. Spatial and spectral characteristics of selected Landsat 8 and Sentinel 2 bands.

Landsat 8			**Sentinel 2**		
Band	**Spectral width (nm)**	**Resolution (m)**	**Band**	**Spectral width (nm)**	**Resolution (m)**
Coastal	16	30	Blue	65	10
Blue	60	30	Green	35	10
Green	57	30	Red	30	10
Red	37	30	RE-1	15	20*
NIR	28	30	RE-2	15	20*
SWIR 1	85	30	RE-3	20	20*
SWIR 2	187	30	NIR	115	10
			NIR-narrow	20	20*
			SWIR 1	90	20*
			SWIR 2	180	20*

*indicates bands that were resampled to 10 m.

Three image scenes with minimal cloud cover (T34HCG, T34HDG, and T34HCH) of S2 Level-1C products, covering the study area were acquired for the 24th of August 2018. The LT8 scene (Path 174/Row 84) that fitted the entire study area and with minimal cloud cover was obtained for 18 July 2018. The selected images for both satellites had a cloud cover of less than 2%. The preferences of cloud free images resulted in a five-week difference between images obtained from the two satellites, in which it was assumed that no major land cover changes occurred within this period.

2.2.3 Image processing and classification

Figure 2.2 summarizes the process taken to classify the satellite images. The atmospheric correction for both LT8 and S2 images was done using the Dark Object Subtraction 1 (DOS1) (Chavez 1988). The S2 images contained radiometric and geometric corrections which include orthorectification and spatial registration (ESA, 2015). Further, images from both S2 and LT8 were then re-projected to the Universal Transverse Mercator (UTM) 34 South based on the World Geodetic System (WGS) 84 Spheroid. In S2, the 20 m vegetation red edge bands (5, 6, 7 and 8a) were resampled using the nearest neighbour technique (Baboo and Devi, 2010) to match the 10 m spatial resolution of the visible (VIS) spectrum bands (band 2 to 4) and the Near Infrared (NIR) band 8. The image scenes were further mosaicked to form a single image scene covering the entire catchment. The mean mosaicking operation was applied where images overlapped. It was assumed that since the image scenes were taken on the same day, the averaging of the mean would have a minimal to no difference. For the LT8 data, only bands 1 to 7, which constitute the Coastal, Visible and Near Infrared regions were used. Image band composites were generated using the common geographic information systems tools. The study area was then extracted from the mosaicked and layer stacked image scenes prior to the classification of IAPs.

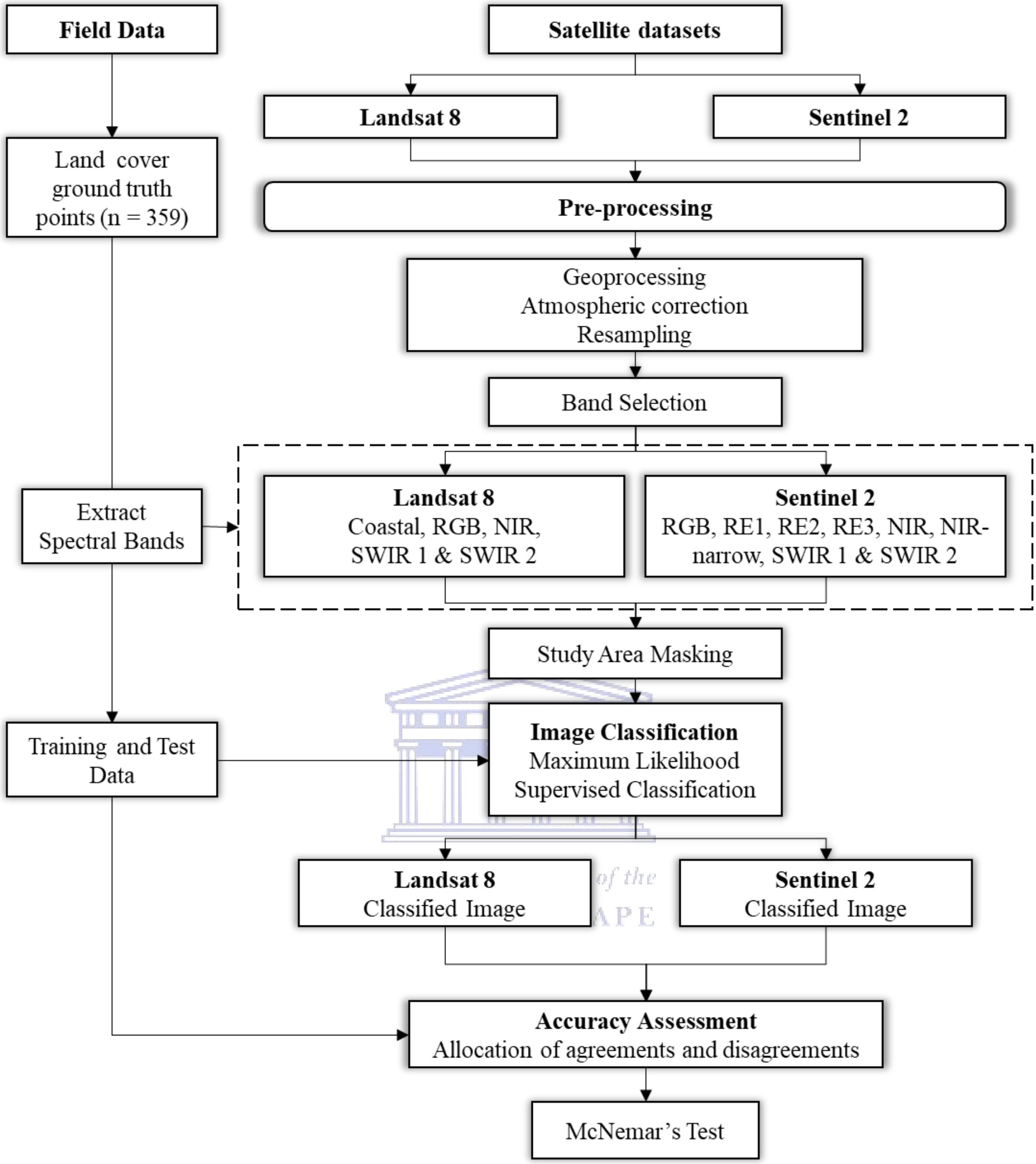

Figure 2.2. Flow chart showing process taken to classify Landsat 8 and Sentinel 2.

The surveyed ground truth points were overlaid on the composite image to create training samples and signature files for image classification. The image classification process made use of raw spectral bands to identify different land cover classes in order to discriminate IAPs from other land cover types. The supervised maximum likelihood classification was used (Sisodia, Tiwari and Kumar, 2014). The following metrics were used to assess the accuracy of image classification; overall accuracy, user and producer accuracy, errors of commission and the errors of omission (Coluzzi et al., 2018). The allocation of agreements and disagreements were determined following Pontius and Millones (2011). The McNemar's test was performed to determine if there were any statistical differences between the two classified images. However, the class areas detected were not reflective of the true estimated size based on the actual acquired accuracies because each land cover type is subjected to accuracy errors. Therefore, the areal extent was further analysed by considering accuracies and errors of each class using the user's accuracy to ascertain the reliability of the model. It is recommended that estimation of the areas invaded should be quantified based on the reference data as it provides the best assessment of ground conditions (Olofsson et al., 2014). The areas covered by IAPs were thus estimated from the classified images. The areal extents of IAPs were assessed by considering accuracies and errors of each class using the user's accuracy to assess the reliability of classification results. The correlation analysis of the areas covered by different land cover types estimated from S2 and LT8 was undertaken.

2.3 Results

2.3.1 Comparison of satellite-derived IAPs distribution at catchment scale

A visual comparison of classification done from the S2 and LT8 images showed similar spatial distribution of IAPs within the catchment (Figure 2.3). IAPs occurred mostly on the hillslopes and riparian zones. As expected, the occurrence of IAPs was limited in areas dominated by crop cultivation, such as the northern part of the catchment. Landowners are likely to clear any woody plant emerging in cropped lands. The IAPs were widespread on the hillslopes of the Koue Mountains, on the north-western part, and Bredasdorp Mountains on the central part. The distribution of areas affected by the IAPs tended to be widespread and patchy, particularly on the southern part on LT8 when compared to the S2 mapping results.

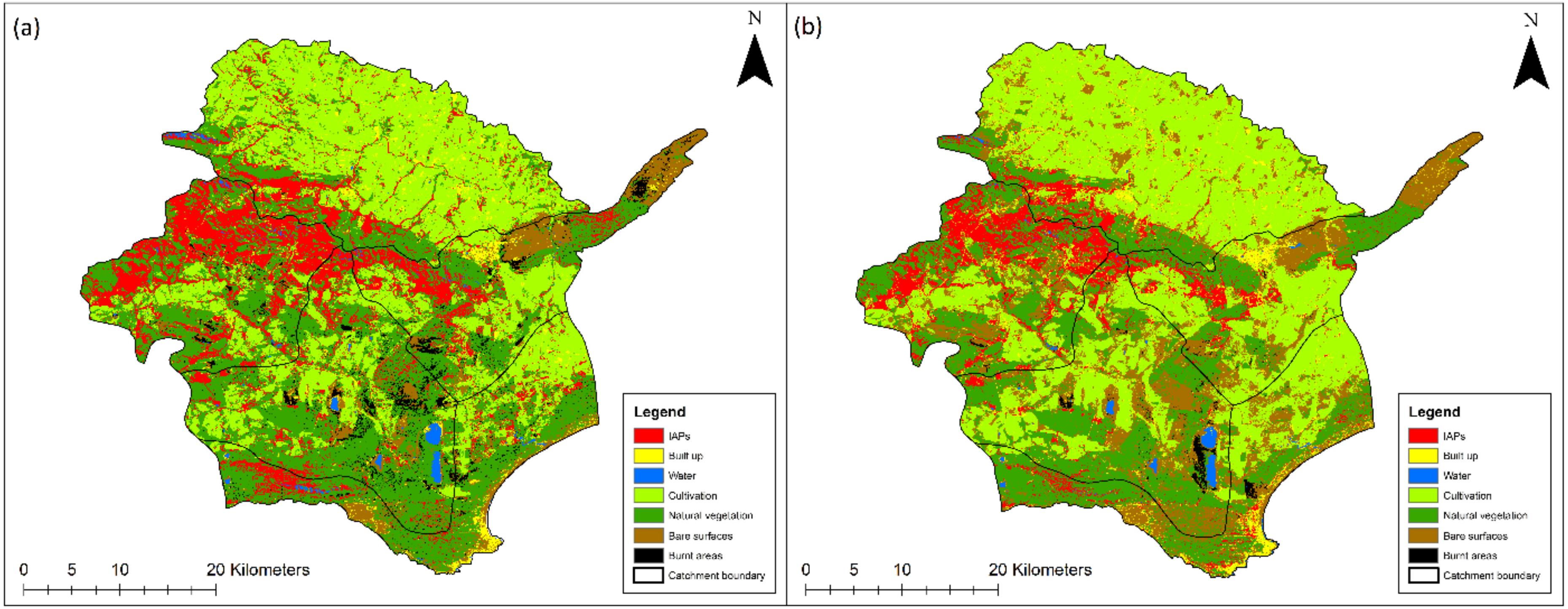

Figure 2.3. Landsat 8 (a) and Sentinel 2 (b) classified images showing discrimination of IAPs from other land cover classes.

2.3.2 Classification accuracy assessments

Table 2.2and Table 2.3 show the accuracy metrics for the classified images of Landsat 8 and Sentinel 2. The classification of LT8 image (Table 2.2) had an overall accuracy of 63% whereas 71% was observed for the S2 image (Table 2.3). For IAPs, the S2 classification obtained better user's accuracy (UA) (67%) and producer's accuracy (PA) (90%), while these accuracy metrics were 56% and 65%, respectively for the LT8 image. The natural vegetation class was mapped, with a similar UA of 58% for both S2 and LT8. However, the PA for the natural vegetation were 83% for S2 and 41% for LT8.

When considering the accuracy differences in class detection within the same satellite, the LT8 similarly represented IAPs and the natural vegetation with a negligible difference in UA (1.27%), but with better PA than natural vegetation due to high omission error. Using the S2, the UA and PA for IAPs were both greater than that of the natural vegetation, with differences of 9.58% and 6.91%, respectively. Overall, the results showed that the S2 performed better than the LT8, when comparing the capability of detecting and mapping both IAPs and natural vegetation.

The allocation of agreements for the IAPs were higher than the allocation disagreement measures (i.e. commission and omission) for both the S2 and LT8 classified images (Figure 2.4 (a) and (b)). However, the allocation of agreements for the S2 (Figure 4(b)) were generally higher when compared to those of the LT8 (Figure 2.4 (a)), for all the land cover types. Overall, the classification of the S2 image had lower disagreements than that of the LT8, across the land cover types. Classification of LT8 had an overall disagreement of 37%, while this was 29% for the S2. The omission for the natural vegetation mapped from the LT8 was very high, at 14% when compared to the 2% for the S2. This could explain the low PA for the natural vegetation in the LT8 image classification results. The classification of the LT8 had a greater quantity and allocation disagreement (19%) when compared to that of the S2 (15%). The results showed that the S2 was slightly better than the LT8, at detecting and discriminating the IAPs. However, the McNemar's statistical test results showed that the performance between the two sensors was not significantly different (p-value = 0.5254).

Table 2.2. Error matrix results for Landsat 8 OLI image classification.

L8	**IAPs**	Built up	Water	Cultivation	Natural vegetation	Bare surfaces	Burnt areas	Total	UA (%)
IAPs	31	8	0	1	13	2	0	55	56
Built up	0	21	0	1	4	5	0	31	68
Water	5	4	31	2	6	7	0	55	56
Cultivation	2	1	1	51	11	0	0	66	77
Natural vegetation	6	5	0	5	34	8	1	59	58
Bare surfaces	4	7	0	4	5	44	0	64	69
Burnt areas	0	3	0	0	10	2	14	29	48
Total	48	49	32	64	83	68	15	359	
PA (%)	65	43	97	80	41	65	93		
Overall accuracy (%)	63								

Table 2.3. Error matrix results for Sentinel 2 image classification.

S2	IAPs	Built up	Water	Cultivation	Natural vegetation	Bare surfaces	Burnt areas	Total	UA (%)
IAPs	37	11	0	2	1	4	0	55	67
Built up	1	26	0	0	0	5	0	32	81
Water	2	7	35	1	1	5	0	51	69
Cultivation	1	9	0	56	1	4	0	71	79
Natural vegetation	0	5	0	1	30	15	1	52	58
Bare surfaces	0	4	1	8	1	55	0	69	80
Burnt areas	0	1	0	0	2	10	16	29	55
Total	41	63	36	68	36	98	17	359	
PA (%)	90	41	97	82	83	56	94		
Overall accuracy (%)	71								

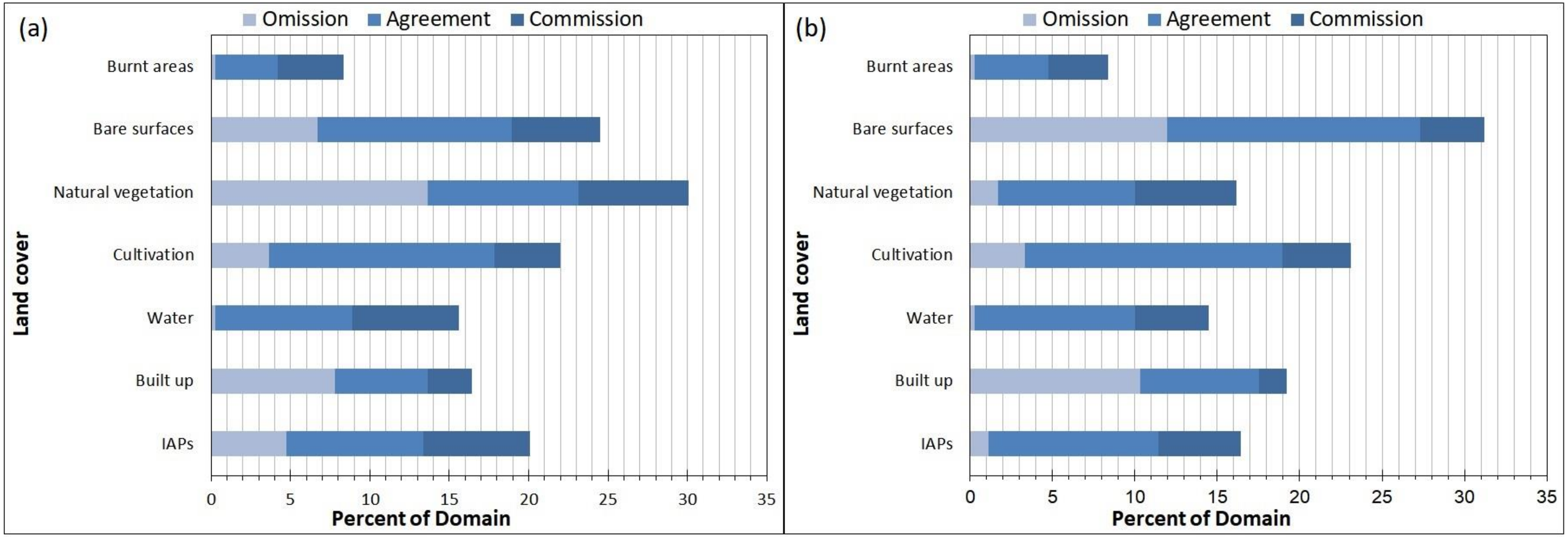

Figure 2.4. Allocation of agreements and disagreements for (a) Landsat 8 and (b) Sentinel 2.

2.3.3 Estimation of the spatial coverage of IAPs as detected by LT8 and S2

The area covered by the IAPs based on the classification of the LT8 images was approximately 22% of the catchment area (~31424 hectares), while the estimated based on the S2 was 13% (~17945 hectares) Table 2.4. It is further shown that the accurately detected area for IAPs was approximately 17 712 hectares (13%) and 12 072 hectares (9%) by the LT8 and S2, respectively. LT8 showed a major difference between the total detected and the accurately detected area, while S2 still retained the 9% cover for the IAPs. It can also further be observed that the area occupied by the IAPs as derived from the LT8 was greatly overestimated when compared to that of the S2. However, the correlation test between the derived areas generated from the two satellites showed a strong relationship between the detected (0.86), accurately detected (0.87) and the undetected (0.91) areas. The opposite was observed for the overestimated areas with a very weak agreement (0.26) between the estimated areas for the two satellites. Both satellite images showed an overestimation in different classes. In total, LT8 obtained a higher overestimation percentage compared to S2.

Table 2.4. Areal estimates of land cover types for Landsat 8 and Sentinel 2 based on classification results in hectares and percentages.

	Area (hectares)							
	Detected		Accurately Detected		Not Detected		Overestimation	
	LT8	**S2**	**LT8**	**S2**	**LT8**	**S2**	**LT8**	**S2**
IAPs	31424	17945	17712	12072	13712	5873	11129	1751
Built up	5703	9867	3863	8017	1840	1850	3259	5795
Water	1534	1216	865	835	669	382	48	34
Cultivation	66197	76367	51152	60233	15045	16134	13446	13476
Natural vegetation	70503	49191	40629	28379	29874	20812	41622	8198
Bare surfaces	13301	37810	9144	30138	4156	7672	4694	16590
Burnt areas	4898	1169	2365	645	2534	524	327	69
Total	**193561**	**193565**	**125730**	**140319**	**67831**	**53245**	**74526**	**45913**
IAPs Area (%)	16	9	14	9	20	11	15	4
Correlation	**0.86**		**0.87**		**0.91**		**0.26**	
Accurately Detected (user's accuracy), **Not Detected** (omission error), **Overestimated** (commission error)								

2.4 Discussion

The main aim of this chapter was to detect and map the spatial distribution of IAPs, using the LT8 and S2 multispectral remote sensors in the Heuningnes catchment, the Western Cape, South Africa. The accurate detection of the IAPs is important to provide accurate information on their occurrence and their spatial distribution for the rehabilitation of the affected areas and related-management strategies.

The results showed that the S2 images provided a better representation of the distribution of the IAPs and the other land cover types in comparison to the LT8 images. The observed results showing the capability of the S2, in this study are confirmed by other recent studies, which have demonstrated its unique ability to outperform the LT8, with better accuracies. Thamaga and Dube (2018) also found that S2 performed better in discriminating water hyacinth when compared to the LT8. Rajah et al. (2018) reported that the S2 images were appropriate for the mapping invasive species across different seasons.

The higher spatial and spectral resolutions of the S2 when compared to the LT8, contributes to the improved detection of the IAPs. The higher spatial resolution of the S2 reduced the problem of mixed pixels, while the spectral resolution contributed to the better classification of the IAPs because of the improved classes' discrimination (Li et al., 2019). This is also evident in this study that used 10 bands for the S2, and 7 bands for the LT8 for the image classifications. The S2 has an increased number of four red edge (RE) bands and two near-infrared (NIR) when compared to the LT8. This increased the ability of the S2 to discriminate vegetation (Cho et al., 2012; Shoko and Mutanga, 2017). Consequently, the S2 had an improved discrimination of the IAPs and the natural vegetation class when compared to the LT8 image. This is evident from the comparison of the overall, user's and producer's accuracy metrics. Other studies have also found that the use of the near-infrared (NIR), red edge (RE) and shortwave infrared (SWIR 1, SWIR 2) bands improved the discrimination of different vegetation types (Astola et al., 2019, Li et al., 2019, Forkuor, 2018, Thamaga and Dube, 2018, Dube et al., 2017).

On the other hand, the LT8 showed more overestimation of the IAPs than the S2 image. The high overestimation by the LT8 is evident when analysing the differences in the distribution of the IAPs in comparison to the S2 because the commission errors and omission errors were general higher for the LT8 than the S2. This can be ascribed to the inability of the sensor to distinguish between the species and the surrounding vegetation, due to the lack of these bands. This is evident in this study because the user accuracy for the natural vegetation and the IAPs were similar, although negligible. Possibly, the use of the robust algorithms is required for the detection and monitoring of the IAPs and the use of the combination of both the VIs and spectral bands to improve classification, when using Landsat data series (Thamaga and Dube, 2018, Matongera et al., 2017),

Both the LT8 and S2 had a similar distribution pattern of the invaded areas, thus showing the capability of both satellites in detecting the IAPs and other classes, within the catchment despite the slight differences in the classification accuracies. The McNemar's statistical test results confirmed that the classification performance between the two sensors was not significantly different (p-value = 0.5254). This observation therefore implied that both the S2 and LT8 can equally be used to map the occurrence of the IAPs, with a reasonable certainty. This was also the case for Sánchez-Espinosa and Schröder (2019), were the distribution of the LULC was similar between the two satellites. The larger patterns of dense stands of the IAPs were similarly detected by both satellite images than the sparse and relatively smaller patches to pixel sizes of the respective satellites. The finer spatial resolution of the S2 has allowed for the better detection and mapping of the IAPs at locations with relatively small or sparse vegetation coverages. The LT8 has a greater limitation over the S2 in adequately detecting the smaller patches of the IAPs. However, the two satellite datasets provide time-scale and spatial complementarity required for ecological monitoring.

In addition, there was a strong relationship between the estimation of the accurately detected areas. But the improved spatial and spectral resolutions in the S2 satellite data has provided the opportunity for more accurate detection and quantification of the areas invaded by the IAPs (Sánchez-Espinosa and Schröder, 2019). The detection and determination of the spatial extent of the IAPs is valuable as it provides the requisite baseline information for mitigating and rehabilitating the invaded landscapes (Mutanga, et al., 2018). Mapping the spatial distribution of the IAPs is also important for conservation, and the allocation of resources for management and planning purposes (Masocha & Skidmore, 2011). The spatial understanding of the extent and distribution of the IAPs is important for providing the appropriate management strategies (Matongera et al., 2017). The use of the S2 can have a better implication for the management of the IAPs at catchment scale, as it has the potential to provide more detail and accurate information. This information can help in decision making to inform the clearing and rehabilitation of these IAPs in invaded areas. The freely available multispectral data of the S2 can reduce the cost of management practises when determining the spatial extent of these IAPs (Rajah et al., 2018, Matongera et al., 2017).

2.5 Conclusion

This study assessed the potential use of the Landsat 8 OLI and Sentinel 2 MSI data in mapping the IAPs. Both sensors were capable to detect and map areas where alien invasive plants were mostly dominant, particularly, within the hillslopes and riparian zones of the catchment. However, the Sentinel 2 demonstrated more potential in the overall classification of the species. The Landsat 8 was not able to detect small patches of alien invasive plants, within the catchment. The unique capability of the Sentinel 2 MSI to discriminate these IAPs is attributed to its improved spatial resolution and the presence of the red-edge band, which is critical in enhancing the ability to distinguish between different types of vegetation, among other bands that include the NIR and SWIR. Overall, the findings of this work can be used for more extensive analyses of the occurrence and the environmental impact of invasive species and aid in proving the extensive reliability of using the easily accessible and cost-efficient satellite data, as a surrogate for in-situ measurements in remote areas. Further, these results can be used as a baseline information for the IAPs eradication programmes such as Working for Water.

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Chapter Three

Modelling the current and future potential distribution of invasive alien plants (IAPs) in the Heuningnes catchment, South Africa under projected climatic scenarios using species distribution models

Abstract

The spread of Invasive Alien Plants (IAPs) into new ecosystems requires accurate, constant and near-real time monitoring particularly under the changing climate to ensure ecosystems integrity and resilience. In this study, bioclimatic, environmental and Sentinel 2 multispectral satellite data were used to map and model areas at risk from IAPs invasions in the Heuningnes catchment, South Africa. Four Species Distribution Models (SDMs) namely; Boosted Regression Trees (BRT), Maximum Entropy (MaxEnt), Random Forest (RF) and the ensemble model were used to map and model the current distribution and future potential catchment areas likely to be affected by IAPs. Different climatic scenarios from the Community Climate System Model (CCSM4) were considered in modelling the future distribution of IAPs within the catchment. These scenarios were for the best-case and worse-case atmospheric carbon Representative Concentration Pathways (RCP) 2.6 and 8.5 for the 2050 time step (average for 2041-2060). The BRT predicted the spatial distribution of IAPs with an AUC of 0.89, Maxent 0.92 and RF at 0.94. Comparatively, all the models were successful in modelling the potential distribution of IAPs in all scenarios. It has been established that the predicted distribution of IAPs will expand under the influence of climate change in the catchment. Riparian zones, bare areas and natural vegetation, which is rich in biodiversity will greatly be affected. The mean diurnal range (Bio2), the warmest quarter maximum temperature (Bio5) and the warmest quarter precipitation (Bio18) were most important bioclimatic variables in modelling the spatial distribution IAPs in the catchment. The study demonstrated the importance of multi-source data and multiple predictive models in mapping and modelling the current potential future IAPs distribution within the Heuningnes. Results from this study are valuable and provide the baseline for effective management and continued monitoring of the further spread of IAPs within the Heuningnes catchment.

***Keywords*:** Biodiversity conservation; Boosted Regression Trees; Climate change; Ecological Niche Modelling; Invasion risk; Ensemble modelling; MaxEnt; Remotely sensed data.

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- 20th SAEON Indibano 2019, **St. Francis, South Africa**

3.1 Introduction

Globally, Invasive Alien Plants (IAPs) pose a great threat to biodiversity and species extinction following habitat loss (Wilcove et al., 1998). The establishment and success of IAPs into new ecosystems is mainly caused by environmental change as a result of anthropogenic influences and changes in climate (Buckley and Catford, 2016). It is expected that the increase in temperatures will facilitate and accelerate the spread of IAPs while reducing the resilience of natural vegetation (Tarabon et al., 2018, Ncube et al., 2020). This is likely to increase areas of invasion risk due to massive losses in biodiversity as a result of the projected species range shifts or extinctions. This is of great concern for the conservation and preservation of native species and water resource management (Haeuser et al., 2017).

The African continent, with highly variable precipitation and already warmer temperatures, makes it most vulnerable to the expected worsening climate change conditions and the associated impacts. (IPCC, 2014, Kotir, 2010). It is predicted that the increase in temperatures for the African continent will rise by a magnitude of between 3°C and 6°C before the end of the century (Serdeczny et al., 2016). Many regions in southern Africa will experience sharp increases in temperatures and frequent droughts (IPCC, 2014). The regions at high elevation will warm at a faster rate with a greater increase in daily minimum temperatures than maximum temperatures on the lower lying counterparts (Bandopadhyay, 2016, Niang et al., 2014). These changes will likely trigger mass extinctions due to the loss of the biological conditions suitable for most species resulting in opportunistic spread of IAPs. Therefore, there is a great and urgent need to accurately model and predict the current and potential future distributions to empirically prioritise areas for control, mitigation and adaptation (Estes et al., 2010).

Localised modelling of IAPs provides critical insights into the processes driving vegetation dynamics, community structure and the general functioning of ecosystems, including anticipated impacts (Muniz et al., 2016). It has been shown that the use of Species Distribution Models (SDMs) to predict habitat suitability for alien and native species under provides useful information on the response of species to climate change. For instance, both (de la Hoz et al., 2019) and (Hoveka et al., 2016) observed that some plant species may decrease in extent while others increase due to climate change. Vorsino et al (2014) also showed that the vulnerability of ecosystems to climate change and IAPs can be successfully determined using SDMs. These studies have used complex machine learning models such as the Maximum entropy (MaxEnt), Boosted Regression Trees (BRT) and Random Forest (RF) coupled with 'presence-only' data because of their robustness, the ability to produce good predictive performances, versatility to handle autocorrelations and complex interactions (Crase et al., 2011; Fourcade et al., 2014; Gils et al., 2012). Lately, the ensemble modelling approach has become relatively popular because of its ability to combine multiple models' predictive strengths, thus increasing the predictive modelling abilities (Mudereri et al., 2020a, Ng et al., 2018). Further, the ensemble of RF and MaxEnt were preferred for mapping the distribution of alien *Chromolaena odorata* and *Mikania micrantha* to reduce spatial uncertainties of the predictions due to their reported performance (Nath et al., 2019). While it is common to use only bioclimatic predictors, incorporating remotely sensed data and environmental variables such as topography, land cover and other geographical data generally improves the predictive ability of models (West et al., 2017, Truong et al., 2017, Vorsino et al., 2014). Therefore, coupling the recently improved Sentinel 2 multispectral data, with strategically placed bands with other environmental variables has the potential to increase species discrimination and improve the performance of SDMs. Several studies have already demonstrated that adding remotely sensed data from Sentinel 2 improves modelling, classification and predictions (Forkuor et al., 2017, Ndlovu et al., 2018, Mudereri et al., 2019, Malahlela et al., 2019).

Therefore, this study aimed to explore the use of multi-source data *viz.* bioclimatic, topographic and Sentinel 2 data as predictor variables in modelling the distribution of IAPs in varying climatic scenarios to improve the understanding of the potential impacts at catchment scale with MaxEnt, RF, BRT and their respective ensemble model. Additionally, the study sort to establish the key climatic factors and their influence on the IAPs distribution under current and projected future climatic conditions. Modelling IAPs under different projected climate scenarios allows better evaluation and anticipation of the future changes in distribution, thus effective management (Tarabon et al., 2018). Also, the information derived from SDMs about areas that are susceptible to invasion by IAPs can aid in effective management and control.

3.2 Materials and methods

3.2.1 Reference field data

A total of 244 ‘presence-only’ occurrence data of the IAPs were collected during the period between 17th and 19th September 2019. The reference data was collected using a purposive sampling approach that targeted areas of dense (>30 trees) IAPs stands identified along the roads and accessible site areas. For each IAP stand identified, a handheld Garmin eTrex Global Positioning System (GPS) device was used to record the reference of the occurrence points at an error margin of ±3 m. The points were collected at the approximate centre of each of the dense IAPs stands to eliminate the edge-effect. Each of the sampling unit was of approximately 30 m x 30 m dimensions.

3.2.2 Predictor variables

3.2.2.1 Sentinel 2 data acquisition and pre-processing

The Sentinel 2 data, processing level-1C of the 24th of August 2018 was freely downloaded from the USGS Earth Explorer platform (http:/earthexplorer.usgs.gov) in three granules namely T34HCG, T34HDG and T34HCH. These tiles were mosaicked into a single scene that covered the entire study area. Level 1C data from Sentinels are provided as Top of the Atmosphere (TOA) reflectance, already orthorectified in cartographic geometry in tiles of 100 km^2, UTM/WGS84 projection. The Sentinel 2 data were converted to level 2A images (atmospherically corrected and surface reflectance) using the Sen2Cor processor in SNAPVR v6.0 software executed using the default parameter settings. The image was acquired on the day of low cloud cover (<5%) and alignment with the period when the field reference data was collected and the availability from the sensor’s archive. The bands that were considered in modelling the distribution of IAPs are indicated in Table 3.1. In addition, these bands were used to classify major land cover classes, which included IAPs, natural vegetation, cultivated lands, water, build up and bare surfaces with an overall accuracy of 71%. The data were resampled to 30 m spatial resolution together with the bioclimatic and environmental variables. This was to provide a fine spatial resolution of the potential of distribution of IAPs, following Ndlovu et al. (2018).

Table 3.1. Spectral and spatial characteristics of the Sentinel 2 data. The predictors marked in bold were used in fitting the three SDMs.

Band number	Description	Central wavelength (nm)	Width	Resolution	Potential application
B1	Coastal aerosol	443	20	60	Atmosphere
B2	**Blue**	**490**	**65**	**10**	**Atmosphere**
B3	**Green**	**560**	**35**	**10**	**Vegetation**
B4	**Red**	**665**	**30**	**10**	**Vegetation**
B5	**Red-edge (RE1)**	**705**	**15**	**20**	**Vegetation**
B6	**Red-edge (RE2)**	**740**	**15**	**20**	**Vegetation**
B7	**Red-edge (RE3)**	**783**	**20**	**20**	**Vegetation**
B8	**Near-infrared (NIR1)**	**842**	**115**	**10**	**Vegetation**
B8a	**Narrow Near-infrared (NIR2)**	**865**	**20**	**20**	**Vegetation**
B9	Water vapour	945	20	60	Atmosphere
B10	Cirrus	1375	30	60	Atmosphere
B11	**Short wave infrared**	**1610**	**90**	**20**	**Vegetation**
B12	**Short wave infrared**	**2190**	**180**	**20**	**Vegetation**

4.2.2.2 Topographic data

The details of topographic variables considered in predicting the distribution of IAPs are presented in Table 3.2. A 30 m spatial resolution Digital Elevation Model (DEM: https://dwtkns.com/srtm30m/) was used as the elevation variable and also to generate the aspect, slope, Topographic Wetness Index (TWI) and Topographic Position Index (TPI). Aspect and slope were generated from the DEM using Quantum GIS through the terrain analysis plugin (QGIS Development Team 2019). Terrain variables influence soil type, soil moisture, sun angle, precipitation hence the occurrence of vegetation components (Perring, 1956, Perring, 1959, Bennie et al., 2006). The soil type data was retrieved from ISRIC data hub (http://data.isric.org/) and used because small spatial scales can be greatly influenced by the land cover (Luoto et al., 2007). TWI is an index for soil moisture which affects vegetation composition (Gábor et al., 2019). TWI has also been successfully used for studying vegetation patterns and predicting the spatial distribution of plants (Sørensen et al., 2006). The TWI was derived based on equation 1:

$$TWI = \text{In}\left(\frac{a}{\tan\beta}\right) \quad (1)$$

where a is the local upslope area and $\tan\beta$ is the slope (Beven and Kirkby, 1979)

TPI is generally used to categorise landform types in an area and describes the biophysical processes occurring on landscapes, which can be key in predicting habitat suitability and species distribution (Weiss, 2001, Seif, 2014) It is defined as the difference between the elevation of a cell in a DEM and a mean elevation of neighbouring cells (Weiss, 2001). Equation 2 shows the calculation of TPI.

$$TPI = M_0 - \sum_{n-1} {}^{M_n}/_{n} \tag{2}$$

where M_0 is the elevation of the DEM point being evaluated, M_n is the elevation of the pixel grid and n is the total sum of the surrounding points (Mokarram et al., 2015).

4.2.2.3 Bioclimatic data

Bioclimatic data have been widely used in species distribution models to determine and explain factors driving species distributions (Gallardo et al., 2017, Booth, 2018, Ndlovu et al., 2018). The bioclimatic data is derived from monthly rainfall and temperatures and can explain the potential species distributions by providing biologically meaningful variables which convey annual and seasonal mean climate conditions as well as intra-year seasonality (O'Donnell and Ignizio, 2012, Hijmans et al., 2005). A total number of 19 bioclimatic variables (Table 3.2) representing each scenario for the current (1950–2000) and future climate (2050) were freely obtained from WorldClim (http://www.worldclim.org/) at 30 arc seconds spatial resolution (~1 km x 1 km). The obtained future climate scenarios were based on the fourth Community Climate System Model (CCSM4) projections commonly referred to by other studies (Gent et al., 2011), Mohammadi et al., 2019). Only two of the four atmospheric carbon Representative Concentration Pathways (RCPs) namely RCP 2.6 (minimum emission) and RCP 8.5 (maximum emission) proposed by the Intergovernmental Panel on Climate Change (IPCC) were selected to show the possible minimum and maximum impacts respectively. The RCP scenarios represent the minimum and maximum radioactive forces of 2.6 and 8.5 watts/m^2 for the CO_2 concentrations by 2050 (IPCC, 2014)

It is predicted that climate change will result in changes in temperatures and precipitation across the globe. The future bioclimatic variables based on the best-case and worse-case

RCPs for temperature and precipitation were used to determine how the projected climate changes will vary to the current climate. Additionally, the change in the most important bioclimatic variables was also calculated. This was achieved by subtracting the projected climatic conditions of the variables from the current climatic conditions (Ncube et al., 2020). The results showed whether there is an increase or decrease in changes in the projected climate to determine how the variations affect the predicted distribution.

Table 3.2. The bioclimatic predictor variables used for modelling species distribution. The predictor variables in bold were selected for final modelling after removing highly correlated variables.

variable Code	Environmental variable description	Unit
Bio1	Annual mean temperature	^{0}C
Bio2	**Mean diurnal range**	**^{0}C**
Bio3	Iso-thermality	
Bio4	Temperature seasonality	
Bio5	**Maximum temperature of the warmest month**	**^{0}C**
Bio6	**Minimum temperature of the coldest month**	**^{0}C**
Bio7	Temperature annual range	^{0}C
Bio8	Mean temperature of wettest quarter	^{0}C
Bio9	Mean temperature of driest quarter	^{0}C
Bio10	Mean temperature of warmest quarter	^{0}C
Bio11	Mean temperature of coldest quarter	^{0}C
Bio12	Annual precipitation	Mm
Bio13	**Precipitation of wettest month**	**Mm**
Bio14	Precipitation of driest month	Mm
Bio15	Precipitation seasonality	
Bio16	Precipitation of wettest quarter	Mm
Bio17	**Precipitation of driest quarter**	**Mm**
Bio18	**Precipitation of warmest quarter**	**Mm**
Bio19	Precipitation of coldest quarter	Mm
Aspect	**Direction of the slope**	**-**
Elevation	Altitude above sea level	M
Slope	**Angle of inclination**	**degrees**
TPI	**Topographic index**	**-**
TWI	**Moisture index**	**-**
Land cover	**Thematic land cover classes**	**-**
Soil types	**soil characteristics**	**-**

3.2.3 Collinearity test for the bioclimatic variables

The problem associated with multicollinearity between predictor variables in SDMs is the inflation of coefficient standard errors, making some significant variables insignificant often resulting in model overfitting (Akinwande et al., 2015). The coefficient of Pearson's correlation and the Variance Inflation Factor (VIF) were used to eliminate highly correlated variables among the predictor variables (Akinwande et al., 2015). The collinearity threshold was set at $| r | > 0.7$ (Dormann et al., 2013, Makori et al., 2017). The VIF measures the degree in which multicollinearity has increased the slope estimate variance based on squaring multiple correlation coefficient derived from regressing predictor variables against each other (Plant, 2012). The 'usdm' package in R-software was used for eliminating variables with high VIF and thus modelling the distribution (Naimi et al., 2014; R Core Team, 2019). The threshold was set at $th = 0.7$ where values greater than the threshold are considered to be highly correlated within a model (Kyalo et al. 2018; Dormann et al., 2013). Therefore, all variables identified as having high correlation based on the set thresholds were removed for model fitting.

A total number of 12 variables selected for the current and future prediction. Only the land cover derived from Sentinel 2 satellite bands was eligible for model parameterization excluding the raw spectral bands. All data sets used were projected to WGS84 coordinate system and clipped to the area of the catchment using QGIS version 3.8.2. The selected variables used for final modelling were then resampled to 30 m pixel size. Several studies have shown that the SDMs improved model prediction at 30 m pixel (Manzoor et al., 2018; Ross et al., 2015).

3.2.4 Predicting the distribution of IAPs in Heuningnes catchment

A total number of 1 000 pseudo-absence points created automatically within the SDM package in R were used against the collected 'presence-only' occurrence. The use of presence-only models with pseudo-absence has been widely been applied considering the applicability of obtaining 'absence data' (Downie et al., 2013). Only three modelling techniques namely; the BRT, RF and MaxEnt were used from the 15 modelling techniques available within the 'sdm' package. The BRT model uses a maximum likelihood approach to merge multiple models to improve on a single regression tree (Elith et al., Hastie 2008). In the RF model, prediction is produced by selecting the class with the highest random combinations in a multiple decision tree (Bangira et al., 2019). The MaxEnt model predicts the species distribution by finding the maximum entropy of the spatial distribution i.e largest spread (Merow et al., 2013). Table 3.3 summarizes the relevant functions and packages used in predicting IAPs distribution for the three models. These models produce relatively high accurate results and complex predictions (Abdel-Rahman et al., 2013; Barakat et al., 2018; Makaya et al., 2019; Mudereri et al., 2019).

Table 3.3. R packages and functions for the three models used in predicting IAPs distribution.

Model algorithm	'sdm' syntax	Package	Reference
Boosted regression trees	'brt'	'gbm'	(Elith et al., 2008)
Random forest	'rf'	'randomForest'	(Liaw et al., 2002)
MaxEnt	'maxent'	'dismo'	(Phillips et al., 2006)
Ensemble	'ensemble'	'sdm'	(Naimi and Araújo, 2016)

An ensemble approach was further used to harmonize the variations produced by the different model predictions. Ensemble models fit and maximize the prediction accuracy of different SDM models by combining the highest performance of all the models while minimizing their weaknesses (Araújo et al., 2019). The TSS is a reliable measure to combine different models compared to AUC which is biased and highly sensitive to the proportional extent of the observations (Kyalo et al., 2018). Therefore, the weighted average TSS approach was used to produce the ensemble model since it improves the predictive ability of the model when compared to the use of the mean or median (Jafarian et al., 2019; Naimi and Araújo, 2016). The threshold was set to TSS = 0.7 for the models to qualify for inclusion in the ensemble. The variable importance values to determine the predictor variables that were most relevant in predicting the distribution of IAPs was computed, using the randomization method which computes the Pearson's correlation between references predictions and the shuffled variable (Benesty et al., 2009).

A geographic information system was used to further process the outputs of all three models with their respective ensembles for analysis. The three predictive models and their respective ensemble models were used to calculate the suitable areas for the occurrence of IAPs in the form of a binary raster image i.e. < 0.3 unsuitable and ≥ 0.3 suitable. The total number of pixels in each category was then used to estimate the suitability or unsuitability coverage of the catchment.

3.2.5 Model evaluation

Measuring the performance of the model is an important aspect to test the reliability of the outcomes (Fois et al., 2018). The accuracy of the models was tested, using a 10-fold cross-subsampling approach (Wells and Tonkyn, 2018). In this study, the performance of the models was measured using the Area Under Curve (AUC) of the Receiver Operating Curve (ROC) of and True Skill Statistics (TSS) (Allouche et al., 2006). The AUC values range between 0 and 1, where inaccurate models have values closer to 0 and perfect models are closer to 1 with 0.5 being no better than random predictions. Generally, models with an AUC value ≥ 0.7 demonstrate high predictive abilities (Mohammadi et al., 2019). The TSS is defined as the product of sensitivity and specificity that explains commission and omission errors performed by a model (Kyalo et al., 2011). Sensitivity is defined as the proportion of true positives and specificity is the proportion of false positives (Grenouillet et al., 2011). The TSS values range between −1 to +1, where values closer to +1 demonstrates a perfect agreement between the observations and predictions while TSS ≤ 0 indicates no agreement and thus poor modelling performance (Allouche et al., 2006, Somodi et al., 2017).

3.2.6 Process taken to model the potential distribution of IAPs

Figure 3.1 shows the four stages that were considered in modelling the distribution of IAPs and the respective processes undertaken at each modelling stage. The stages included input data which involved data collection and consideration of predictor variables to be included. This was followed by the predictor variables preparation for modelling, using the three selected models and their ensemble. Finally, the important bioclimatic variables were identified and the outputs of the potentially suitable habitats ensemble were obtained for the three climate scenarios. The mapping of risk areas was produced to identify ecosystems that are likely to be affected by the predicted distribution in order to consider the potential impacts.

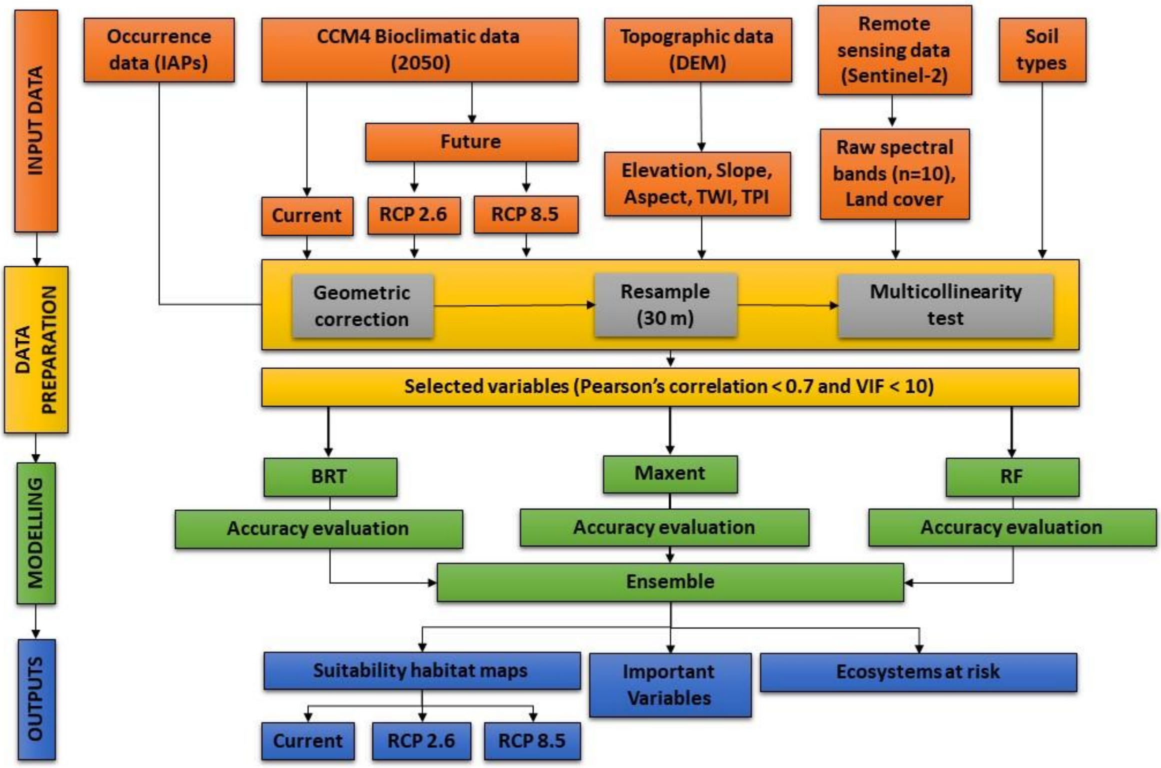


Figure 3.1**.** Flow chart showing processes undertaken to determine current and future suitable habitats for IAPs.

3.3 Results

3.3.1 Land use and land cover across the catchment using Sentinel 2 data

Figure 2.3 (b) shows the distribution of IAPs and other land use and land cover classes across the catchment in Sentinel 2 data. The majority of the land use within the catchment is cultivation, especially within the northern parts. IAPs are predominantly within the central belt, whereas natural vegetation occupies the southern parts of the catchment, with some bare surface areas, with absence of vegetation. Also, among the different quaternary catchments, G50B seems to be the most invaded by IAPs compared other quaternary catchments. G50D and G50E are greatly characterised by cultivated lands with some extent of invaded areas. G50C is characterised by occurrence of wetlands of varying sizes.

3.3.2 Changes in projected bioclimatic conditions

The calculated changes show that the annual mean temperatures will increase for both RCP 2.6 and RCP 8.5 (Table 3.4). However, the CCMS4 model shows that RCP 2.6 has a greater magnitude of increment in annual mean temperature compared to RCP 8.5 projection. The annual precipitation also shows a general decrease in both future RCPs, with an increase in mean for RCP 8.5. Therefore, the catchment is expected to receive lower rainfall and increased temperatures.

Table 3.4. Projected changes in bioclimatic variables for 2050 in Heuningnes catchment. Positive values show an increase while negative values show a decrease by a specified magnitude.

Parameter			**Changes**	
		Current	RCP 2.6	RCP 8.5
Annual Mean Temperature (°C)	Min	14.55	1.97	1.55
	Mean	16.83	2.25	1.75
	Max	17.67	2.34	1.84
Annual Precipitation (mm)	Min	427	-28.00	-18.00
	Mean	487	-7.00	9.00
	Max	619	-26.00	-4.00

3.3.3 Model performances for predicted species distribution under current climatic

Using the ROC, the patterns of the smoothened graphs of the ten replicated ROCs showed that RF and MaxEnt were relatively consistent in their prediction amongst the model replicates compared to BRT. The ROCs (Figure 3.2) show that RF (AUC = 0.93 and TSS = 0.82) yielded the highest accuracy metrics for both AUC and TSS followed by MaxEnt with BRT obtaining the least accuracies. Further, all models show high values of the specificity and sensitivity as demonstrated by the high values of TSS produced by both RF and Maxent (TSS > 0.8). All reported accuracies are based on current bioclimatic climatic variables. Accuracy was not measured for 2050 variables due to lack of presence data for the future timestamp period.

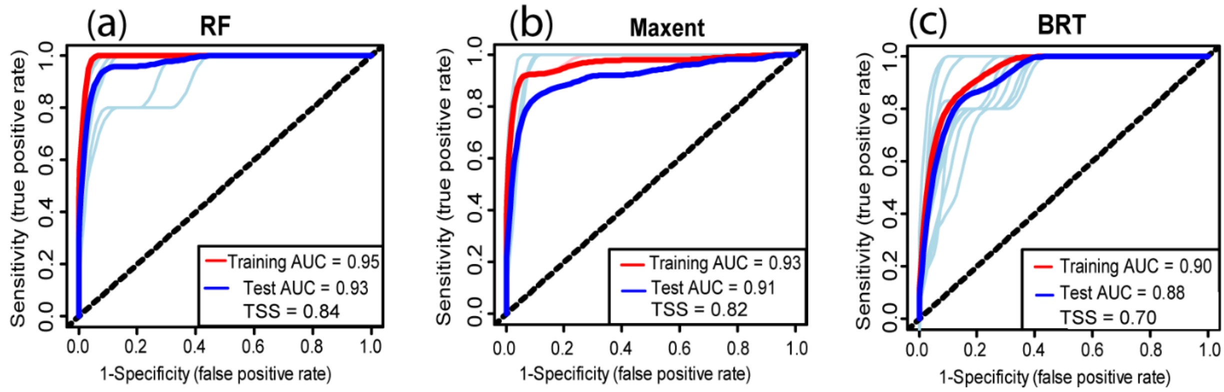


Figure 3.2. Results of the ROC for (a) RF (b) MaxEnt and (c) BRT. The red curve represents the smoothened mean AUC using the training data, while the blue curve depicts the smoothened mean AUC using the test data from the 10-fold cross-validation sampling.

3.3.4 SDMs selected important IAPs distribution predictors

Land cover was the most important variable in predicting current species distribution across all models (Figure 3.3). Soil type was the second important variable in both RF and Maxent, with aspect as the third most important variable. Sentinel 2's Band 8 (NIR centred at 842 nm) was among the least important variables in all three models.

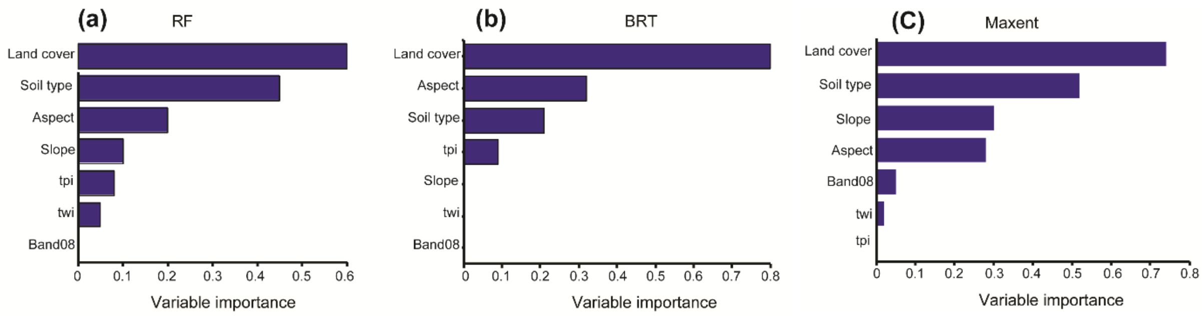


Figure 3.3. Variable of importance measure for the prediction of IAPs under the current climatic scenario.

The important variables for future climate were similar for RF and BRT except for aspect and Bio18 with Maxent showing different variable importance (Figure 3.4). The land cover was the most important non-climatic variable across all the models while TPI was the least important variable. Bio18, Bio2 were the most important bioclimatic variables for RF and BRT, while for MaxEnt, it was Bio2 and Bio5. Notably, the variable of importance for the Maxent model was importantly dominated by bioclimatic factors. The variation among the variable importance predictors between the models can be accounted for by the unique statistical approaches of each model. Also, the comparison of these variables across the models shows the influence of climate in predicting species distributions and land cover as a fundamental driver of habitat suitability.

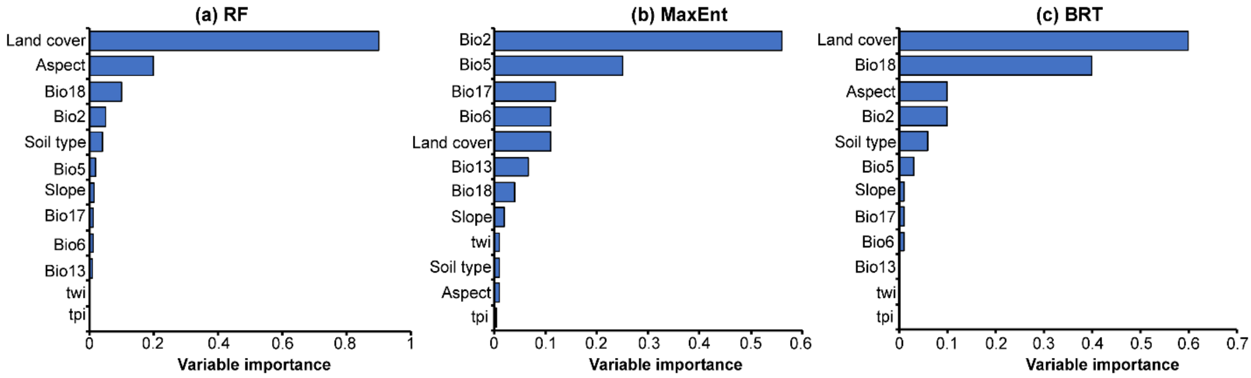
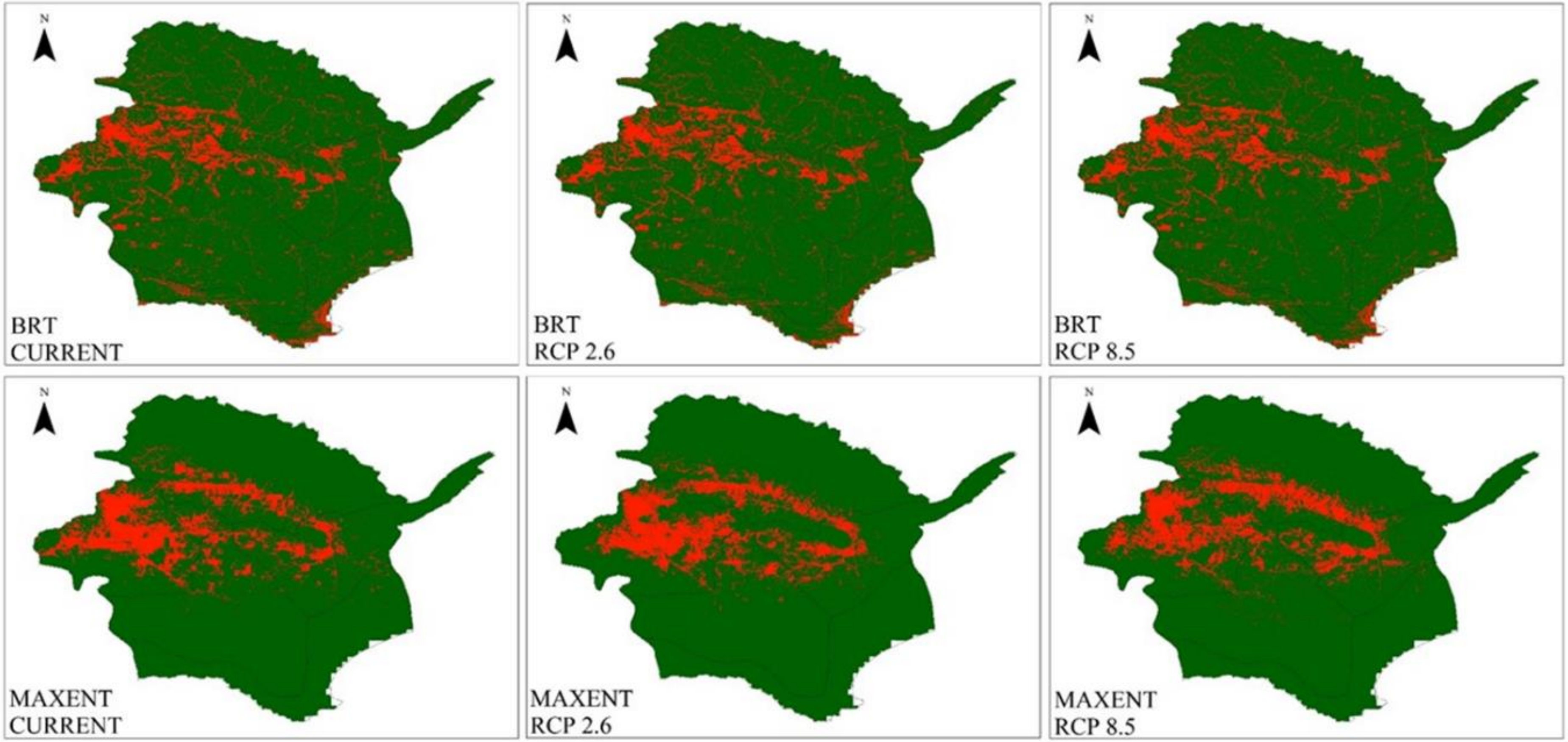


Figure 3.4. Variable of importance measure for the prediction of IAPs under the future climatic scenario.

3.3.5 Prediction of potential distribution

The predicted distributions vary across the models but show a similar pattern with suitable areas greatly occurring in the central regions of the catchment (Figure 3.5). However, BRT predictions show very distinct spatial differences at the southern part of the catchment when compared to both the MaxEnt and RF in all three climatic scenarios. Maxent shows the expansion of IAPs in RCP8.5 while showing a contraction in the RCP2.6 relative to the current prediction. This contraction is also observed in both future climate scenarios in RF. However, the future suitable areas for the occurrence of IAPs will expand in both the RCP2.6 and RCP8.5. This expansion of IAPs is shown to be towards southeast part of the catchment, along the riparian zones in the G50B sub-catchment, with great intensity. Overall, BRT shows clear spatial differences from the predicted suitable areas detected by MaxEnt and RF SDM models.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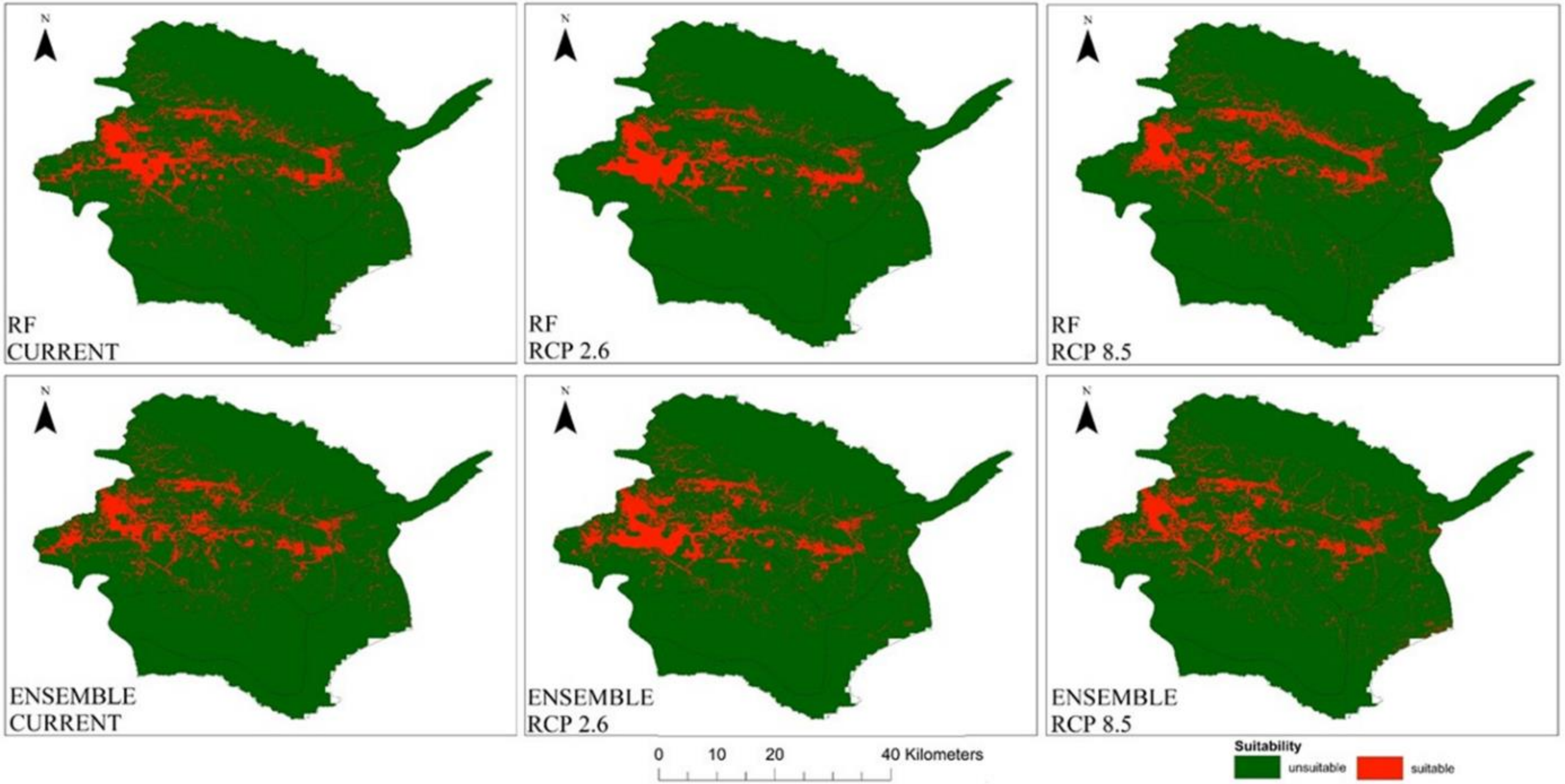

Figure 3.5. Predicted suitability maps derived using the three SDMs used and their respective ensemble to predict the potential distribution of IAPs. The red areas represent suitable habits and green areas unsuitable areas.

3.3.6 Estimated areas for the potential habitat of IAPs in Heuningnes catchment

Figure 3.6 shows the estimated areas suitable for the occurrence and spread of IAPs. The BRT model shows that the estimated areas suitable for IAPs currently is 14.32% and this will increase by a negligible 0.01% for RCP 2.6 and decrease to 14.28% in RCP 8.5. For MaxEnt, it is expected that the suitable habitats will decrease to 12.67%, for RCP 2.6 and increase to 13.21% under RCP 8.5 from the current predicted 13.12%. RF shows a decrease from the current 10.64% suitable areas in both RCP 2.6 and RCP 8.5 to 9.97% and 9.63% respectively. Nevertheless, RCP 2.6 shows a greater decrease than RCP 8.5. Generally, the percentage of the estimated areas vary across all the three individual models. However, the overall predictions using an ensemble model show that there will be an increase in suitability areas for IAPs in both RCP 2.6 and RCP 8.5 by 1.21% and 0.25%, respectively.

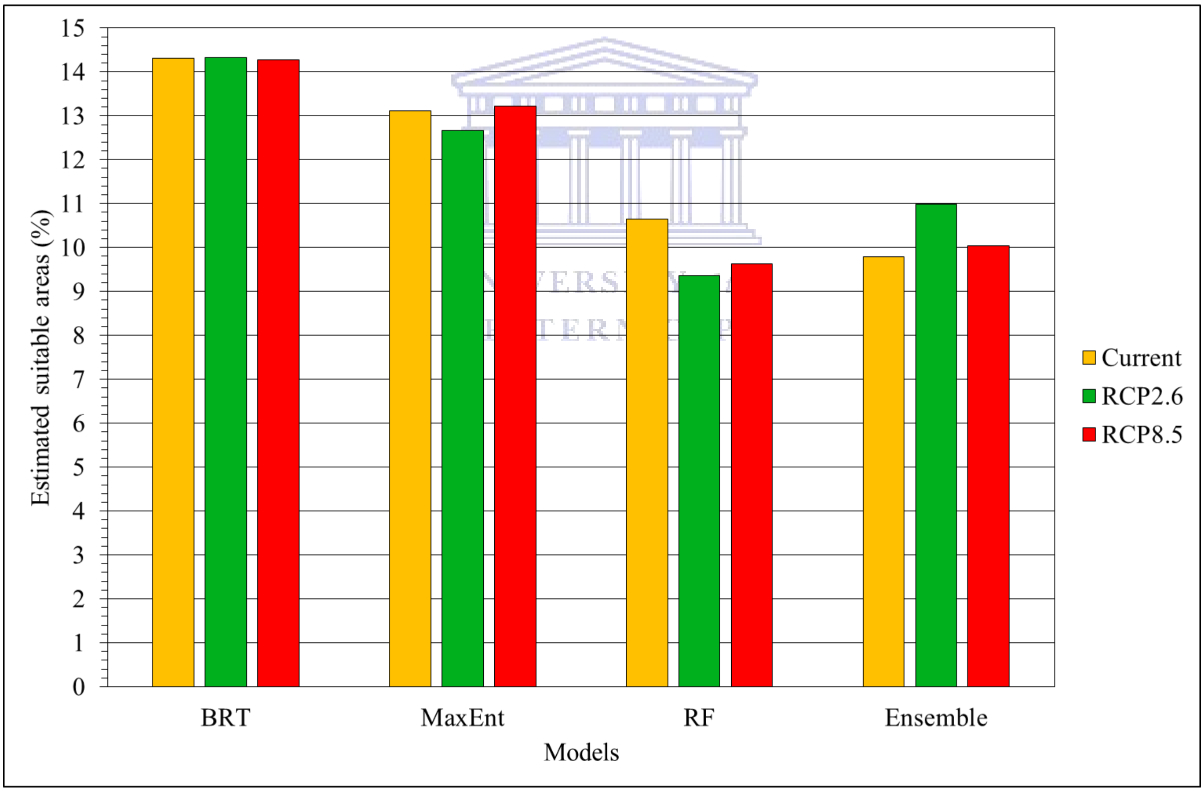

Figure 3.6. Estimated suitable areas (%) for the occurrence of IAPs distribution in Heuningnes catchment for current and RCP 2.6 and RCP 8.5 climate scenarios.

3.3.7 The potential risk of invasion by IAPs in the Heuningnes catchment

The results of the predicted IAPs distribution demonstrate the future invasion range and potential negative impacts, which could result due to the spread of IAPs (Figure 3.7). It is shown that the currently most infested sub-catchments (G50B, G50D and G50E) are most vulnerable to further spread of IAPs. The areas adjacent to the Jan Swartskraal and Koue rivers will be greatly be affected. These rivers upstream feed lower catchment, and invasion could mean reduced streamflow downstreams. The areas adjacent to the major wetlands (Voevlie and Soetendalsvlei) showed some extent of suitable areas, which could potentially invade the wetlands in future. The areas surrounding the settlements are susceptible to invasion. The protected areas likely to be considerably invaded are those with already established IAPs, hence these areas do not show great extent of susceptibility.

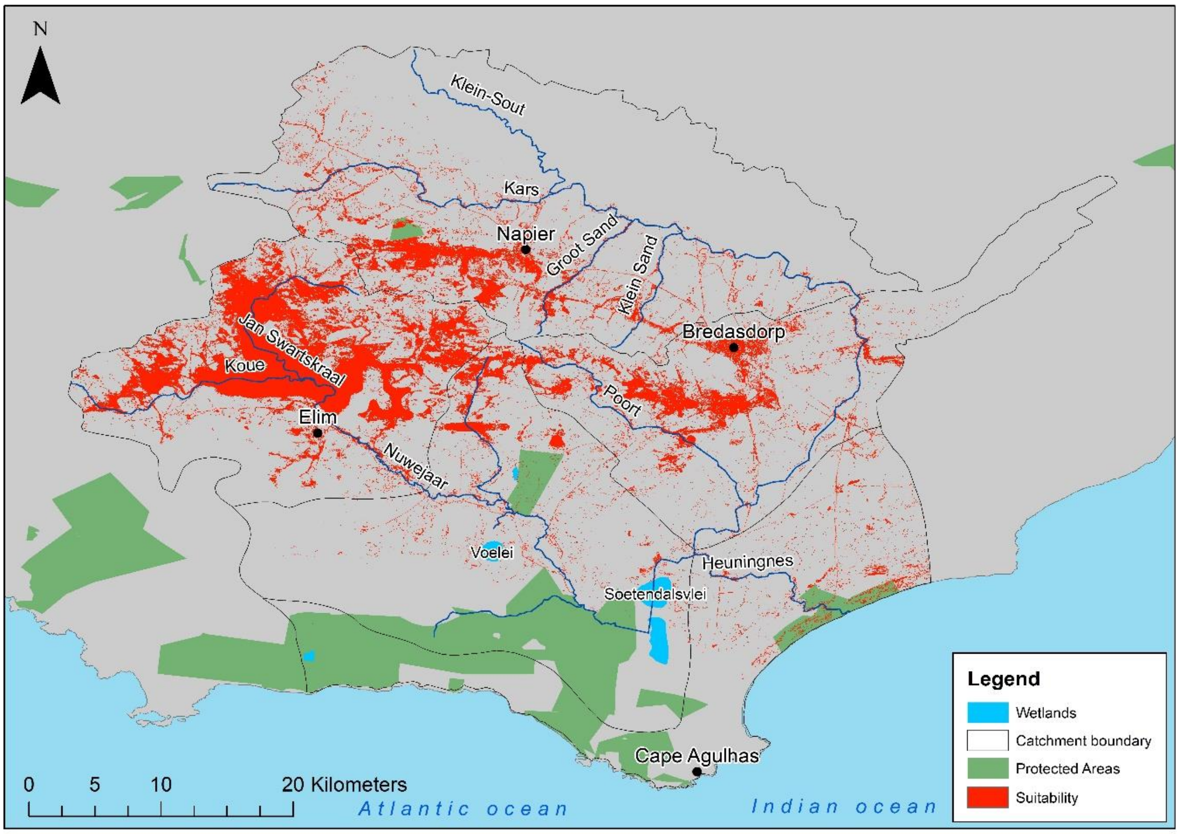

Figure 3.7. Potential risk area map posed by IAPs in the Heuningnes catchment, using ensemble predictions.

3.4 Discussion

The continued naturalization and spread of IAPs creates a major concern on how climate change will alter and affect the distribution of these species. Climate change is expected to alter the dynamics and ecological niches of many species (Lazo-Cancino et al., 2020). As a result, this can even be more detrimental to ecosystem's provision services with the impacts severely affecting both biodiversity and hydrological systems (Otieno et al., 2019). This study aimed to investigate how climate change might affect the distribution of IAPs under the best-case (RCP2.6) and worse-case (RCP8.5) climate projections by applying the SDM approach, using BRT, MaxEnt, RF and the ensemble. It is imperative to explore different models to identify the models that can accurately predict the species distribution to develop optimized model approaches (Beaumont et al., 2016, Araújo et al., 2019, Warren et al., 2019). To achieve this, multisource datasets were used to predict the potential suitable areas for IAPs at 30 m spatial resolution in Heuningnes catchment, South Africa.

3.4.1 Predicted and estimated future distribution patterns of IAPs

The overall predicted distribution showed that IAPs abundance will increase towards planes, particularly riparian zones, mostly in sub-catchment G50B where most invasion currently occurs. This was also reported by (Kotzé et al., 2010) that *Acacias* are likely to occur within river flood plains. Some parts of the cultivated and natural vegetated areas also show great suitability for IAPs These findings are in line with (Gutierres et al., 2011) who found that these species can be associated with lowlands, agricultural lands and margins of lakes. Furthermore, it was estimated that the suitable potential habitats of IAPs currently cover ~ 9% of the study area and will increase to ~11%. This increase conveys that the suitable habitats have not been fully invaded and such will continue under the influence of the changing climate. Notably, it had been pointed that IAPs have not reached equilibrium in South Africa (Rouget et al., 2004). Therefore, it is likely that the potential suitable areas for IAPs in this study have been underestimated due to sampling effort, predicted suitable areas not showing some of the currently invaded areas and the small difference between the currently invaded areas and future predicted suitable habitats for 2041 to 2060. This is also because the dominant *Acacia* species are known for rapidly spreading.

3.4.2 Important predictor variables in predicting the potential distribution of IAPs

There was a variation in important predictor variables across the models which can be related to the predictive power of the models. This observation suggest that the prediction of suitable habitats is dependent on the type of model used. Nonetheless, land cover showed to be an important predictor variable for IAPs distribution in BRT and RF with climate variables showing dominantly great importance for Maxent. Studies have shown that land cover is an important driver of habitat change (Maron et al., 2012, Tylor et al., 2014). In contrast, land cover had minor importance in modelling IAPs distribution in a study conducted by (Terzano et al., 2018) on a larger scale. Some studies have also shown that climate predictors are most important in predicting species distribution were demonstrated in this study as indicated by Maxent model (Nath et al., 2019, Terzano et al., 2018). The incorporation of these important variables however has been understood to provide realistic predictions for suitable habits (Thalmann et al., 2015).The mean diurnal range, maximum temperature of warmest quarter and the precipitation of warmest quarter were considered to be climatically the most important predictor variables. Even though remote sensing data facilitates the prediction of IAPs over inaccessible areas (Pearce and Boyce, 2006), raw spectral bands showed no contribution in prediction of suitable habitats for IAPs except the land cover derived from these bands. Other studies were able show relatively considerable contributions of remote sensing derived such as vegetation indices. Therefore, the use of remotely sensed derived variables may provide more insights into species physiochemical properties for improved prediction than raw spectral bands.

3.4.3 Impacts of IAPs under projected current and future climate changes

The future climate projections suggest that there will be an increase in the annual mean temperature for the catchment while there will be an observable decrease in annual precipitation. There has been already observable declines in available water resources and rainfall patterns due to climate change drought impacts (Orimoloye et al., 2019). The dominant and rapidly spreading *Acacia* species (*A. saligna*, *A. longifolia* and *A. cyclops*) found in the catchment can adapt in these conditions since they show high drought tolerance (Traore, 2012). Their increasing spread in riparian zones will largely contribute to the reduced streamflows (Prinsloo and Scott, 1999). It has been found that these species are most likely dependent on surface water and thus may be a great threat when expanding to these areas (Sher et al., 2010). It was also found that the water use of *A. longifolia* occurring in riparian zones in lowlying areas than in hillslopes was dependent on soil moisture and used more water (Mkunyana et al., 2018). Protected areas, natural vegetation, particular low shrubland (fynbos) is potentially at risk of being invaded causing in biodiversity loss due to increased competition for available ecosystem resources. These areas are also currently invaded by IAPs to some extent. Therefore, the predicted future expansion of IAPs will exacerbate the negative impacts to the rivers, wetlands and biodiversity of the catchment.

3.4.4 Model performances in predicting potential distribution of IAPs

The predictions of the potential distribution of IAPs were better than random (AUC and TSS > 0.5) for all three individual models. It was noted that RF produced the highest accuracy followed by Maxent and BRT with marginal differences. Similar studies by (Guan et al., 2020) and (Stohlgren et al., 2010) showed the same pattern with the latter models predicting IAPs habitat suitability at relatively high accuracy across the models although based on different algorithms (Mohammadi et al., 2019; (Pearce and Boyce, 2006, Downie et al., 2013). The robustness of these models was further evident in the spatial distribution of predicted suitable habitats. All three candidate models predicted a similar distribution pattern across all the climatic scenarios in major suitable areas although spatial differences can also be observed. This could be attributed to the predictive power of the algorithm approaches used by each model (Araujo et al., 2019; Hao et al. 2019). For example, both MaxEnt and RF models, which performed better than BRT did not predict suitable habitats along the southern catchment boundary in all three climate scenarios. This contradicts with the land cover results, which show presence of IAPs occurrence close to build up areas in the southernmost part of catchment. This can possibly suggest reduced ability to deal with sampling bias towards areas where sampling is most accessible. Even though MaxEnt can handle sparse and irregular occurrence data, it assumes that the area of interest is systematically sampled (Kramer-Schadt et al., 2013).

Several studies showed that there is no convincing evidence to suggest that there is an overall one model which is better than all (Guo et al., 2019, Hao et al., 2019, Mudereri et al., 2020b). Therefore, the use of the ensemble analysis becomes paramount in all predictive modelling especially for management (Araujo et al., 2019). As such, the ensemble models was successfully used to produce predictions by including only models with a TSS > 0.7 as opposed to AUC due to associated criticisms to ensure only strong models are included (Allouche et al., 2006). The advantage of ensembles is to minimize the spatial uncertainties of the models for each climate scenario to enabled reliable spatial estimates (Downie et al., 2013, Guan et al., 2020, Pearce and Boyce, 2006).

3.5 Conclusion

Climate change effects characterized by reduced rainfall and increased temperatures will facilitate the distribution of IAPs and increase their abundance in the catchment. Riparian zones, lowlying areas and natural shrublands are most vulnerable areas and must be prioritised in management efforts to reduce the impacts on biodiversity loss and water losses through increased evapotranspiration. These results have also demonstrated the combination of multiple strong predictive models to reduce spatial uncertainties for realistic suitable habitat predictions for effective management practices. The estimated areas suitable for IAPs in this study are better than random but may have been underestimated. Further investigation is required by considering species-specific potential distribution and more ecologically meaningful remotely sensed derived variables as opposed to raw spectral bands. Nonetheless, the results provide useful insights in effective management of IAPs and may be used for prioritized monitoring.

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Chapter Four

Spatial modelling of invasive alien plants species distribution in water-limited environments using remotely sensed data and climatic scenarios: Synthesis

4.1 Findings summary

Firstly, the use of Landsat 8 and Sentinel 2 were assessed in detecting, discriminating and mapping IAPs to provide reliable information on the occurrence of IAPs. In this study, the results have successfully demonstrated the capability of both Landsat 8 and Sentinel 2 data in discriminating and predicting the distribution of IAPs. The results have shown that both satellite data sets were able to adequately detect and discriminate IAPs from other land cover types. The McNemar's test showed that there was no significant statistical difference in discrimination of IAPs from other land cover types between the two sensors (p-value = 0.53). However, Sentinel 2 yielded better overall accuracy results, with improved user's and producer's accuracy in detecting IAPs compared to Landsat 8. This can be attributed to the high spatial and spectral resolution of Sentinel 2 when compared to Landsat 8 data. The coarse spatial resolution of Landsat 8 showed great overestimation for IAPs as compared to Sentinel 2, which can result in reduced accuracy in estimation of areas invaded by IAPs in the catchment. Overall, the results have demonstrated the improved capability of Sentinel 2 in detecting IAPs at catchment scale with less overestimation, thus more accurate for quantifying their abundance.

Secondly, remote sensing data showed a great potential in predicting the future spatial distribution of IAPs in the catchment. As a result, it has been observed that land cover derived from Sentinel 2 was greatly important in predicting IAPs current and future spatial distribution than raw spectral bands. This indicates the need for including more ecologically meaningful satellite remote sensing variables in predicting IAPs than the use of only raw spectral bands. Further, the mean diurnal range (Bio2), maximum temperature of warmest quarter (Bio5) and the precipitation of warmest quarter (Bio18) were the most important bioclimatic variables in modelling the spatial distribution IAPs in the catchment. The Bio5 is associated with extreme hot temperature conditions while Bio18 is related to the extreme low precipitation received during period of low precipitation, indicating that extreme conditions drive the spread of IAPs in the catchment. Evidently, the best-case climate projection (RCP 2.6) associated with higher magnitude of increase in annual temperatures and decrease in rainfall greatly accounts for the largest increase in spread of IAPs than the worse-case projection (RCP 8.5). As a result, there will be an increase in suitable areas for IAPs spread in the catchment based on the projected climate change scenarios. Further, Sentinel 2 predicted that the actual area currently invaded by IAPs in the catchment is approximately 9%. This is predicted to increase to approximately 10% under the worse-case climate scenario (RCP 8.5) and 11% for the best climate scenario (RCP 2.6). The spread of IAPs will thus move towards low-lying areas, especially towards riparian zones and areas adjacent to already highly infested areas.

Overall, the detected and predicted distributions of IAPs in the catchment has been achieved at with model accuracy providing reliable and insightful baseline information on the spatial distribution of IAPs with the Catchment. Therefore, these results provide necessary information for managing the spread of IAPs in catchment and to help reduce the impacts posed on water resources including biodiversity.

4.2 Conclusions

The results have demonstrated that both Landsat 8 and Sentinel 2 have a great capability in detecting and discriminating IAPs. It was possible to determine the distribution patterns of these species, using only a simple parametric classifier such as the maximum likelihood classification. However, improved image classification results could be obtained, using non-parametric classifiers with robust algorithms. In addition, the combined use of strong varying predictive models such as BRT, MaxEnt, RF, with multisource data predicted the potential distribution of these alien species with reduced uncertainties. Specifically, the following were concluded based on the objectives and research questions of the study.

- Sentinel 2 satellite data has an improved detection and discrimination ability with less overestimation of IAPs than Landsat 8 data. This can be attributed to the improved spatial and spectral resolution of the characteristics of sensor when compared to Landsat 8. As a result, it can have a positive impact in management and decision making for eradication plans. However, given that Landsat has a long history of earth observation, new satellites like Sentinel therefore provide a complementary role.
- It was predicted that the abundance of IAPs in the catchment will increase under the influence of extreme climate change conditions. However, it is possible that the

estimated suitable areas have been underestimated given possible sampling bias towards accessible areas.

- The land cover derived from Sentinel 2 had a great influence in predicting the potential distribution of IAPs compared to the raw spectral bands.
- The mean diurnal range, the warmest quarter maximum temperature and the warmest quarter precipitation were most important bioclimatic variables in modelling the spatial distribution of IAPs in the catchment. This suggest that the spread of these species in catchment is greatly influenced by the change in these bioclimatic conditions.

Overall, the results can be useful to provide routine monitoring and effective management of the spread of IAPs in the catchment. Thus, this approach can inform eradication plans and contribute to towards minimizing their impacts on water resources and the ecosystem especially in arid and semi-arid areas. Land managers should focus on monitoring key biodiversity areas and riparian zones for clearing of these species to mitigate their spread.

4.3 Recommendations

- Improve the detection and discrimination IAPs using robust classification algorithms such as non-parametric classifies
- To determine the optimum season for detection and mapping of invasive alien plants using time series
- Model species specific potential distribution of IAPs
- Incorporating ecologically meaningful satellite derived variables in predicting suitable habits such as vegetation indices.
- Model the distribution of IAPs using alternative Global Circulation Model projections and all scenarios to obtain a full insight of the potential distribution of these species.