



Modelling the spatial distributions and water use of Mauritius thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) using remote sensing and geographic information system techniques in the Vhembe Biosphere Reserve

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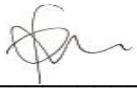
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For my grandfather (Amos Muneke Dondofema) and grandmother (Tendai Dondofema)

Declaration

I, **Farai Dondofema**, hereby declare that the thesis for the degree of Doctor of Philosophy in Environmental Science at the University of Venda, hereby submitted by me, has not been previously submitted for a degree at this University or any other University, that it is my work in design and execution and that all referenced material contained therein has been duly acknowledged.

Signature  _____

Date **__20 August 2024__** _____

Publication timeline and disclaimer

Please note that chapters two to five of this dissertation are stand-alone papers (see below), and a certain degree of repetition was, therefore, unavoidable. The following chapters are already published, submitted or are in preparation for submission for publication in peer-reviewed journals:

- **Chapter 3:** Dondofema. F, Nethengwe. N, Taylor. P.J, Ramoelo. A. Comparison of Satellite Platform for Mapping the Distribution of Mauritius Thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) in the Vhembe Biosphere Reserve. (Published).
- **Chapter 4:** Dondofema. F, Nethengwe. N, Taylor. P.J, Ramoelo. A. Using species distribution models to predict and monitor the distributions of Mauritius Thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) in the Vhembe Biosphere Reserve (VBR). (In preparation).
- **Chapter 5:** Dondofema. F, Nethengwe. N, Taylor. P.J, Ramoelo. Assessing the effects of Mauritius thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) on water availability in the Luvuvhu catchment in Vhembe Biosphere Reserve. (Under review).

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Extended abstract

There is a need for in-depth knowledge of the spatial distributions and water use by Mauritius thorn (*Caesalpinia decapetala*) and River red gum (*Eucalyptus camaldulensis*) in the Vhembe Biosphere Reserve (VBR). Three remote sensing imagery platforms were assessed in terms of their ability to classify land cover within the VBR accurately. Supervised classification of Colour Digital Aerial Imagery (CDAI), SPOT 6 and Worldview 2 images was done using Harris Environment for Visualizing Images (ENVI) 5.3 and Environmental Systems Research Institute (ESRI) ArcGIS 10.8.3 software. The Spectral Angle Mapper (SAM) algorithm was used for the three images to identify the best image for the species-level classification. The accuracy of the classifications produced by the three images was evident that had a Kappa coefficient of 0.757 (substantial strength of agreement) for CDAI, 0.80 (substantial strength of agreement) for Worldview 2 and 0.857 (almost perfect strength of agreement) for SPOT 6 imagery.

The classification performance of SPOT 6 imagery led to its use for species-level classification. The species-level classification produced an accuracy with a kappa coefficient of 0.8750 (almost perfect strength of agreement). The highly accurate performance of the SPOT imagery was used for subsequent analysis of variation in the distribution of *C. decapetala* and *E. camaldulensis*. The species-level classification shows an increased suitable habitat from west to east along the Soutpansberg mountain and riparian areas.

Stepwise Logistic Regression (SLR) and Maximum Entropy Modelling (MaxEnt) were used to show the distribution of *C. decapetala* and *E. camaldulensis* in the VBR. Twenty-one predictor variables split into environmental and remote sensing data were collected across two seasons (hot-dry, cool-dry) from seventy-four (39 presences and 35 absence sites) for *E. camaldulensis* and seventy-eight (32 presences and 46 absence sites) *C. decapetala* from fourteen belt transects and forty quadrants measuring 200 x 200m within the VBR. The stepwise logistic regression analysis shows that variables accounted for significant variations in *C. decapetala* and *E. camaldulensis* distribution. The model increases suitable habitat from west to east along the Soutpansberg mountain and riparian areas. The MaxEnt modelling produced an AUC of 0.811 for river red gum, the random, and 0.668 *C. decapetala*. The two

models' high performance indicates high accuracy for the predictability of spatial distribution at the global and local levels.

Water is used by IAPS using remotely sensed Evapotranspiration (ET) derivatives from the Food and Agriculture Organisation's (FAO) Water Productivity Open-access Portal (WaPOR). ET products as a proxy for plant water focusing on *E. camaldulensis* and *C. decapetala* in the VBR. The study focused on the WaPOR remote sensing-based products, such as actual Evapotranspiration and Interception (ETIa) and Gross Biomass Water Productivity (GBWP). Analysing the relationship between water loss and biomass productivity products extracted from the FAO WaPOR platform at various spatiotemporal scales. WaPOR products enabled comparing plant water used by *C. decapetala* and *E. camaldulensis* within the Luvuvhu catchment. The correlation results indicate that plant water loss (ETIa) and plant productivity (GBWP) show a significant relationship that can be used to understand IAPS distribution. The analysis of the site and ETIa showed significant relationships between F (60.28) and P (0.000) between the ETIa for *C. decapetala* sites. In contrast, the analysis of GBWP did not show any significant relationship between F (0.85) and P (0.359). In the case of river red gum, analysis of variance (ANOVA) on the sites and ETIa showed significant relationships between F (33.9) and P (0.000) and the ETIa for *C. decapetala* sites. In contrast, the analysis of GBWP did not show any significant relationship between F (1.59) and P (0.212). Establishing the relationship between vegetation's evaporation and biomass components can broadly indicate how *C. decapetala* and *E. camaldulensis* proliferation affect the water use in the Luvuvhu River catchment. This was achieved using water, as represented by ETIa, and plant biomass production in the form of GBWP.

A synthesis of the results and provide possible frameworks that can be used for managing IAPS. A framework (Biotic, Abiotic, and Movement (BAM) Framework) that can be considered when using GIS, RS, and modelling to understand the distribution of IAPS was developed. Combining findings, providing recommendations and conclusions for conservation and management. We conclude that GIS, RS, and modelling can be used to monitor and assess the significant spread of IAPS in the VBR. We advocate the inclusion of GIS, RS, and modelling in the management of IAPS in protected areas.

Abbreviations used in text.

A&IS	Alien & Invasive Species
a.s.l.	Above Sea Level
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
APIS	PhenoCam, Advanced Phenology Information System
ARC-ISCW	Agriculture Research Council's Institute for Soil, Climate and Water
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AUC	Area Under the Curve
AVHRR	Advanced Very-High-Resolution Radiometer
AVIRIS	Airborne Visible/Infrared Imaging Spectrometer
BAM	Biotic, Abiotic, and Movement
BCE	Before Common Era
BGIS	Biodiversity GIS
BP	Before Present
C-I-B	Centre of Excellence for Invasion Biology
CABI	Centre for Agriculture and Bioscience International
CARA	Conservation of Agricultural Resources Act
CBC	Centre for Biological Control
CBD	Convention on Biological Diversity
CDAI	Colour Digital Aerial Imagery
DEM	Digital Elevation Model
DFFE	Department of Forestry, Fisheries, and the Environment
DMP	Dry Matter Productivity
DRS	Direct Receiving Station
DST	Department of Science and Technology
DWS	Department of Water Affairs and Sanitation
E	Evaporation
ENM	Ecological Niche Modelling
ENVI	Environment for Visualizing Images
EOS	End of the Season
ESA	European Space Agency
ESRI	Environmental Systems Research Institute
ET	Evapotranspiration
ETIa	Actual evapotranspiration and interception
ETM+	Enhanced Thematic Mapper Plus
EVI	Enhanced Vegetation Index
EWT	Endangered Wildlife Trust
FAO	Food and Agriculture Organisation
fAPAR	fraction of Absorbed Photosynthetically Active Radiation
FDA	Flexible discriminant Analysis
GBIF	Global Biodiversity Information Facility
GBWP	Gross biomass water productivity
GBM	General Boosting Models
GIS	Geographic Information Systems

GISD	Global Invasive Species Database
GLM	Generalized Linear Model
GLMM	Generalized Linear Mixed Model
GPP	Gross Primary Productivity
GPS	Global Positioning System
GSD	Ground Sample Distance
GUI	Graphic User Interface
Hyperion	Hyperspectral Imager (Hyperion) Atmospheric Corrector.
I	Interception
IAPA	Invasive Alien Plant Alert
IAPS	Invasive alien plants
IAS	Invasive Alien Species
IBIS	Island Biodiversity and Invasive Species Database
IDW	Inverse Distance Weighting
IKONOS	High-resolution satellite operated by MAXAR Technologies Inc.
ISIRIC	International Soil Reference and Information Centre
ISP	Invasive Species Programme
ISSG	Invasive Species Specialist Group
IUCN	International Union for Conservation of Nature
JCEA	Jointed Cactus Eradication Act
KNP	Kruger National Park
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
LSR	Linear stepwise logistic regression
MAB	Man and Biosphere
MARS	Multivariate adaptive regression splines
MaxEnt	Maximum Entropy Modelling
MCAA	Mountain Catchment Areas Act
MLD	Minimum Likelihood Distance
MNP	Mapungubwe National Park
MODIS	Moderate Resolution Imaging Spectroradiometer
MSS	Multi-Spectral Scanner
MT	Mauritius thorn
NDNI	Normalised Difference Nitrogen Index
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NEMBA	National Environmental Management: Biodiversity Act
NEON	National Ecological Observatory Network
NGI	National Geo-spatial Information
NIR	Near-Infrared
NOAA	National Oceanic and Atmospheric Administration
NPN	National Phenological Network
NRF	National Research Fund
NRT	Near-Real-Time
NSBA	South African National Spatial Biodiversity Assessment
P	Precipitation

PCA	Principal Component Analysis
PEN	Phenological Eyes Network
PO	Presence-only
QuickBird	was a high-resolution commercial Earth observation satellite owned by DigitalGlobe
RADARSAT	an advanced Earth observation satellite system developed by Canada to monitor environmental change and support resource sustainability.
RET	Reference Evapotranspiration
RF	Random Forest
RFM	Random Forest Model
ROC	Receiver Operating Curve
RoI	Region of Interest
RRG	River Red Gum
RS	Remote sensing
SAEON	South African Environmental Observation Network
SAM	Spectral Angle Mapper
SANBI	South African National Botanical Institute
SANSA	South African National Space Agency
SAPIA	Southern African Plant Invaders Atlas
SAWS	South African Weather Service
SDG	Sustainable Development Goals
SDM	Species Distribution Model
SOS	Start Of the Season
SPOT	Satellite Pour l'Observation de la Terre
T	Transpiration
TBP	Total biomass production
TM	Thematic Mapper
TSD	Temperature Sex Determination
UAS	Unmanned aerial systems
UN	The United Nations
UNEP	United Nations Environmental Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization
VBR	Vhembe Biosphere Reserve
VDM	Vhembe District Municipality
VIF	variance inflation factor
WaPOR	Water Productivity Open-access portal
WfW	Working for Water
Worldview	The Worldview series consists of high-resolution commercial Earth-imaging satellites. Owned by MAXAR
XLSTAT	Excel data analysis add-on

Chapter 1 : Background and motivation for modelling invasive alien plant species in the Vhembe Biosphere Reserve.

1 Introduction

This chapter introduces the background and motivation that led to constructing the research hypothesis for modelling invasive alien plants (IAPS) in the Vhembe Biosphere Reserve (VBR). Chapter one also presents an outline of the thesis structure.

1.1 Background

The United Nations (UN) Sustainable Development Goal (SDG) (15) recognises the effects of IAPS proliferation on human health, biodiversity, ecosystem services, and livelihoods. Thus, it is alarming that only a minority of the world's countries have prioritised biosecurity interventions to minimise the impacts of IAPS globally (Pyšek, 2020). This observation argues for the need to understand the effects of IAPS which, is crucial because, as they cover about 6.7% of the global land surface which is persistently expanding (Bartz & Kowarik, 2019). The adverse impacts of this expansion are more pronounced in developing countries compared to their developed counterparts (van Wilgen et al., 2001; Pratt et al., 2017) with evidence from the literature showing that this phenomenon is associated with the proliferation of numerous hot-spot areas (Pejchar & Mooney, 2009; Gallardo, 2019). IAPS cost South Africa tens of trillions of Rands annually in lost agricultural productivity (Pratt et al., 2017) and administrative costs related to monitoring, management and clearing (Paini et al., 2016; Van Wilgen & Wilson, 2018).

IAPS often decrease the quality of the soil through excessive use of available nutrients (Teixeira, 2020), with their expansion often leading to the lowering of groundwater table (Van Wilgen, 1997; Le Maitre et al., 2015), reduced runoff (Enright, 2000; Chamier et al., 2012), and decrease in streamflow. In South Africa's VBR for example, invasion by Mauritius thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) has produced the same trends where these species have spread to invade native savanna ecosystems beyond homes and forestry plantations (Clusella-Trullas & Garcia, 2017).

1.2 Rationale

The rationale for this study is premised on the growing developments in the field of invasion biology that have increasingly adopted the use of remote sensing to monitor spatiotemporal variations in the distributions of IAPS (Asner et al. 2008). The use of remote sensing techniques reduces the costs associated with field data collection, which is labour-intensive and helps in overcoming the inability of field-based measurements to provide optimum spatial coverages. Remote sensing (RS) and geographic information systems (GIS) have proven beneficial in identifying and mapping IAPS (Babkina et al., 2019) and forecasting their present and future potential distributions and consequences (Hellmann et al., 2017). RS and GIS techniques have provided well-documented benefits by a) providing a panoramic perspective and, b) cost-effectively enabling detailed characterisation with multispectral data at multi-temporal and spatial scales (Van der Meer et al., 2002). These capabilities offer valuable ways to analyse complicated geographic terrain types and various inaccessible habitats. Hyperspectral satellite data, available now and by the end of the decade, will provide additional spectral information to distinguish invasive species rapidly. These missions use imaging spectrometers rather than more limited spectral data from multispectral image data. Available hyperspectral imagery includes the Italian Space Agency's (ASI) PRISMA, Hyperspectral Precursor of the Application Mission, and the German Aerospace Center's (DLR) DESIS (DLR Earth Sensing Imaging Spectrometer). Further, by ~2030, NASA's Surface Biology and Geology or SBG is planned to be launched, as well as the European Space agency's (ESA) CHIME (Copernicus Hyperspectral Imaging Mission for the Environment), planned for launch in 2029. These emerging technologies will advance the studies of invasive species detection.

Aerial photographs, airborne multi-spectral scanners, high- and low-resolution satellite images, and ground-based spectrometer readings are some of the remote-sensing sources of information which have been widely used to monitor IAPS (Vaz et al., 2018, 2019). RS and GIS have been used to map the spread of IAPS, their ecosystems, landscapes, bio-climatic conditions, and variables that facilitate invasions (Rowlinson et al., 1999).

The availability of high-resolution spatially explicit data over large areas, combined with ground surveys (Hattab et al. 2017), could provide the building blocks for the development of a framework for the detection, monitoring, and assessment of IAPS in a manner that generates products which can be used for management at multiple spatial and temporal scales.

The study site is in the savanna biome of South Africa, which has experienced high rates of invasion in the past century contributing to the potential extinction of native species. The increase in invasion rates also affects an area's hydrology. It threatens ecosystem services, hampering an ecosystem's ability to generate resources required for fauna, flora, and human survival as the essential role of vegetation in carbon sequestration (Mworia, 2011).

1.3 Study area

The research site covered within this thesis falls within the VBR. The VBR is a member of the World's reserve network organised by Man and Biosphere (MAB, UNESCO). It is in the northern part of South Africa and covers five local municipal areas of the Limpopo province which include (Blouberg, Musina, Makhado, Thulamela, and Collins Chabane) (Figure 1-1). It is bordered by Botswana and Zimbabwe in the north and Mozambique in the East.

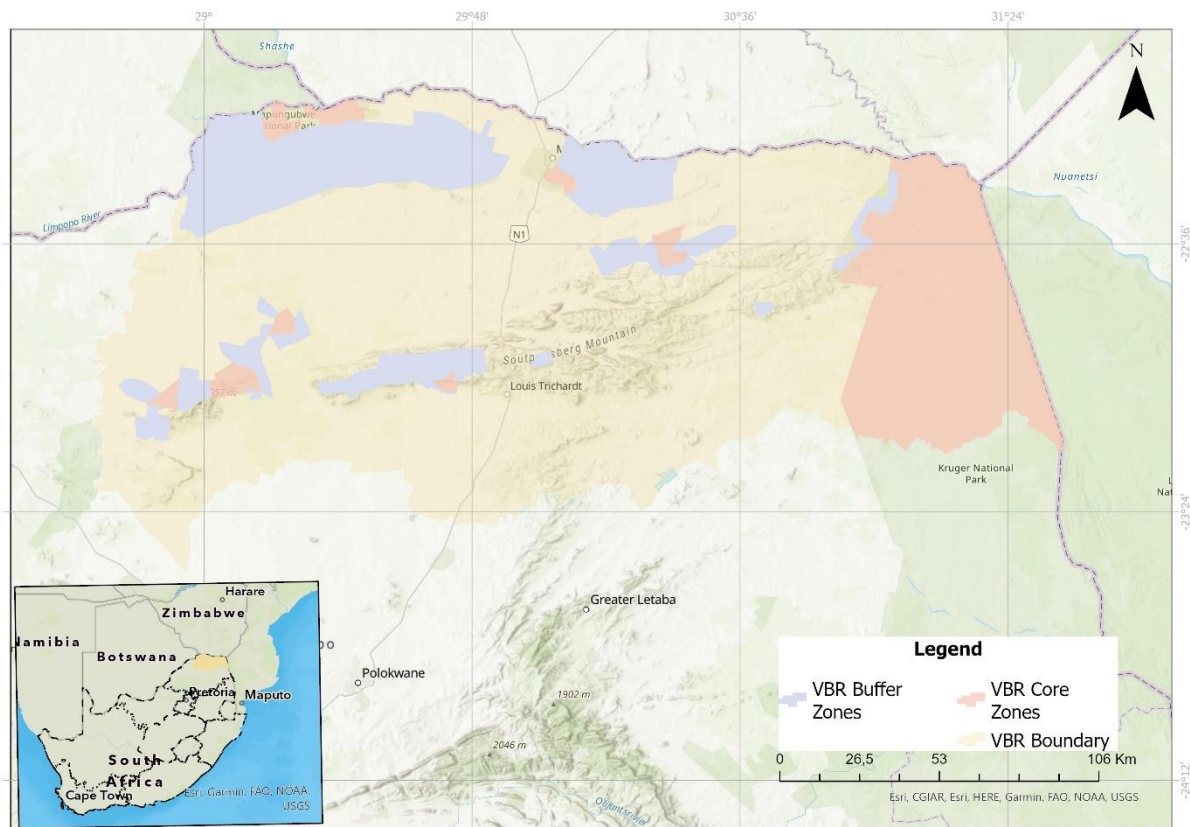


Figure 1-1: Locality map of Vhembe Biosphere Reserve in the Limpopo province.

1.4 Topography and geomorphology

The VBR covers an area of 3 070 000ha (30 701 km²) in the Kruger National Park (KNP), north of the Shingwedzi river. The eastern border is formed by the Mogalakwena river, and the southern border extends roughly from just south of the Blouberg – Makgabeng and Soutpansberg mountain ranges. The altitude of the VBR ranges from 250 metres to 1748 metres above mean sea level.

1.5 Climate

The VBR experiences average maximum temperatures of 21°C to 37°C in January, average minimum temperatures of 5°C to 12°C in July and has annual average temperatures of between 13°C to 27°C (South African Weather Service, 2006). The winters in the VBR are generally mild, and frost sometimes occurs only in the southern valleys (Mpandeli, 2014). Entabeni is the highest observation station in the area, with mean annual rainfall ranging from 850 mm to 2000 mm but rain-shadow areas in the low-lying localities around Pafuri and Alldays receive lower amounts ranging between 200 mm and 300 mm/annum (Figure 1-2). Most of this area's precipitation is captured

by the mountains along the eastern part, with decreasing amounts falling over the hill further westward, even though some western peaks are higher in elevation than those in the east. It should be emphasised that local variations cannot be stated accurately because of the sparse rainfall measuring network in the area.

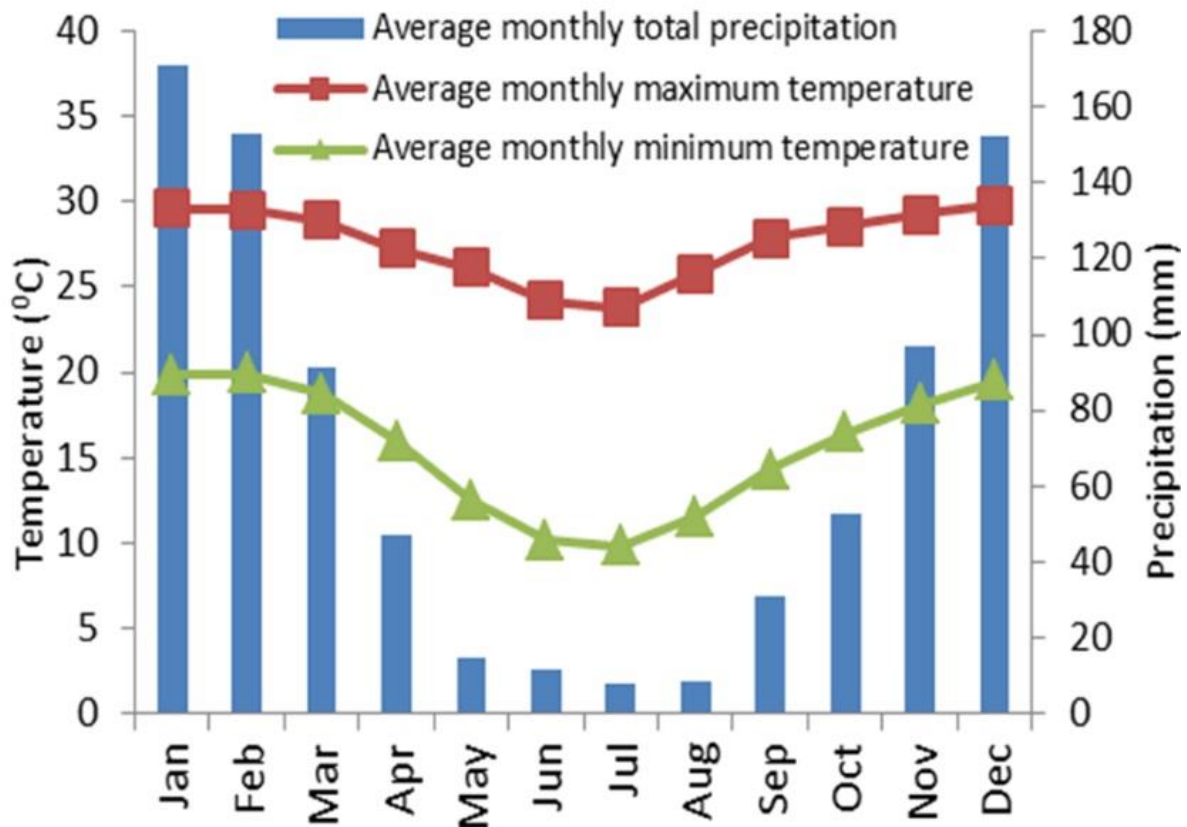


Figure 1-2: Average monthly total precipitation, maximum and minimum air temperature over the period 1985–2020 University of Venda (Lam et al., 2023).

1.6 Vegetation of the Vhembe Biosphere Reserve

The VBR's bushveld vegetation unit of the Savanna biome conservation status is categorised as 'vulnerable' (Mucina and Rutherford, 2006). The vegetation of the VBR consist of evergreen montane forests and dense deciduous woodlands with a poorly developed grassy layer, relatively open savanna in some places and exotic *pinus* and *eucalyptus* plantations on the mountain range. Generally, the vegetation communities in the Soutpansberg mountains occur as east-west bands, following the mountain range ridges orientation, which follows the east-west moisture flow from the Indian ocean. Eight major vegetation types have been identified in the Soutpansberg mountain range, indicating that is biologically rich in plant species (Evans, 2017). These vegetation types include the *Northern Plains Bushveld*, *Eragrostis lehmanniana* var. *lehmanniana*–*Sclerocarya birrea* subsp. *Caffra*, Soutpansberg arid northern

bushveld, *Euclea divinorum*–*Acacia tortilis*, an *Catha edulis*–*Flueggia virosa* Soutpansberg (Evans, 2017). To the north of the VBR towards Musina into Pafuri in Kruger national park (KNP), Mopane bushveld vegetation dominates this area (Figure 1-3).

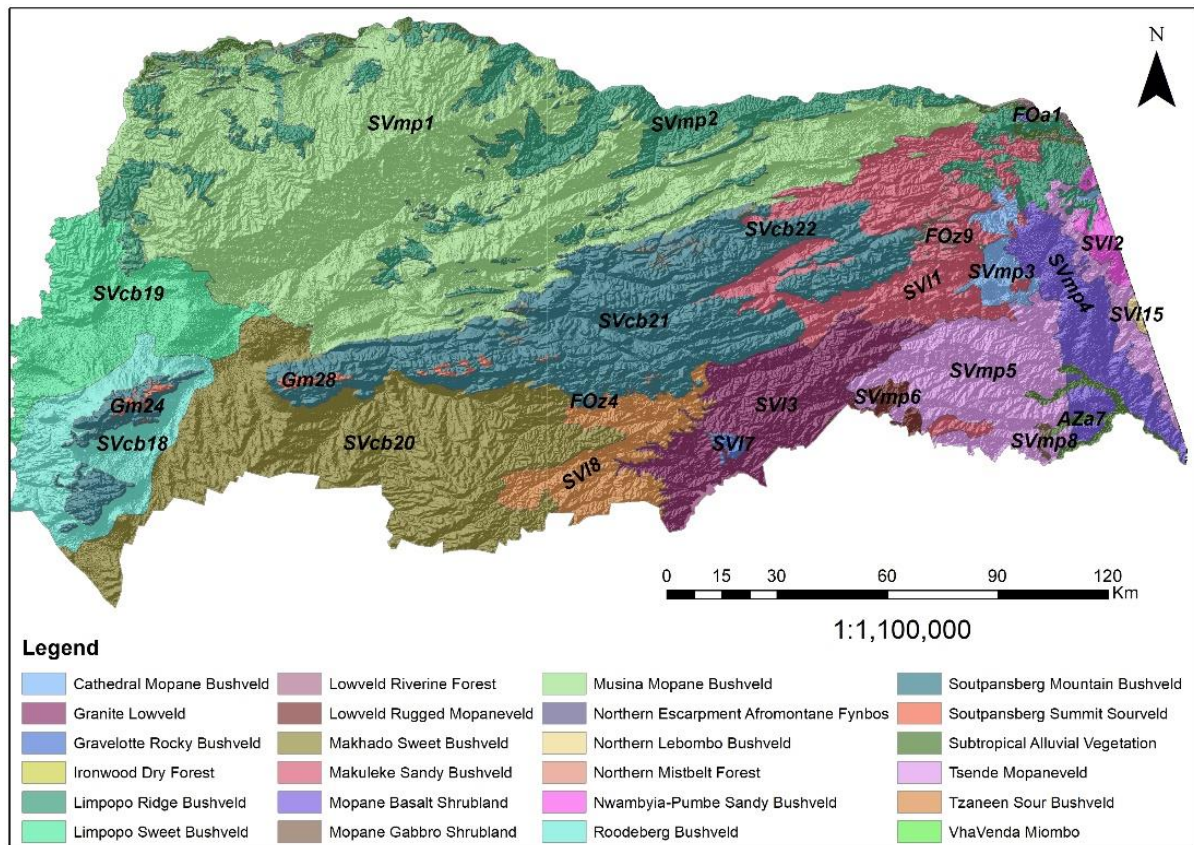


Figure 1-3: Vegetation of the Vhembe Biosphere Reserve (Mucina and Rutherford, 2006).

1.7 Land Use and Conservation

The VBR include the, Mapungubwe National Park (MNP), the northern part of the KNP, two recognised centres of biodiversity and endemism (Soutpansberg and Blouberg mountains), some provincial nature reserves and the Makgabeng Plateau with over 1 000 rock painting sites. The VBR is covered by 39.7% of the protected areas (Evans, 2017). Most of the protected areas in VBR consist of indigenous vegetation, which is dominated by grasslands, open and dense woodland bush. From 1990 to 2013, the VBR land has been altered by 1 697.7 square kilometres with this change occurring at a rate of 2.3% per annum. Human anthropogenic activities such

as over-harvesting of fuelwood by the ever-increasing rural population within the VBR lead to the loss or decline of thicket bushes and grasslands.

The conservation status of the VBR's bushveld vegetation unit of the savanna biome is officially categorised as 'vulnerable'. The unit consists of a rainfall gradient distribution of dense deciduous woodlands and evergreen montane forests with a poorly developed grassy layer and open savanna in some places. Exotic eucalyptus and pine plantations on the Soutpansberg range put added pressure on maintaining the status of the Soutpansberg mountain bushveld vegetation unit. Generally, the vegetation communities in the Soutpansberg Mountains occur as east-west bands, following the orientation of the ridges of the mountain range, along the easterly moisture flow from the Indian Ocean.

1.8 Ecological characteristics

The VBR include three biomes, namely savanna, grassland, and forest, four bioregions and twenty-three different vegetation types or biotopes. Eight of these biotopes are endemic to South Africa. The area is also a bio-geographical node, comprising the Kalahari, and Lowveld bioregions having temperate, tropical climatic conditions. This creates zones of ecologically important interactions, which must be protected to ensure conservation viability.

The South African National Spatial Biodiversity Assessment (NSBA) has included the Blouberg and Soutpansberg complex as one of its nine priority areas for conservation action based on a combined analysis of species, ecosystems, and ecological processes. The same area is also listed by Van Wyk and Smith (2001) as a hotspot of South African biodiversity and endemism. Lake Fundudzi in the Soutpansberg mountains is the one of the few natural inland lakes in South Africa. Several wetlands in the same mountain range contain peat which provides a record of environmental conditions during the historical past dating back to 12 000 years Before the Present (BP).

1.9 Introduction to the physiology and distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*.

In this section we introduce the taxonomy and distribution statistics of the two IAPS (*Caesalpinia decapetala* and *Eucalyptus camaldulensis*) at local, regional and global level.

1.9.1. Taxonomy and description of *Caesalpinia decapetala*

The genus *Caesalpinia spp.* is a legume family of flowering plants of the *Fabaceae* family. According to Baldim et al. (2012), more than 500 species belong to the *Caesalpinia* (*Caesalpinieae* spp) genus. Plants of the *Caesalpinia* genus are native to tropical, subtropical, and lowland rainforest scrub in New South Wales, Australia (Starr et al., 2003). *Caesalpinia spp* is common in South Africa as a 'Mauritius thorn' and widely known as a 'Mysore thorn' in India (Coetzer & Neser, 1999).

1.9.2. Biology and Ecology of *Caesalpinia decapetala*

Caesalpinia decapetala is a woody, clambering shrub with pale-yellow flowers and bipinnate leaves and clusters (Figure 1-.4). The plant produces large, rounded seeds in flattened, unsegmented, beaked pods (Byrne et al., 2011). The exact centre of origin of the *Caesalpinia decapetala* remains unknown. It is, however, certainly not indigenous to Mauritius as its common name suggests Indonesia and Malaysia are its natural areas of provenance and nativity. *Caesalpinia decapetala* was initially grown in South Africa as security hedges and has become widespread in Limpopo, Mpumalanga, KwaZulu-Natal and Eastern Cape provinces, neighbouring countries that include Eswatini, Mozambique, and Zimbabwe (Byrne et al., 2011).



Figure 1-4: Mauritius thorn (*Caesalpinia decapetala*) flowers produced in long racemes between winter and spring and the compound leaves of this shrub. The photo was taken in Levubu, Limpopo province, in June 2019.

Caesalpinia decapetala invades pastures, commercial plantations, riparian vegetation, forest margins, and savannas in the humid parts of the world, creating an impenetrable, prickly thicket that can wound animals and humans and cause the collapse of host trees (Byrne et al., 2011). If the species grows close to dams, it can damage fishing nets, making the watercourse inaccessible. Studies have shown that *Caesalpinia decapetala* uses excessive water and increases fire risk (GISD, 2020).

Caesalpinia decapetala produces thin, dark brown, large ellipsoid seeds measuring 8-12 mm long and 6-8 mm wide (Figure 1-5). Between spring and summer, woody leguminous pods with seeds are produced (Turnbull, 2002). Turnbull (2002) states that *Caesalpinia decapetala* seeds can remain viable in the soil for up to a decade. *Caesalpinia decapetala* cotyledon and embryo are enclosed in a hard seed coat which needs scarification before germination (Baskin & Baskin, 2014). Teketay (1996) states that scarification or acid treatment decreases germination time and raises the number of seeds germinating from about 80% to nearly 100% within 30 days.

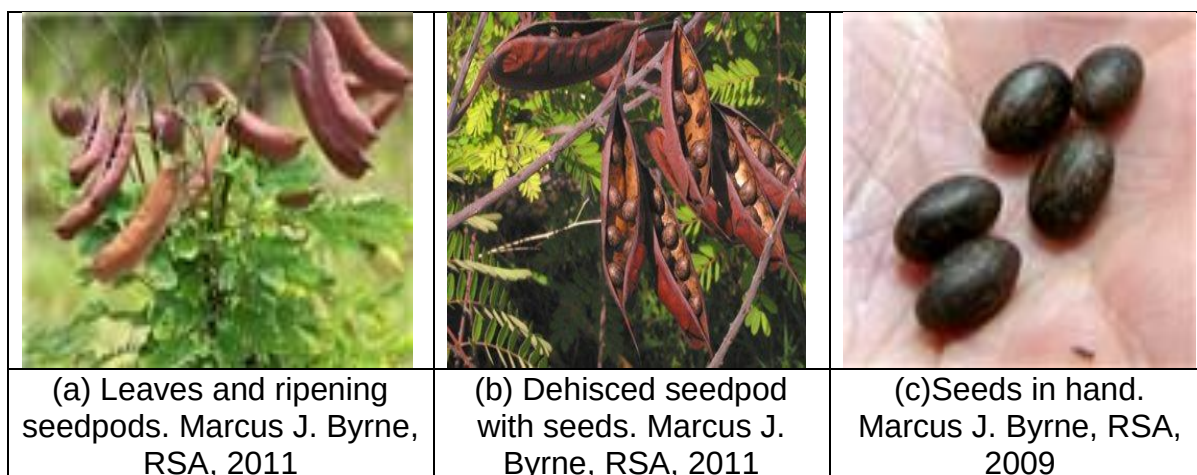


Figure 1-5: *Caesalpinia decapetala* (a) leaves and ripening seedpods, (b) dehiscent seedpod with seeds, c) seeds in hand. (M. J. Byrne, RSA, 2011).

1.9.3. Distribution of *Caesalpinia decapetala* in South Africa

Coetzer and Naser (1999) mention that the possible initial introduction of *Caesalpinia decapetala* into South Africa is unknown. However, they suggest that the first reported cases of *Caesalpinia decapetala* in South Africa date from 1904-1908 (CABI, 2020). *Caesalpinia decapetala* has been invasive in South Africa since the 1960s but was only officially declared a weed in 1983 when the legislation on declared weeds and invaders plants, including a list of invader plants, was promulgated as Conservation of Agricultural Resources Act 43 of 1983, Schedule, Regulations and List (Coetzer & Naser, 1999). Today, the IAS regulations, National Environmental Management: Biodiversity Act (NEMBA) (Act No 10 of 2004), list *Caesalpinia decapetala* as a species of category 1b, which includes its monitoring or elimination and destruction where appropriate.

Caesalpinia decapetala threatens, amongst other things, the agricultural industry by occupying grazing land and injuring livestock. Thus, its planting is prohibited. *Caesalpinia decapetala* invades commercial plantations of timber and natural areas such as riverine habitats, riparian vegetation, forest margins and savannas in the moist eastern parts of the country (Coetzer & Naser, 1999; Coetzer, 2000). The IAPS have invaded four (Limpopo Province, KwaZulu-Natal, Mpumalanga) of the nine provinces of South Africa (Coetzer & Naser, 1999; Henderson, 2001) (Figure 1-6 & 1-7). By 1998, *Caesalpinia decapetala* was ranked number 20 out of 25 invader species in South Africa and was estimated to utilise 33.82 million m³ of water per annum (Versfeld et al., 1999). Several herbicides have been registered against *Caesalpinia decapetala*,

mainly targeting plants up to one meter (1m) in height. Still, access to plants growing in the canopy of tall trees is problematic. *Caesalpinia decapetala* has been declared a category 1b species in three South African biomes (Figure 1-6).

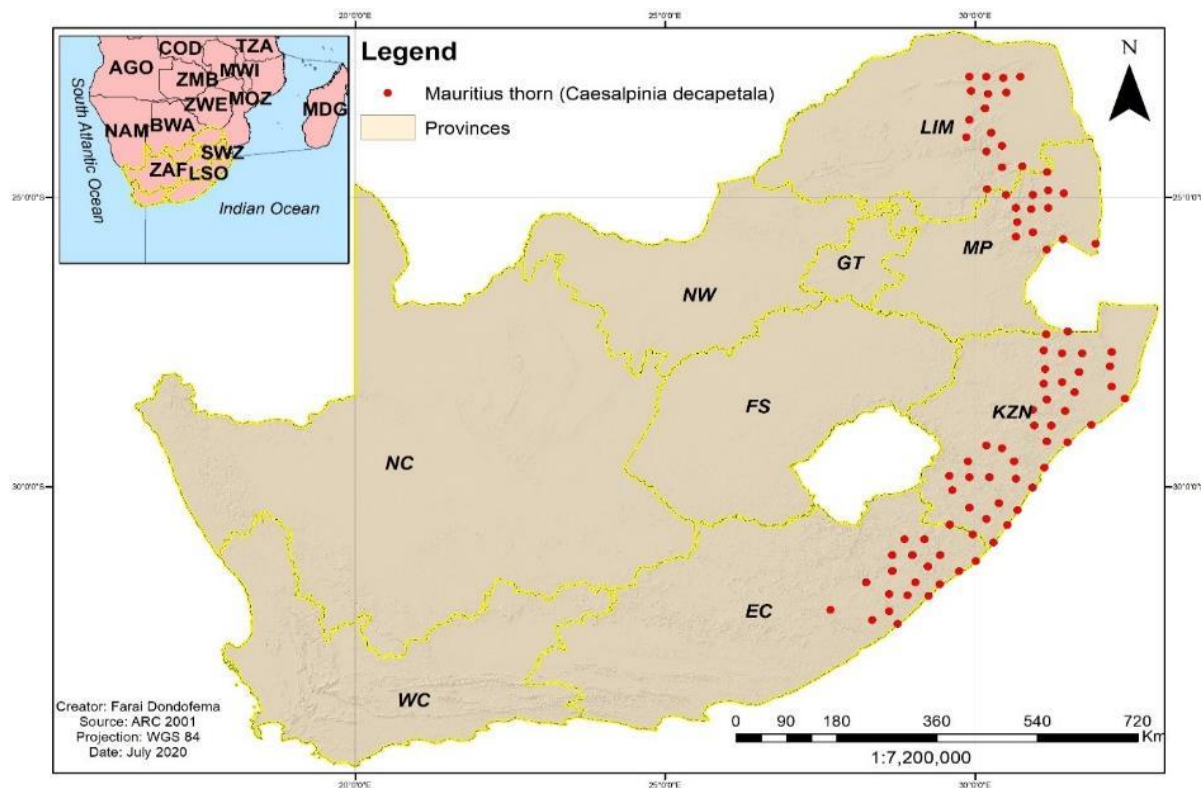


Figure 1-6: Distribution of *Caesalpinia decapetala* in South Africa. (Drawn Compiled by F. Dondofema from L. Henderson; data source: SAPIA database, ARC-Plant Protection Research Institute, Pretoria. 2002)

Surveys to identify promising biocontrol candidates were initiated during the 1990s but have resulted in the release of only one insect species: the seed-feeding beetle *Caesalpinia decapetala* Seed-Weevil (*Sulcobruchus subsuturalis*). Despite the release of more than 350,000 beetles at more than 200 different localities in South Africa, evidence indicates that they reproduce in the field in meagre numbers and at a limited number of sites (Figure 1-7). The investigation into a second candidate agent, the leaf-mining moth *Acrocercops hyphantica*, was terminated before conclusive results were obtained but might be revived if the opportunity arises (Coetzer & Naser, 1999).

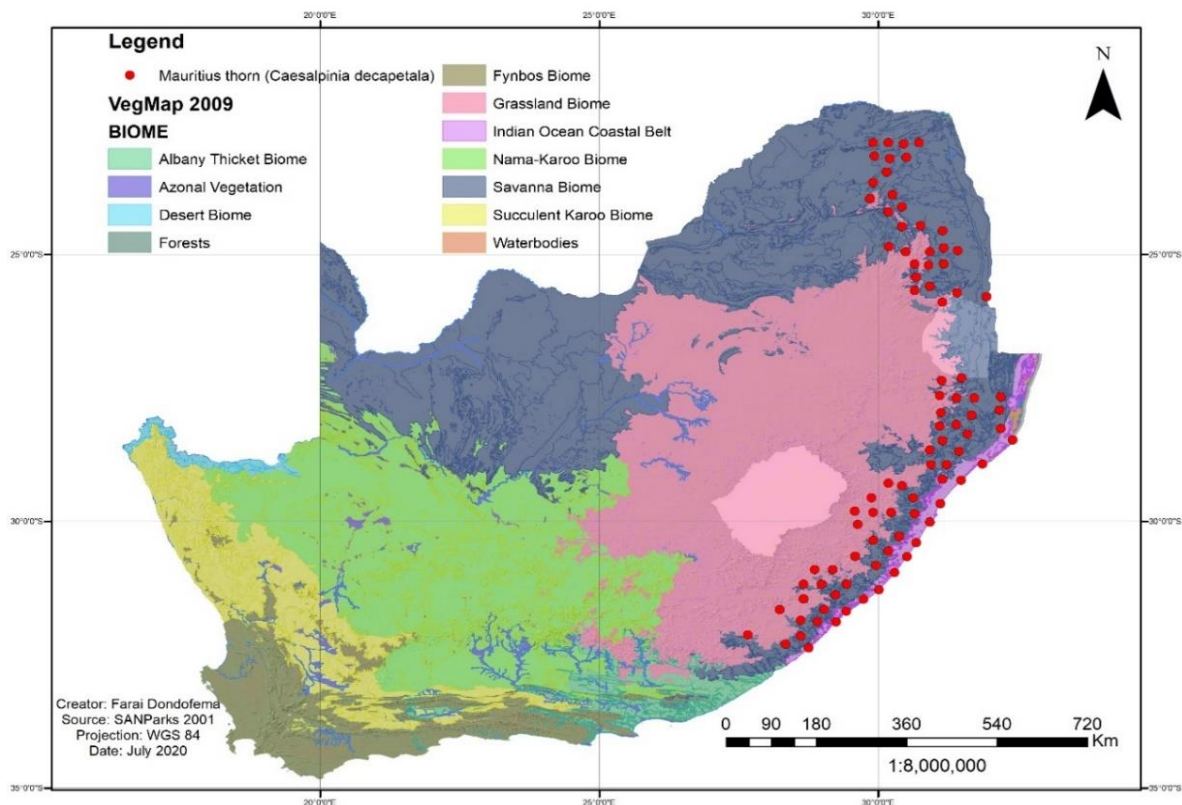


Figure 1-7: Distribution of *Caesalpinia decapetala* in South African Biomes BGIS (2012)

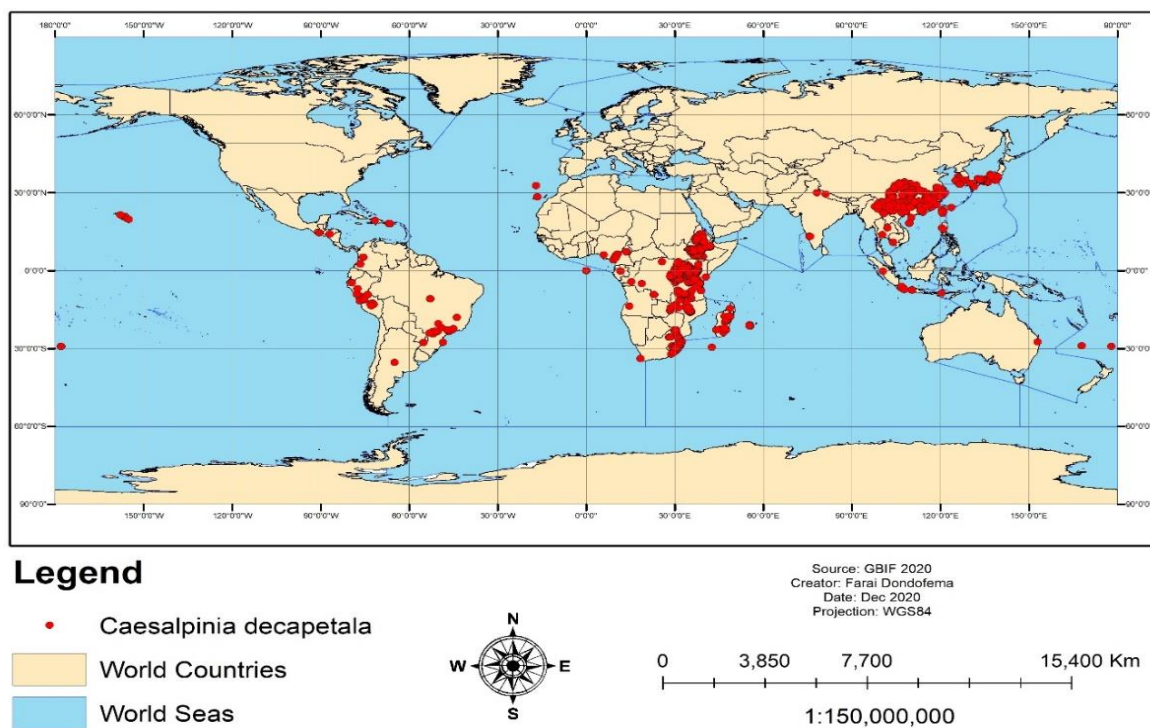


Figure 1-8: Global distribution of GBIF.org (17 December 2020) GBIF Occurrence Download <https://doi.org/10.15468/dl.bcp9k9> Global distribution of GBIF.org taxonomy and description of *Caesalpinia decapetala*.

1.10 Taxonomy and description of River Red Gum (*Eucalyptus camaldulensis*)

The genus *Eucalyptus* is a legume family of flowering plants of the *Myrtaceae* family. About 789 species belong to the *Eucalyptus* genus, with another 123 subspecies or varieties, giving 912 eucalyptus taxa (Wilcox, 1997). Friedrich Denhardt is the first to formally describe *Eucalyptus camaldulensis* by publishing the description in *Catalogus Plantarum Horti Camaldulensis*. Blakely (1965) published a formal report on six varieties of *Eucalyptus camaldulensis*. Contemporary botanists generally overlooked such due to determination problems, yet some texts differentiate between the *camaldulensis* and *obtusa* varieties (Brooker & Kleinig, 1994).

1.10.1. Biology and Ecology of *Eucalyptus camaldulensis*

Generally, a medium-sized *Eucalyptus camaldulensis* tree grows up to 30 m, with large trees reaching 45 m. It has a thick trunk covered with peeling bark (Figure 1-9). The colour of the smooth bark may be blue, pinkish-blue, white, or brown in different shades. The leaves alternate at each node, taking the form of a lance 18-25cm long and 2 cm wide. *Eucalyptus camaldulensis* leaves are green or bluish-green, usually the same on either side of the leaf, with clearly visible oil glands (Klein et al., 2015) with inflorescence 2.5 cm long. The buds are scarred, and the tops of the plant are tightly beaked or conical. The flower's stamens or male reproductive parts are usually inflexed, bent inward, downward, or erect. *Eucalyptus camaldulensis* fruit is hemispheric (0.6 x 1 cm) in size, containing yellow to yellow-brown seeds with a terminal hilum and a scar showing the point of attachment to the branch.

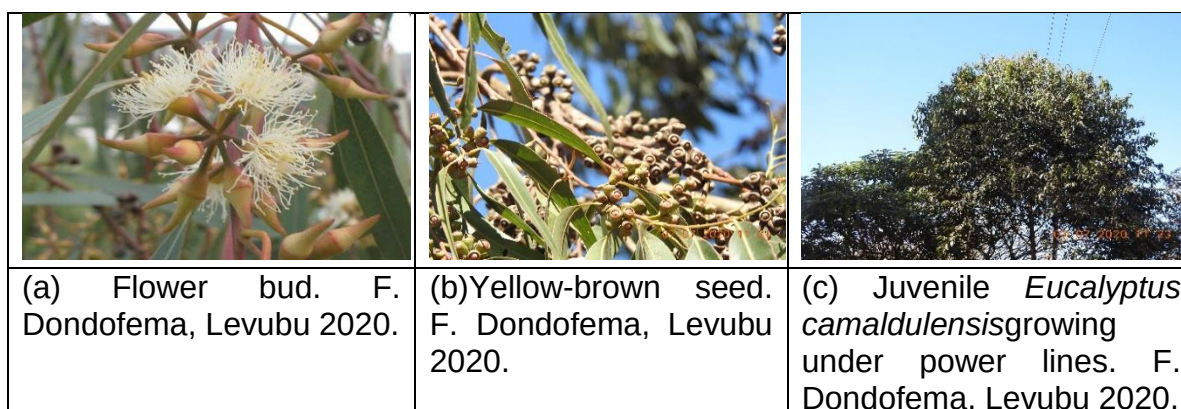


Figure 1-9: *Eucalyptus camaldulensis* (a) Leaves and flowers, and (b) Seeds. (Farai Dondofema, 2020) *Eucalyptus camaldulensis* (a) Leaves and flowers, and (b) Seeds. (Photographs by Farai Dondofema, 2020)

Eucalyptus camaldulensis is a plant that originated in Australia and is prized for its cool shade and ornamental uses in South Africa and for its ability to survive cold and drought (Figure 1-10).



Figure 1-10: River red gum (*Eucalyptus camaldulensis*). The photo was taken in Levubu, Limpopo province, (F. Dondofema, 2020).

Together with other gum species, it is a vital source of pollen and nectar that supports honeybees, which serve as the primary pollinators for deciduous fruits, vegetable seed crops, subtropical fruits, nuts, oilseeds, and berries (Hirsch et al., 2019). However, it is no longer planted as a timber tree due to its branched shape. Despite its beneficial properties, *Eucalyptus camaldulensis* is highly invasive in river situations where dense riverbanks are damaged, watercourses choke, and excessive amounts of water evaporate (Hirsch et al., 2019).

1.10.2. Distribution of *Eucalyptus camaldulensis* in South Africa

Eucalyptus camaldulensis is one of the most widely spread IAPS in South Africa. Its distribution covers all nine provinces of South Africa. The levels of invasion by *Eucalyptus camaldulensis* vary across the province, ranging from high infestations to low infestations (Figure 2.9)

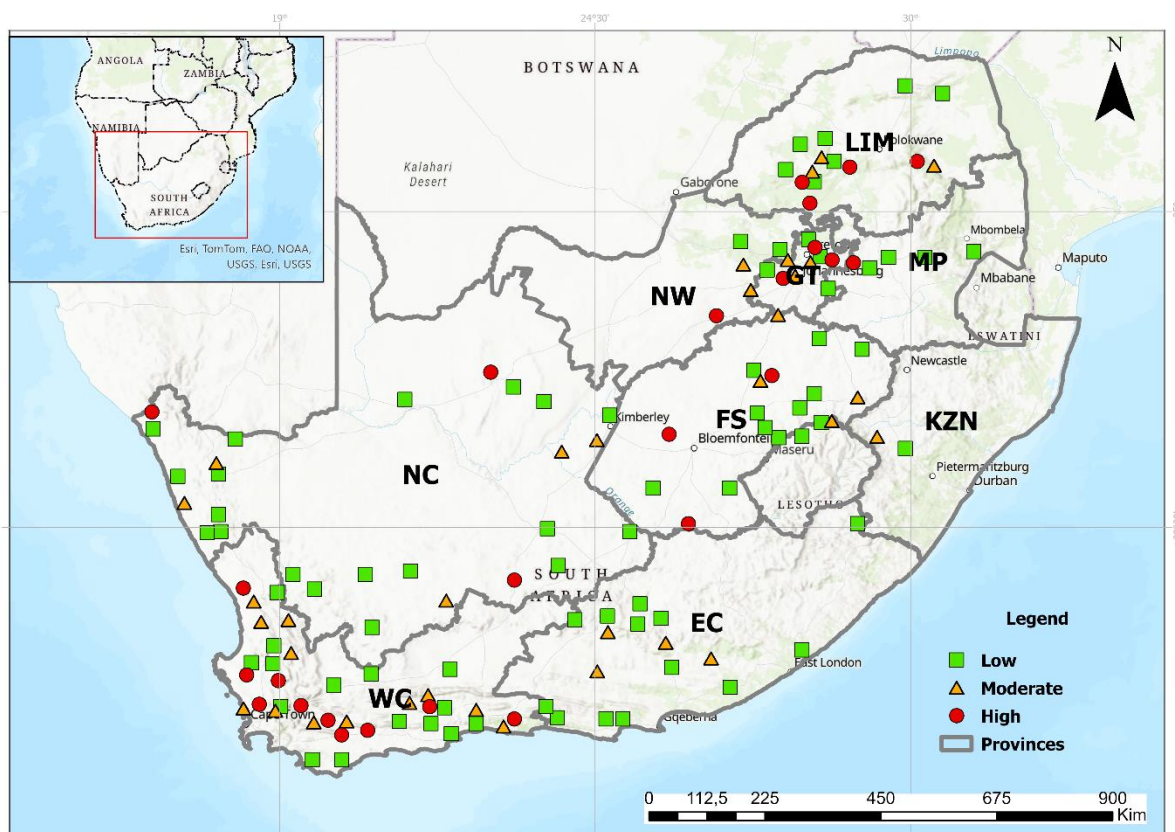


Figure 1-11: Distributions of river red gum (*Eucalyptus camaldulensis*) based on SANParks occurrences as reported by Spear et al. (2017)

In the alien and invasive species regulations, as enshrined by the NEMBA (Act No 10 of 2004), *Eucalyptus camaldulensis* has been declared a category 1b species in six South African biomes (Figures 1-12 & 1-13). Category 1b status necessitates control or removal and destruction, if possible. As a concession to those dependent on *Eucalyptus camaldulensis*, this species is not considered invasive within the Karoo and Desert biomes. It is also not listed as an IAS within cultivated land up to 50m away from untransformed land and 50m from a farmhouse. The NEMBA regulations classify all *Eucalyptus camaldulensis* trees with diameters exceeding 400mm growing in urban edge as category 1b species, except when growing in riparian or protected areas, listed ecosystems and ecosystems identified for conservation.

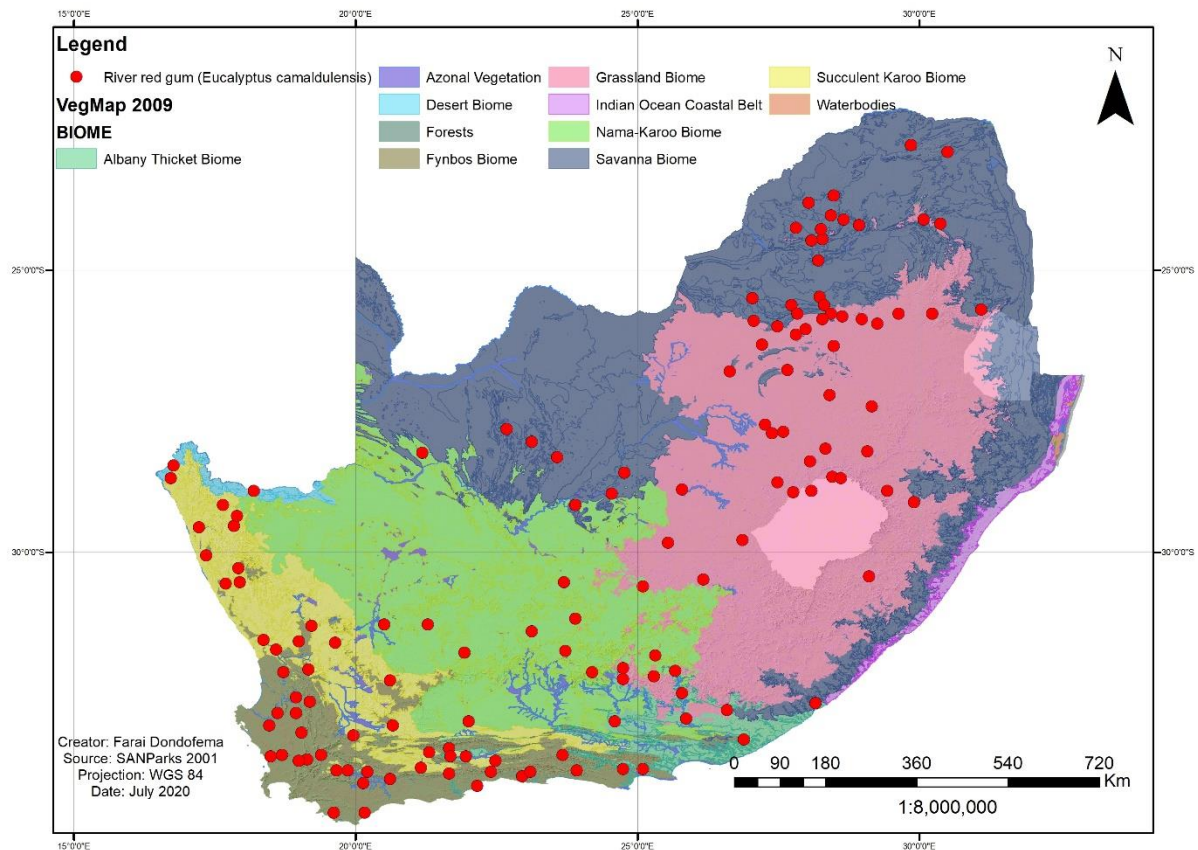


Figure 1-12: Distribution of river red gum (*Eucalyptus camaldulensis*) in South African Biomes based on SANParks occurrences as reported by Spear et al. (2017)

Eucalyptus camaldulensis, used in plantations, woodlots, bee-forage areas, windrows, and the lining of avenues, except for trees in the exempted biomes, are declared category two species. Land managers must apply for a permit to conduct a restricted operation such as possessing, increasing, breeding, propagating or spreading the trees in a demarcated area.

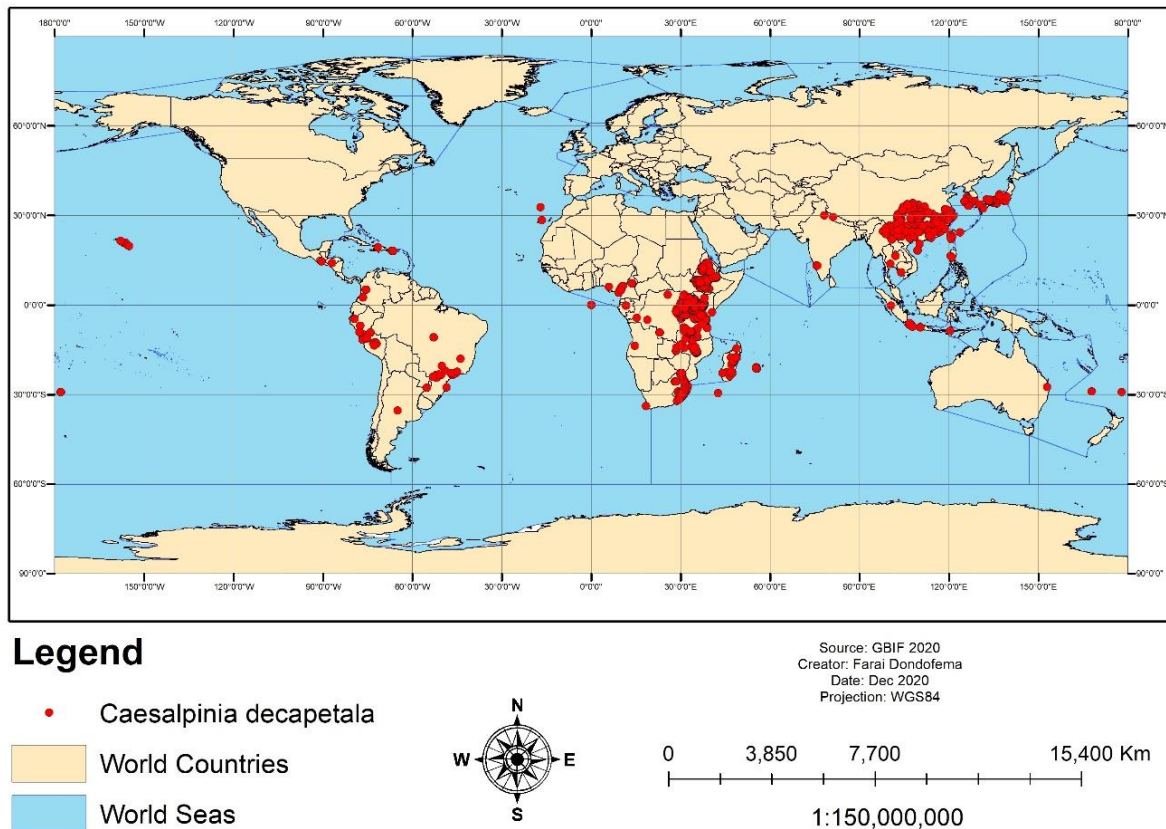


Figure 1-13: Global distribution of *Eucalyptus camaldulensis*. Source: <https://doi.org/10.15468/dl.xzeabc>

1.11 Motivation

Extensive research has been undertaken on IAPS in South Africa; however, little has been done to understand the spatiotemporal distribution of Mauritius thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) in South Africa. This knowledge gap has led to uncertainty and contention over restoration and rehabilitation techniques. This research provides informative and more significant insights that enhance our understanding of the direction of change in selected IAPS quantifying spatial variations in the distributions of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR and their potential water-use impacts. Results from this study facilitate the more realistic modelling of possible forest management approaches and may provide guidelines for the effective monitoring and management of IAPS. To achieve this goal, presence, and absence data of the two above IAPS, environmental data, RS and GIS variables and estimates of water-use impacts for two introduced species identified as economically or ecologically significant. This

information was used to validate the spatial variations in the distributions of the proposed modelling approach.

1.12 Research hypotheses

- i. *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distributions can significantly be distinguished based on their phenophase, physiology, and environmental characteristics through remote sensing and geographic information system approaches (Chapter 3).
- ii. *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distributions could be significantly estimated using stepwise logistic regression and species distribution modelling (Chapter 4).
- iii. Water use variability between *Caesalpinia decapetala*, *Eucalyptus camaldulensis* and native species can be determined using remote sensing derived evapotranspiration and biomass productivity data (Chapter 5).
- iv. A framework based on remote sensing and a geographic information system can be used to monitor and manage *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the Vhembe Biosphere Reserve (Chapter 6).

1.13 Aims and Objectives

To address the research hypotheses, the objectives of this project are to:

- i. Evaluate the effectiveness of using remote sensing and a geographic information system for the discrimination of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* from endemic vegetation in the Vhembe Biosphere Reserve (Chapter 3).
- ii. Predict the potential spatial distributions of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* using stepwise logistic regression and species distribution modelling in the Vhembe Biosphere Reserve (Chapter 4).
- iii. Use remote sensing-based evapotranspiration and biomass productivity to determine water use by *Caesalpinia decapetala* and *Eucalyptus camaldulensis* on water availability in the Luvuvhu catchment in Vhembe Biosphere Reserve (Chapter 5).

- iv. Develop a remote sensing and a geographic information-based framework for assessing water use by IAPS and native vegetation in the Vhembe Biosphere Reserve (Chapter 6).

1.14 Research Questions

From the objectives the following research questions were asked:

- i. Can *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distributions be accurately distinguished from native or endemic vegetation using remote sensing and a geographic information? (Chapter 3)
- ii. Can stepwise logistic regression and species distribution modelling be used to predict the spatial distributions of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the Vhembe Biosphere Reserve using? (Chapter 4)
- iii. Can evapotranspiration and biomass productivity remote sensing data be used to determine water use by *Caesalpinia decapetala* and *Eucalyptus camaldulensis* on water availability in the Luvuvhu catchment in Vhembe Biosphere Reserve (Chapter 5)
- iv. Can a framework integrating remote sensing and GIS be used to monitor *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in Vhembe Biosphere Reserve? (Chapter 6)

1.15 Concluding Remarks

South Africa is one of the world authorities in invasive alien species (IAS) research spearheaded by the government, academic institutions, the private sector, not-for-profit organisations, farming, and conservation communities. Most research on IAPS has focused on specific areas of interest depending on the expected outputs. IAPS research in the VBR was based on modelling species distribution and focusing on two introduced tree species and their water use.

To support the South African government's programmes, there is a need to expand current research to include the impacts of invasive alien species on indigenous trees and, the rehabilitation of degraded lands and the restoration of riparian zones. One of the biggest problems with current rehabilitation programmes is that IAPS are also used to restore ecosystem services. However, this ignores the importance of ecosystem structure and functioning. Research and policy support in South Africa are required to

promote environmentally friendly and scale-up management initiatives in degraded areas.

The impact of invasive alien trees on catchment hydrology is crucial in a water-scarce country. Therefore, it is essential to understand water use by invasive alien trees in degraded landscapes and riparian zones. Plant water use monitoring can be improved by estimating the energy balance for the whole canopy using total evaporation as a proxy. The use of indigenous trees for rehabilitation can increase income generation for rural communities through ecosystem services while simultaneously improving the condition of badly degraded catchments.

1.15 Outline of the Thesis Structure

This thesis comprises a series of papers, which have been presented in the form of chapters. These papers have either been published, in the press, submitted or intended for submission. Some unavoidable overlap occurs between publications, particularly in the methods, literature, and research site descriptions sections. Each piece differs in that it represents a different area of research. Reference lists have been provided at the end of each chapter and conform to the style recommended by the journal in which that paper was published or submitted. The outline of each piece is as follows:

- The next chapter (**chapter 2**) provides a detailed overview of IAPS in South Africa, regionally and globally. Both local and international scientific knowledge of techniques is discussed. An overview of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distributions at local, regional, and global scales was provided. This chapter sets the scene for the techniques used in modelling IAPS and aims to contribute to a national database of IAPS findings.
- **Chapter 3** evaluates the best RS and GIS methods. Assesses the accuracies of RS and GIS methods in classifying species-level land cover using colour infrared, SPOT 6/7 and Worldview imagery coupled with field-collected data on the presence and absence data of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR.
- **Chapter 4** provides a technical insight into the different commonly used modelling techniques (Multi-Species Distribution Model, Migratory Modelling, Generalized Linear Model (GLM), MaxEnt, Random Forest (RF), and Artificial

Neural Network (ANN)) used in estimating plant distribution. The theory behind each modelling technique and data requirements are discussed and compared. The chapter provides further detail on actual field measurements, environmental and remote sensing variables used in the modelling process, and the upscaling of local model outputs to local (e.g., Biosphere) and global scales.

- **Chapter 5** provides an investigation of how effective the Food and Agriculture Organisation (FAO) Water Productivity Open-access portal (WaPOR) RS and GIS products (actual evapotranspiration and interception (ETIa) and Gross Biomass Water Productivity (GBWP) can be used as proxies of water use by plants thus can be used to assess the effects of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* on water availability in the Luvuvhu catchment in the VBR.
- **Chapter 6** is a synthesis and conclusion on the modelling of IAPS and development of a framework based on RS, GIS and modelling that managers can adopt to monitor and manage the expansion of IAPS.
- **Chapter 7** provides recommendations based on RS, GIS, and the modelling that managers can adopt to monitor and control IAPS.

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Chapter 2: A literature review of the role of remote sensing (RS) and geographic information systems (GIS) in modelling the distributions of invasive plant species (IAPS), with relevance to two problematic species in the Vhembe Biosphere reserve (VBR).

This chapter is based on the publications of Farai Dondofema, Nthaduleni Nethengwe, Peter Taylor and Abel Ramoelo. “Scope and context of invasive alien Mauritius thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) at local, national, regional, and global levels”. Under preparation.

Abstract

Over the past decades, invasive alien plant species (IAPS) have threatened South African biodiversity, ecosystem services, environmental quality, and straining the country's water supplies. Modelling of IAPS in the Vhembe Biosphere Reserve (VBR) using an integrated approach, which factors environmental, climatic, geographic information systems (GIS) and Remote sensing (RS) data, is critical for understanding the spatiotemporal distributions and impacts of two IAPS that is Mauritius thorn (*Caesalpinia decapetala*) and River Red Gum (*Eucalyptus camaldulensis*). Recent technological advancements in GIS, RS, species distribution modelling, and the widespread availability of new RS datasets have resulted in novel applications for assessing and monitoring distributions of IAPS at different scales. This chapter discusses and evaluates scientific research advancements in ecological niche modelling (ENM), GIS, and RS. GIS and RS-based ENM have great potential to improve the monitoring and management of IAPS distributions. Managing *Caesalpinia decapetala* and *Eucalyptus camaldulensis* will be more successful if phenology information is incorporated into IAPS modelling in the VBR. Combining plant phenology knowledge with RS techniques has the potential to provide valuable tools for optimising the timing of management practices; additionally, these data may help better inform IAPS management and restoration efforts. Compared to climatic and environment-based estimations of broader appropriate habitats, RS data sources give more detailed information about the plant's realised niche in the landscape. Because remotely observed reflectance of a plant community is primarily a function of variable plant species composition throughout the landscape, developing Species Distribution Models (SDMs) using RS predictors is more likely to yield models that account for plant community diversity patterns. This work combines community assembly procedures with RS methodologies to fit SDMs with acceptable conservation and ecological mapping accuracy. Biophysical metrics in remote sensing data may assess plant habitats' spatial and temporal features and detect vegetation phenology and structural changes.

2.1 Aim of this chapter

This chapter reviews the literature on invasive alien species (IAS), focusing on two invasive alien plant species (IAPS), Mauritius thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) at the local level in the Vhembe Biosphere Reserve (VBR), South Africa, and at regional and global levels. It does this by providing a brief synopsis of how comprehensive information on *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, climate, phenology, remote sensing (RS) and geographic information system (GIS) can be used to model the distributions of IAPS.

2.2 The rationale for the research

Invasive alien plant species tend to outcompete native species, resulting in extinction and decreased biodiversity in areas of introduction (Mooney, 2005). It is projected that increased competition from IAPS may lead to broadening the spatial extent of areas at risk of invasion, resulting in biodiversity losses due to species range alterations or extinctions. As a result, there is a significant and urgent need to quantify the probable present and future IAPS distributions to prioritise regions for control, mitigation, and adaptation scientifically. Localised IAPS modelling provides insights into the mechanisms that drive vegetation dynamics, community structure, ecosystem overall functioning, and anticipated impacts.

2.3 What are IAS?

Invasive alien species are species not native to an area and can establish and spread quickly (Thompson & Davis, 2011), often resulting in environmental or economic damage (Jeschke *et al.*, 2014). Most species that end up as IAS are not invasive in their native ranges (Richardson *et al.*, 2000; Pysek & Richardson, 2006), mainly due to environmental factors and predators that keep the species in check (David *et al.*, 2017; Vilà & Hulme, 2017). When a species reaches a new territory, it can flourish and take over without the same controls as those found within its natural ranges (Richardson *et al.*, 2011). IAS rapidly depletes available resources, out-competing indigenous species and induces habitat changes after successful establishment. In certain circumstances, the terms invasion and bush encroachment are used interchangeably. Bush encroachment, on the other hand, refers to the increase in

density, cover, and biomass of indigenous woody or shrubby plants in diversified grasslands, arid and semiarid grasslands (Van Auken, 2000).

Some schools of thought (Mooney & Cleland, 2001) argue that IAS distributions are a natural phenomenon that triggers the process of biological evolution (Cox, 2004; Pyšek *et al.*, 2020). However, most conservationists and ecologists stress that IAS are purposely, or involuntarily dispersed, and human activities significantly harm the environment (McNeely *et al.*, 2001). There are several pathways for transmitting species from one region to another, with maritime and leisure activities among the most common conduits (Peyton *et al.*, 2019). This has led the International Union for Conservation of Nature (IUCN) to rank IAS as second among the factors affecting biodiversity loss after habitat defragmentation (Gaertner *et al.*, 2009).

Over the past 60 years, growing evidence suggests bush encroachment and invasion have modified the savannas (Moleele *et al.*, 2002; Stevens, 2016; Belayneh & Tessema, 2017). These ecological bush encroachment and invasion processes, which suppress usually suppressed grasses and herbs by encroaching woody species, which are often unpalatable to domestic livestock, can affect livelihoods (Kangalawe, 2009; Evan, 2017). Threats from climate change, pollution, habitat change, overexploitation land-use conversions, and IAPS affect the VBR (Munyati & Kabanda, 2008). IAPS may have catastrophic impacts on native biota within the VBR, causing extinctions and impacting natural and agricultural ecosystems (Noonan-Mooney & Gibb, 2014). Richardson *et al.* (1997) allude to the state of invasion in the Savanna biome as being poorly quantified; therefore, a better understanding of how IAS are introduced and spread has significant implications for management.

Typical characteristics of IAS include fast growth, expansion, massive distribution, phenotypical plasticity, survival in different forms of resources and various environmental conditions (Ordonez *et al.* 2010; Vilà *et al.*, 2010; Gallagher *et al.*, 2015). A good indicator of invasion depends on a species' success in invading a new area (Divišek *et al.*, 2018; Mathakutha *et al.*, 2019).

2.4 Causes of IASs spread.

With globalisation, the planet has seen the culmination of extended trading, transportation, and tourism, all of which are conduits that can help introduce and spread IAS (Early *et al.*, 2016; Eiswerth, 2011). If a species successfully establishes itself in a new habitat like its native habitat, it may survive and reproduce. (Vilà *et al.*, 2011; Thomas *et al.*, 2016). To be invasive, a species must effectively outcompete native species for resources and habitat and proliferate in its new environment, thus increasing its population and colonising new habitats (Wilson *et al.*, 2020). The spread of IASs presents a complex and costly problem in most countries (CBD, 2006; Novo *et al.*, 2015; Rai *et al.*, 2020). The continuously growing threat of IAS requires urgent attention to address the problem to reduce its economic and environmental impacts (Mcneely, 2013; Woodford, 2016; Zengeya *et al.*, 2017; Tobin, 2018).

2.5 Why are IASs a problem?

Due to anthropogenic and stochastic causes, many species (between 95% and 99%) have become extinct (Hamblen, 2004). In the Living Planet report, the Worldwide Fund for Nature (WWF) (2018) mentions that the Earth's current biodiversity loss is between 0.01% and 0.1% of all species becoming extinct annually. Considering a conservative estimate, this translates to approximately 200 and 2,000 extinctions within one year, with introduced species accounting for 50% of species loss (Smith *et al.*, 2003). IASs are ranked in the top five common threats to biodiversity and ecosystems by changing community composition, biotic interactions, and other ecosystem processes (Pyšek *et al.*, 2012; Gallardo *et al.*, 2016; Vilà & Hulme, 2017). Given this scenario, it is surprising that few countries give little attention to biosecurity initiatives (Gardener *et al.*, 2010; Jeschke *et al.*, 2014). Ricciardi *et al.* (2013) state that the cumulative impacts of IASs on the environment are measurable. On the other hand, Simberloff *et al.* (2013) postulate that IASs can cause significant changes to species composition and ecosystem functioning.

Ricciardi *et al.* (2013) suggest that the cumulative impacts of IAS on the environment can be measured. However, it is essential to realise that the effects of IAS can be multidirectional (Jeschke *et al.*, 2014). There is a need for ecologists and managers to learn that not all negative impacts of IAPS can have deleterious effects, as societies typically tend to accept minor negative consequences resulting from the establishment of invasive alien species (Bartz *et al.*, 2010). For the negative impact of the IASs to

become significant, it must surpass a certain threshold, like a notable decline in a native species population size (Bartz et al., 2010).

2.6 Types of IASs

Invasive alien species, irrespective of spatial location, occur in all taxonomic groups (Blackburn et al., 2014), including animals, plants, fungi, and microorganisms (Pyšek et al., 2020). Thus, none of the global ecosystems is immune to invasion (Simberloff et al., 2013). While many species transported into new habitats are invasive, the harmful effects may be broad and essential over time (Perrings et al., 2005; Meyerson & Mooney, 2007). The introduction of species is usually vectored by human transportation and trade (Meyerson & Mooney, 2007).

If the new habitat resembles the IASs native range, it can survive and replicate (Roy et al., 2014; Robinson et al., 2020). When IASs are established, it typically takes some time to proliferate at low densities because they have low chances of reproducing (Ricklefs, 2005; Catford et al., 2018). To become invasive, a species must compete effectively against endemic species in its new environment, improve population density and damage habitats. (Yek & Slippers, 2014; Florencio et al., 2015). In summary, for an alien species to become invasive, it must arrive, survive, and thrive.

2.7 Pathways of invasion

Many mechanisms, pathways, and vectors can introduce IASs (Wilson et al., 2009; Essl et al., 2015). The invasion routes involve but are not limited to the transportation of agricultural goods, animal and plant products, pet and ornamental crops, human beings bearing disease agents such as viruses, tourism, and the transport of souvenirs. Figure 2-1 and Table 2-1 illustrate how the status of a species can be attained during the invasion process as defined in any invasion step. To make a smooth transition from one level of invasion to the next, specific actions must be taken that make it possible to solve a certain number of problems.

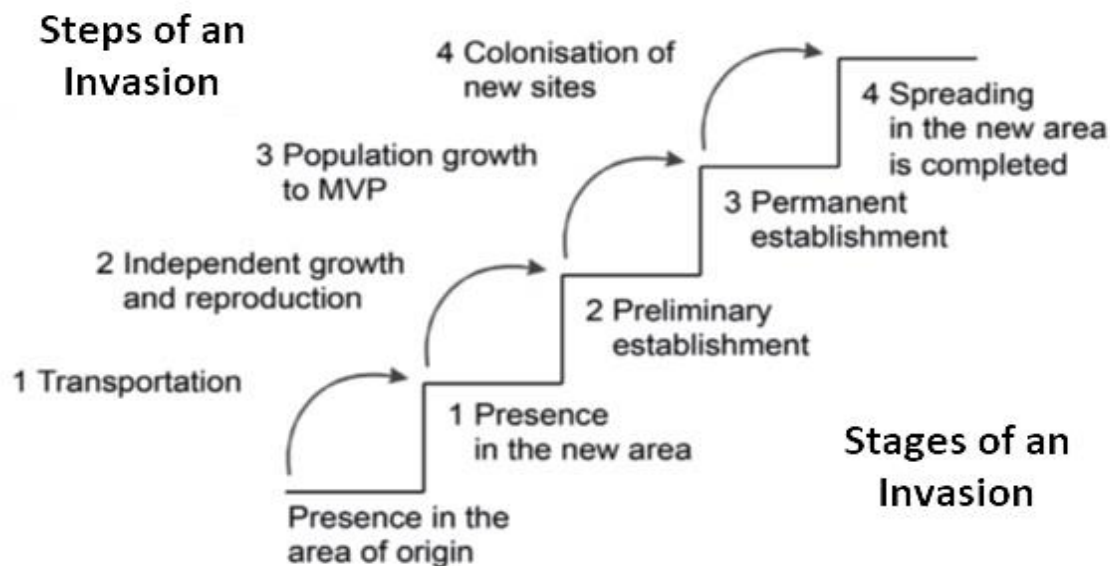


Figure 2-1: Chronological dissection of an idealised invasion process into steps and stages (Heger & Trepl, 2003).

Table 2-1: Illustrates the rationalisation of eight locally relevant invasive alien species' introduction and dispersal pathways, as well as the definition and interpretation of pathways of introduction (Rumlerová et al., 2016).

Pathway	Interpretation
Rivers	Unintentional: The species is introduced by rivers (e.g., seeds that float downstream into the park).
Roads, paths, trails, tracks	Roads, paths, trails, and tracks facilitate the movement of the species.
Contaminated construction material, equipment, and soils	Unintentional: The species (seeds or small plants) is spread in construction material (e.g., building sand, crushed stone, gravel, bricks, timber, thatch), equipment (pumps) and soil (excluding material on transport vehicles like bulldozers or trucks).
Ornamental plants	The species is deliberately introduced as ornamental by staff living in ark landscaping in tourist facilities. Former farmsteads or abandoned structures incorporated into new gardens may have ornamental plants.
Agriculture	The species is deliberately introduced for agriculture (small scale for the staff or tourist use) or was the previous land use in areas that may be incorporated into new parks.
Clothing	Unintentional: The species is introduced on human clothing (commonly seeds).
Food or produce	Unintentional: The species is introduced along with food substances brought into the park for staff, tourists, pets, and animals. Note that the category "Agriculture" should be used for intentional food imports.

Animal dispersed	Unintentional: The species are spread by animals (e.g., seed burs transported in animals' coats, birds and baboons eating fruit).

2.8 A South African Perspective on IAPS

van Wilgen et al. (2012) indicate that alien plants occupy as many as two million hectares of land in South Africa, adversely impacting hydrology, nutrient cycling, and fire regimes (Le Maitre et al., 2015a). However, it should be noted that invaded ecosystems in South Africa have lower species richness than purely natural environments. Many explanations exist for this low IAPS diversity, such as limited resource availability or the requisite thermal requirements for survival. van Wilgen et al. (2020) estimate that a possible 1400 alien species have been established outside of captivity or cultivation in South Africa, costing the country at least US\$1 billion per year (~ZAR 15 billion) and threatening South Africa's unique biodiversity. As indicated by abundance, richness, and composition, species populations may provide valuable baseline data as measures of changes in diversity between invaded and uninvaded areas. Nevertheless, the degree and magnitude of the effects of alien plants on species populations are highly dependent on several factors that are affected, including but not limited to the extent and intensity of plant invasion, the stage of invasion and the affected area's environmental characteristics (Kumschick et al., 2017).

In South Africa, most of the recorded IAPS are a product of introductions for commercial (commercial forestry) or amenity value. This has stimulated active engagement in managing the best IAPS (van Wilgen & Richardson, 2014; Woodford et al., 2016). As early as 1861, South Africa had initiated regulating the control of invasive Bur Weed (*Xanthium spinosum*). The realisation of the need to regularise and control the introduction of alien species that have the potential to be invasive led to the promulgation of acts focusing on a specific species and providing punitive means to hold landowners responsible for the control of any alien species on their land (Richardson et al., 2003; Lukey & Hall, 2020). Moran et al. (2013) allude to the introduction of the Cochineal insect (*Dactylopius ceylonicus*) to control Drooping Prickly Pear (*Opuntia monacantha*) in 1913 as the first recorded case of active management of biological invasions in South Africa.

This led to the promulgation of the Jointed Cactus Eradication Act (Act 52 of 1934), marking a change in the legislative approach (Moran & Annecke, 1979). The Mountain Catchment Areas Act of 1971 further empowered the minister to broaden

their jurisdictional control measures to cover species within a 5km buffer zone around formally protected areas. The 1983 Conservation of Agricultural Resources (CARA) Act 43 of 1983) provided one of the most comprehensive regulatory protocols for the effective management of IAS by providing three categories, comprising IAPS of no value, recognised invasive species that also have commercial value, and recognised IAPS that have ornamental, but no retail value (Lukey & Hall, 2020).

South Africa's ratification of the Convention on Biological Diversity (CBD) in 1995 can be noted as one of the turning points of its regulatory framework on invasive alien species, as the CBD mandates each contracting party to prevent the introduction, control or eradication of those alien species which threaten ecosystems, habitats, and other species. van Wilgen and Wannenburgh (2016) allude to the Working for Water (WfW) programme's launching in 1995 as another turning point because of its broad reach and ability to actively involve rural communities in the control of IAPS for the protection of water resources while at the same time providing employment opportunities. The programme became the most significant environmental programme on the African continent (van Wilgen et al., 2020a).

Another significant milestone in understanding IAPS was achieved in 2004 when the Department of Science and Technology (DST)-National Research Fund (NRF) launched a Centre of Excellence for Invasion Biology (C·I·B). van Wilgen et al. (2014) describes the formation of the C·I·B as an initiative that improved access to research funding for biological invasions on a national scale. The C·I·B has contributed substantially to understanding invasive alien species in South Africa and beyond (Richardson et al., 2020). Kumschick and Richardson (2013) mention the vital role the C·I·B played in reviewing South Africa's international best practices in the risk assessment of invasive alien species and development of risk assessment guidelines for the implementation of national protocols that are intended to prevent the introduction of new invasive species.

In 2014, the South African government published the Alien & Invasive Species (A&IS) regulations, which repealed the rules under the CARA, broadening scope and coverage by addressing all invasive alien taxa (not just plants). The 160 years of working with invasive alien species make South Africa one of the leading countries

in terms of research on biological invasions globally, thus contributing over half of the research on invasions in Africa (Pyšek et al., 2008) by setting up a conducive platform for a robust collaborative network of researchers (Abrahams et al., 2019).

Richardson et al. (2014) allude to extensive studies in South Africa that have focused on the impacts of several IAPS, including the Australian *Acacia*, *Hakea*, and *Pinus* species. Although most studies examine the effects of IAPS on invertebrates, mainly insects, little is known about the impact of alien invasive plant species on reptiles and amphibians. The number of tortoises, lizards, snakes, and amphibians is exceptional in South Africa. However, there are not many studies that address these species. Researchers like de Groot et al. (2008) noted the possibility of the direct and indirect impacts of IAPS on the availability of nutrients to species and communities. While several studies suggest adverse effects of IAPS, some positive results have also been identified, including improved habitat or new resources for recipient species. (Schlaepfer et al., 2010).

Rhodes University 2017 established the Centre for Biological Control (CBC). van Wilgen (2020) describes the CBC's mandate to focus on existing research collaborations to control environmental and agricultural pests sustainably. Thus, allowing the protection of ecosystems and the societies that depend on them through excellence in research, implementation, and community engagement science to robustly forecast the possible impacts of new and emerging invasions and move away from merely viewing them as a series of unique invasion case studies. This chapter presents a literature review reviewing research exploring the effects of IAPS on South Africa's biodiversity. Combining all the critical elements of the research framework would allow invasion.

2.9 Effects of IAPS on biodiversity

There are critical key introductory pathways of species into new ecosystems by humans: unintentional introduction, species introduced for a controlled purpose, and intentional introduction (Levin, 2000). Most intentional introductions are driven by man's interest in cultivating species that are helpful to humans. This applies especially to agricultural, forestry, and ornamental species. Most man's dietary needs are met

globally by species imported from elsewhere (Hoyt, 1992). Imagining an Africa without all introduced species such as guava, sisal, maize, and cassava is impossible.

Introducing species is thus essential to human health in nearly every aspect globally. Preserving introduced species is a practice that offers an indisputable net benefit to humans, and it may be helpful to introduce additional species for use in biological control programs that bring in natural enemies, such as agricultural pests, for example, the polyphagous shot hole borer (Thomas & Willis, 1998). In some instances, IAPS have led to disasters in dry forests and rangelands in sub-Saharan Africa. The United Nations Environmental Programme (UNEP) estimates that alien invasive species cost the global economy approximately US\$1.4 trillion annually. A few studies have been carried out in Africa to measure the costs of IAPS. Studies in South Africa alone indicate that costs of up to ZAR 2 billion (US\$142 million) can be attributed to IAS control and threaten the country's unique biodiversity (van Wilgen et al., 2020).

To envisage the impact of IAS on South African biodiversity, it is, therefore, essential to first understand the status of South Africa's biodiversity. Biodiversity can easily be defined as the variety and variability of living organisms and their ecological complexes. Measuring biodiversity, however, is one of our time's most significant scientific problems. Species diversity or species abundance is the most straightforward element of biodiversity to be understood and quantified. Still, even that is far from easy to quantify, as biologists have long debated what constitutes a species (Hamblen, 2004).

Pyšek et al. (2012) indicated how IAPS could cause degradation to natural ecosystem structure, function, and productivity with a general association with declines in the diversity and health of endemic biota. Mason and French (2007) illustrate how IAS impacts various landscapes and how introduced species may alter the state of the endemic species in affected ecosystems. It is widely agreed that the proliferation of IAPS has significant adverse effects on ecosystem properties, with evidence indicating how IAPS can lead to deterioration in the condition of invaded ecosystems (Barney et al., 2013; Hulme et al., 2012). A common problem arises when one considers that the impacts of IAPS are significantly scale-dependent (Chase et al., 2015). Several researchers allude to a positive correlation between the diversity of IAS and endemic flora and fauna (Maskell et al., 2006).

The abiotic factors include climate, nutrients, herbivore pressure, and pollinator activity (Sax, 2002). The spatial extent at minor scales where management strategies are feasible before an ecosystem adjusts in response to invasion is crucial because it determines how natural habitats are altered (Barney et al., 2013). Alternative viewpoints suggest a linear reaction to the invasion, an ecosystem that changes at all points along the invasion pathway, or a specific threshold beyond ecosystems change as invasive plants become dominant (Muthukrishnan et al., 2018).

Empirical evidence shows that ecological responses to dominant invasive plants with negative impacts on native ecosystems are non-linear, occurring only after a certain invasion threshold has been exceeded (McAlpine et al., 2015; Fried & Panetta, 2016). The limited chronic shortages of available resources for the management of IAPS can lead to an overreliance on unproven practices that enable IAPS to cross the threshold limits of expansion. The challenge confronting managers is that the prevalence of threshold relationships cannot be estimated as most studies on the impacts of IAPS do not sample over broad spatial coverages. What this implies is that there is a need for monitoring techniques that can address this limitation. Accomplishing this would reduce the ever-increasing costs of controlling IAPS by enhancing the adoption of management approaches informed by sound economic and ecological considerations. These and other approaches can deliver win-win benefits by enhancing our capacities to mitigate the negative impacts of the persistent expansion of IAPS in cases that exhibit linear risk.

IAPS are also known to change the proper functioning of ecosystems by altering nutrient cycling and soil pH (Hickman et al., 2013). Decreased pH is detrimental to ecosystems because it often reduces the availability of nutrients leading to reduced growth of native plants, particularly in sites that are poor in nutrients., leading to reduced growth of native plants, particularly in sites that are poor in nutrients. IAPS can further induce significant alterations in the compositions of plant and insect communities and microbial biodiversity. This is so because they tend to expand their range non-selectively in different habitats, selected examples of which include road servitudes, abandoned and agricultural lands, wastelands, and forests where the absence of natural enemies facilitates their expansion. Once established, they continue expanding to form dense monocultures that alter the pre-invasion structure of natural ecosystems by outcompeting and replacing many indigenous species.

Ecosystem services are the benefits humans usually take for granted from ecosystems with most of these services, but they are essential to human well-being (Van Wilgen, 2018). Ecosystem services fall into four groups: support through nutrient conservation, resource provisions such as food, fibre, carbon sequestration legislation, and leisure and tourism cultural services. Pejchar and Mooney (2009) discuss how many IAPS have been known to influence ecosystem services, in other words, aesthetic, recreational, cultural, and regulatory.

The type of habitat being invaded determines changes in ecosystem services. Invasive plants that invade agricultural land significantly reduce productivity and land values (Pejchar & Mooney, 2009). Loss of forage and its importance are synonymous with pasture invasion (Witt et al., 2018; O'Connor & van Wilgen, 2020). Forest fires and loss of aesthetics in parks and agricultural land are the other ecosystem services that invasive plants have severely affected (Brooks et al., 2004; van Wilgen, 2009). Fire frequency may increase in areas invaded by IAPS that completely alter habitat ecology. The large-scale invasion of *Acacia mearnsii* (Black wattle) in South Africa has changed the local plant communities (de Wit et al., 2001).

In addition, growing IAPS affect the soil's nutrient-cycling role through extreme changes in nutrient cycling, causing critical disruption in the nutrient regimes that lead to species replacement. Port Jackson Willow (*Acacia saligna*) has been attributed to increased soil conductivity, pH, phosphorus, and a decline in fungal/bacterial ratios. IAPS have increased flood risk by narrowing stream channels and reducing soil holding capacity in some instances.

2.10 Benefits of invasive alien plant species

Studies have shown possible mutualistic benefits between IAPS and native species (Schlaepfer et al., 2011), in some cases contributing to the provision of ecosystem services (Riley et al., 2018). Several benefits accrue due to the proliferation of some IAPS, ranging from providing vegetables and fruits to providing other valuable purposes. Invasive alien plant species are also used, for example, to treat certain medical conditions such as skin, reproductive, digestive, and respiratory problems. Other documented benefits from IAPS in specific environments relate to practical uses that include but are not limited to building poles, rafters, firewood, and sleighs.

Consumption of IAPS is as old as the initial transcontinental migrations by Homo sapiens between 120 000 BC and 10 000 BC. Diaz-Betancourt et al. (1999) indicate how consumption of IAPS has increased globally due to their ubiquity and abundance. There have been increases in cookbooks focusing on recipes based on IAPS, like invasive kelp and kudzu (Reed, 2002). Using the consumption of IAPS as a control measure has recently started to gain traction as research illustrates how humans can act as voracious consumers as their populations increase, thus aiding the control of IAPS and, in some instances, driving them into extinction. Lewu & Aflolayan (2009) reports that the major ethnic groups, including the Xhosa, Zulu, Venda, and Swati, use 34 IAPS as medicinal plants. In their research, Semanya et al. (2012) discuss how IAPS play a pivotal role in the traditional medical practices of the Bapedi tribe of South Africa. Njoroge et al. (2004) mention using approximately 75 IAPS by indigenous tribes for medicinal purposes in central Kenya. Singh et al. (2010) comment on how local communities utilise as many as 152 IAPS for medicinal purposes in India. Studies in North America indicate that approximately 620 IAPS are traditional medicines by the highland Maya of Chiapas (Rios & Garcia, 1998).

Globally, IAPS are substitutes for construction materials, typical for species that provide timber, like *Eucalyptus* spp. There are instances in which declared IAPS have been harvested and used on a small scale by communities to substitute native species as roof trusses.

In certain instances, the mining sector has also used some species as mining props to buttress underground mines. IAPS has been used to control erosion and other forms of land degradation. This is common with plants like Sisal (*Agave sisalana*) (Figure 2-2). The same species in communal setups are used as a source of cordage or to manufacture sisal bags for postharvest storage and transport of grain produce. Other IAPS, like Vetiver grass (*Vetiveria zizanioides*), have become pivotal in the fight against erosion in Africa's degraded communal areas.



Figure 2-2: Sisal Plant (*Agave silisiana*) plant growing along the R523 road in the Vhembe Biosphere Reserve (VBR). (F. Dondofema, 2020)

Other notable uses of IAPS include their use as fuel (firewood), which reduces, as has been the case in most communal areas in South Africa. In the VBR, IAPS have been used to manufacture school desks (Figure 2-3).

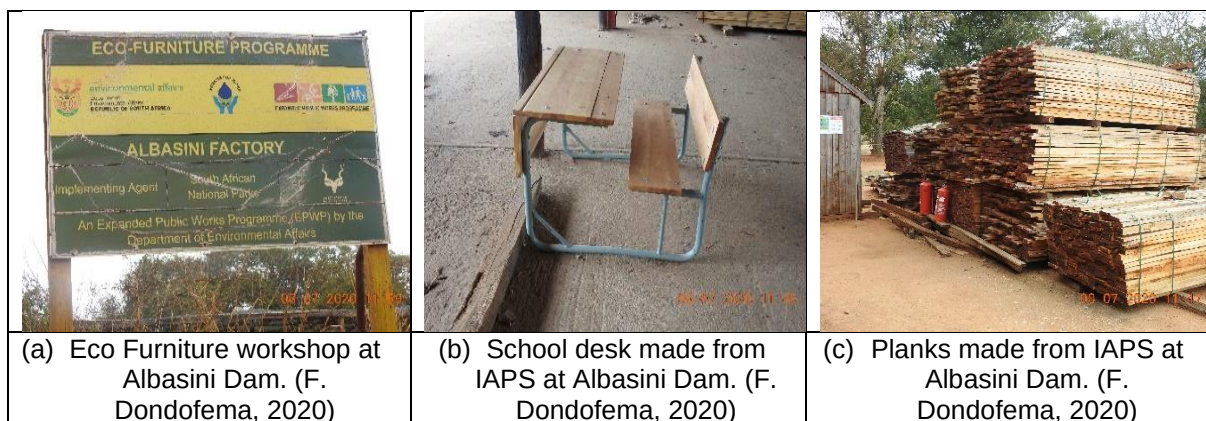


Figure 2-3: The Eco furniture workshop at Albasini Dam (a) and some of its products (b & c) Eco-Furniture Programme at the Albasini Dam in the VBR

Research at Lake St. Lucia in the KwaZulu Natal province of South Africa exemplifies how IAPS affect native animals (Perissinotto et al., 2014). In some studies, IAPS have shaded Nile crocodile dens and nests. This cover improved habitat conditions compared to exposed nests, resulting in more female crocodiles. Because temperature includes populations and animals, IAPS can influence the population dynamics of reptilian species and affect the environment.

LaFleur et al. (2007) discuss how IAPS can benefit avian species by providing fruit and a safe nesting place. Van Wyk & Gericke (2000) also mention how numerous species of butterflies feed on the IAPS milkweed (*Gomphocarpus fruticosus*) and provide the butterflies with a poison that they use as a defence from predation (Dalu et al., 2020). Gonsalves et al. (2018) also noted how species like *Eucalyptus camaldulensis* could benefit bats by providing perches and sustenance in the form of nectar (Winter et al., 2001).

2.11 The economics of IAPS

Managing human activity through effective behavioural instruments, such as policies and procedures within a systematic and robust institutional structure, is central to IAPS management. Decision-makers and policymakers must consider how current structural, legislative, and market conditions should best be used to promote the control, monitoring, and management of IAPS and their distributions over time, including the costs of externalities associated with IAPS.

A few decades ago, the focus was mainly on determining the most cost-effective treatment strategies for specific invasions (McConnachie et al., 2012). However, there have been changes in prioritising the advantages and costs of mitigations to decide whether IAPS can be best managed (Wittenberg & Cock, 2005). It should also be acknowledged that assessing the economic impacts of invasive alien plant species can be both problematic and imprecise (Hanley & Roberts, 2019). The full spectrum of the financial costs of IAPS can be far-reaching beyond the immediate impacts on the affected landowners (Diagne, 2020). Secondary and tertiary effects also play a pivotal role in decision-making as market demand shifts, changes in relative product prices, loss of substantial biodiversity, and other natural resource and environmental amenities need to be factored into the assessments (Mikeladze, 2015).

Considering the growing cost and resultant economic burden of managing IAPS in agricultural and natural habitats, it is necessary to assess the spatial and temporal scale of impacts, the identities of IAPS that have the most significant impacts and the most vulnerable habitats as means of prioritising the allocation of limited resources. In most cases, limited funding is available for controlling IAPS in natural environments, meaning the possibility of eradicating widespread and well-established invaders is minimal (Panetta & James, 1999). In these situations, regulating the spread of IAPS

in sites of high conservation importance must be given priority (Cousens, 1987). Some critical issues eluding land managers and invasion ecologists include understanding how IAPS can be retained within an ecosystem regarding cover and biomass without compromising essential ecosystem functions and biodiversity values and making informed decisions on stages at which this control should be implemented.

Bigsby and Whyte (2001) outline how economic impacts can be categorised into direct and indirect effects. Direct impacts focus on the impact of invasive alien plant species on ecosystem functions, whereas indirect impacts are those that are extensive, without exhibiting any links to ecosystem functions (Gallardo et al., 2019). The latter would be the general effects generated by the existence of a species but not unique to the nature of the environment that could impact public health concerns, such as disrupting critical functions of the climate or market-related effects, such as potential changes in trophic responses to ecosystem products (Charles & Dukes, 2007). The criteria on which scientific research affects access to environments and the impacts on tourism and other sectors of an economy also need to be addressed.

FAO (2001) lists six significant impacts of IAPS as follows: (i) production impacts, (ii) impacts on prices and markets, (iii) trade impacts, (iv) impacts on food security and nutrition, (v) impacts on human health and the environment, and (vi) production impacts have direct economic effects on the environment by adversely impacting the delivery of unique ecosystem services and causing loss or reduced performance. Most production impacts direct economic effects on the environment in delivering unique ecosystem services that may cause loss or reduced performance. Although these impacts can be easy to detect, they are generally difficult to quantify. Invasive alien species, in ways that are not always apparent, may have lasting effects on the environment. Arboricides that destroy specific IAPS may pollute the soil and the surface water. It is also essential that it could be challenging to differentiate the impacts of the AIPs from other effects, such as temperature.

The price and market impacts, like increases in IAPS, can directly affect the quantity of native biodiversity and productivity of the ecosystem. The precise effects on markets and the market-related impacts depend on numerous factors, including but not limited to the magnitude of the invasion, ecosystem services sector size, and the relative elasticity of demand and supply. In cases where ecosystem health is affected, as in

invasions by *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, ecosystems' productivity and ability to provide ecosystem services are adversely affected, leading to slow ecosystem recovery and lasting negative impacts on ecosystem productivity. Therefore, the multiplier effect can cause a few side effects.

Invasive alien plant species can also have significant negative impacts on trade, but there is a need to assess whether the adverse effects on business outweigh losses in productivity. Effects on employment depend on several factors, including the response of trading partners to policies and news on biological invasions, the value of traded goods, the severity of the disruption, and the elasticity of demand and supply. To strike a good balance, attention must be given to possible losses in competitive advantage within an export market, which often arises from the failure to provide premium disease-free goods. Concerns like these are valid as nonaffected countries either forbid the entry of the affected country's goods or carry out several precautionary measures. The economic impacts of IAPS can be as far-reaching as affecting a country's food security and nutrition. Thus, the need to focus on invasive alien plant species reduces domestic food supplies or negatively affects international trade, possibly impacting national food security, particularly in developing countries.

Invasive alien plant species can harm human health and have significant adverse environmental impacts on the national *fiscus*. Quantifying the effects of IAPS on human health and the environment, as the results are not well known in many situations. However, there is increasing evidence on how IAPS can lead to biodiversity loss and affect developed and developing countries health and socioeconomic status. Financial costs also negatively impact economic decision-making as individual, collective, and international steps. The need to control, eliminate, or reduce invasive alien plant species implies consequences on the *fiscus*. These costs could include testing, tracking, mitigation, and response costs.

The economic issues above justify a precautionary approach to IAPS management and further studies on risks associated with no control and various forms of power. Cost considerations can serve as an effective motivator for management interventions. However, the inability of monetary valuation techniques to provide fully inclusive estimates of these costs presents a significant pitfall. Estimating the economic impacts of IAPS requires considerable information on biotic and abiotic factors over vast spatial

and temporal scales, which can be expensive and unaffordable (Kumar-Rai & Singh, 2020).

Studies in many developed countries have managed to measure the impacts of invasive alien plant species through protocols based on monitoring, eradication, and mitigation funding and objective estimation of projected losses in productivity, biodiversity and associated ecosystem services caused by the emergence of IAPS (Vilà et al., 2010). Such an approach is, however, incapable of handling localised expansions of IAPS because some cases suggest that an indirect effect from the trade gains may easily outweigh the impacts of production losses (Hanley & Roberts, 2019). Because determining the impacts of IAPS is costly, economists often use cost-effective, dynamic optimisation and ex-ante simulation analyses to assist decision-making (Evans et al., 2002). Methods like "contingent assessment" and "willingness-to-pay to get or stop equal gains or losses" are also used.

2.12 Addressing the invasiveness problem

For a long time, economists have been concerned with decision-making, focusing on the type of decisions to be made rather than how they are made (Pratt et al., 2017). However, the latter has begun to be adopted to some degree by discipline. The discipline of economics has a range of analytical tools that can assist decision-makers (Hanley & Roberts, 2019). The analytical skills applicable to the IAPS issue include informed decision-making on invasive species risk and management interventions, numerical valuations, cost-benefit analysis for assessing public response strategies, resource allocation, and systematic risk and uncertainty assessment (Emerton & Howard, 2008). The discipline has also established many methodologies for determining the importance of environmental and health consequences not advertised or marketed. Due to pressure from international agreements and commitments to different interest groups, there has been an increasing demand for transparency in decision-making to implement desired policies (Shine, 2007; Ormsby & Brenton-Rule, 2017). Focusing on sound economic analysis can significantly enhance bargaining and management performances.

2.13 IAPS risk mapping

The spread of IAPS has had far-reaching consequences, both environmentally and ecologically. An in-depth understanding of the patterns and processes that drive invasions is crucial to predicting and managing invasions. To provide scientifically informative outputs, a combination of statistical methods that characterise factors that influence spread at the local level and the use of simulated historical data on IAPS is needed.

In-depth knowledge of IAPS can create future scenarios that enable dynamic annual tracking of invasive plant progression (Dawson et al., 2017; Dyer et al., 2017; Seebens et al., 2017). This is helpful because it enables the timely identification of emerging problem species in a manner that makes it possible to inform policy through seamless data-driven risk assessment protocols by timely assessing current and future risks (van Wilgen et al., 2016). Risk assessment protocols are tools to condense species information into their perceived risks according to a common framework (D'hodnt. et al., 2014; D'hodnt et al., 2015).

Risk assessment tools for listing IAPS must incorporate all available evidence and expertise. Nonetheless, several protocols claim to be generic across regions or taxonomic groups (Leung et al., 2012). Uncertainty may be correlated with a lack of knowledge, contradictory facts, context-dependency, or ambiguous formulations in invasive alien species listing processes. (Leung et al. 2012; McGeoch et al. 2012). Recent analyses of risk assessment protocols overcome uncertainty by encouraging evaluators to include a confidence score for their answers (González-Moreno, 2019). Standardised protocols are required to quantify the severity of invasive species' effects and determine their risk. Proper IAS management decisions depend on the precise spatial and temporal characterisation of the entry, exposure, and effect assessment. (Venette et al. 2010).

Spatially explicit invasion risk assessments may be extracted from species distribution models (SDMs), usually referred to as ecological niche models (ENMs), which are calibrated based on knowledge from the distribution of native species and are more often integrated into the risk evaluation of IAS (Beaumont et al., 2014). According to Araújo and Peterson (2012), statistical methods can link species incidence information to predictors of the spatial environment. These models estimate a species' suitable climates and environmental factors (Zengeya et al., 2020).

2.14 Modelling IAPS

Dynamic computer models that can incorporate applicable measurement data and information need to be developed to provide actionable management strategies for managing the persistent expansion of IAPS (Elith & Leathwick, 2009). Models used to calculate invasion risk can also recreate the dynamic invasion process across large areas infested by IAS, their points of entry, distributions of susceptible hosts and potential human-assisted movement pathways along transportation corridors. The map outputs generated by running these models give managers valuable decision-making, display the expected rates, and spread trends, and give managers valuable decision-making insights in the timely monitoring trends in the aggressive expansions of IAS. The information generated by these models is helpful because it can be used to raise awareness of anticipated trends in the expansion of new IAPS and their impacts.

Estimating distributions of IAPS is critical to improving prevention and management strategies (Pyšek & Richardson, 2010; Ojaveer et al., 2015). There are numerous approaches available to ecologists. These range from documenting invaders to examining possible interactions between invaders and native species and assessing invasion's ecological and economic impacts using various modelling techniques (Wonham & Lewis, 2009). Using modelling techniques provides a powerful way to understand better the drivers and reactions of species and habitats to human contributions to invasion processes, identify information gaps, and predict future dynamics (Fath et al., 2012; Hannon; Ruth, 2014). Species distribution models (SDMs) are scientifically validated tools that can evaluate and forecast the effects of climate change and environmental variables on flora and fauna (Sobek-Swant et al., 2012; Chitale et al., 2014).

Species distribution models can determine relationships between species and their environment. Species distribution models can use presence only or presence/absence data to predict the distributions of species of interest (Pearce & Boyce, 2006). The information derived from SDMs is pivotal for ecologists to understand the conditions that affect species distributions and formulate appropriate adaptation measures to counter the impacts of climate change on IAPS (Aguirre-Gutiérrez et al., 2013; Royle et al., 2012). As much as SDMs have proven effective in providing estimates of species

distributions, one of the main difficulties faced when conducting SDMs is selecting appropriate modelling algorithms and relevant datasets (Gallardo & Aldridge., 2013). Depending on the species, SDMs dealing with presence-only data might be more advantageous than presence/absence modelling methods (Chitale et al., 2014; Phillips & Dudík., 2008).

The maximum entropy (MaxEnt) method is a general-purpose machine learning method for producing species distribution maps using presence-only data (Royle et al., 2012; Phillips & Dudík., 2008; Phillips *et al.*, 2005). It is a bioclimatic model widely used by conservation practitioners and researchers to predict and map distributed species (Fourcade et al., 2014). Wilson et al., (2011). For more accurate species distribution and risk maps, there is a need to complement MaxEnt with Generalised Linear Mixed Models (GLMMs) in identifying areas of possible spread for conservation purposes (Royle et al., 2012). The MaxEnt model was used to predict the distribution of invasive alien plants across eight global biodiversity hot spots in different areas (Tropical Andes, Madagascar, Brazil's Atlantic Forest Region, The Philippines, Meso-American forests, Wallacea, Western Sunda and South Africa's Cape floristic region), through climatic and non-climatic variables, (Chitale et al., 2014). Adhikari et al. (2015) modelled hot spots of IAPS through Ecological Niche Modelling (ENM) using the MaxEnt model to guide the formulation of an effective policy for controlling the IAPS. Using the same model, West et al. (2016) modelled the invasive species Cheatgrass (*Bromus tectorum*) using presence data and evaluated this model's usefulness in a management context.

Qin et al. (2016) investigated the spatial patterns of *Lantana Camara* habitat changes from its current distribution to future potential occupied areas using the MaxEnt ecological niche modelling technique to achieve high levels of predictive accuracy. Shrinkage in the sample size is usually associated with decreased model accuracy; however, the MaxEnt model is less sensitive than other approaches to the number of presence locations (Phillips & Dudík., 2008; Wisz et al., 2008). In most instances, the regularisation can be tuned for the MaxEnt model; this is usually done about sample size to avoid overfitting (Wisz et al., 2008). Presence-only data are good enough for species distribution modelling. The area under the curve of the Area under the curve (AUC) (Figure 2-4) prediction scores can be sufficiently accurate (Elith et al., 2013; Pearce & Ferrier. 2000). SDMs have some limitations, such as overestimating the

presence of species. The assumption of a random sampling of species' existence on the grid cells made by SDMs predicts each cell's significant probability of fact, which could be overestimated (Aguirre-Gutiérrez et al., 2013). MaxEnt uses presence-only data, which gives high for environmental conditions outside the range (Phillips et al., 2005).

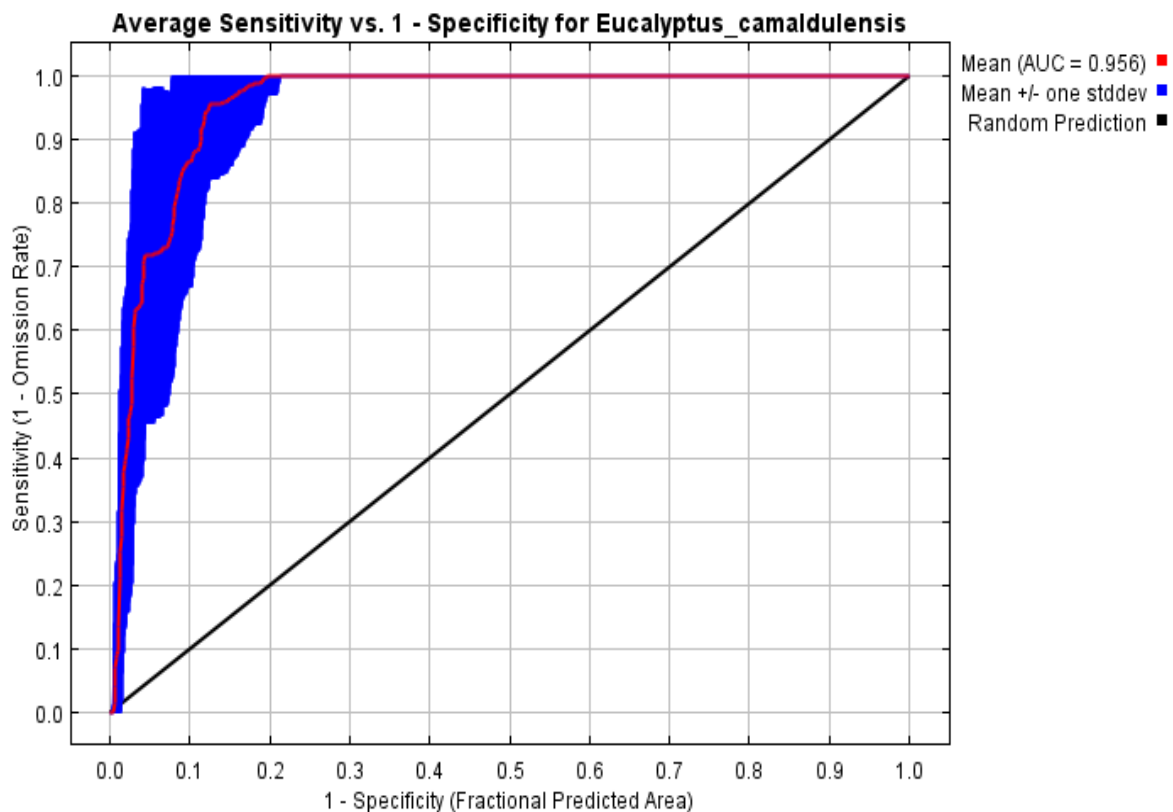


Figure 2-4: Receiver Operating Curve (ROC) showing the AUC for *E. camaldensis*. (Source: F. Dondofema, 2020)

2.15 The importance of plant phenology

Every plant species has defined growth cycles; spatiotemporal studies using RS and GIS can be used for accurate species differentiation. Phenology involves the study of biological phenomena's annual cycles, specifically climatic variability. Phenological activities include important events like seasonal cycles or beginning growth phases like budding and flowering. Several research on plant phenology have been conducted, most of which have been conducted in the field. However, in studies, RS and GIS are increasingly used to explore phenology at plot, county, and continental dimensions. The RS and GIS approaches are gaining momentum because there is an

increasing variety of earth observation satellites collecting data with different Spatial, Spectral, and Temporal characteristics.

A good understanding of a plant's phenological phase provides ecologists and managers with a detailed calendar for a plant species. An understanding of plant phenology has several significant scientific implications in understanding the growing cycle of plants, coupled with the ability to predict plant yields over large areas. Knowledge of the ability of RS and GIS to detect plant species with a high degree of accuracy makes these techniques essential for IAPS detection using a detailed understanding of the phenological cycles of IAPS. This makes RS and GIS accurate tools for identifying the two IAPS this research will focus on (*Caesalpinia decapetala* and *Eucalyptus camaldulensis*). Detecting the selected IAPS using RS and GIS techniques is more feasible since most savanna species are deciduous and lose their foliage in winter. Making the winter season the best time for detecting evergreen plant species and IAPS with satellite data. This is mainly pigments in evergreen foliage are enhanced in the visible and infrared portion of the electromagnetic spectrum.

2.16 Factors affecting plant phenology,

Some of the well-documented factors that affect plant phenology include (i) genetics, (ii) photoperiodism, (iii) temperature, and (iv) precipitation.

Genetic variability significantly contributes to phenological differences between individual plant species and populations (Hendry & Day, 2004). A plant's genotypic makeup acts as a trigger for growth or reproduction irrespective of environmental conditions, or they may affect the responsiveness of a plant to the timing-influencing environmental conditions (Tauber et al., 2007). Van Dijk & Hautekèete (2007) illustrated that the ability to predict seasonal plant changes about the light-to-dark cycle in sub-Saharan Africa makes the photoperiod reliable for the time of year plants flower, grow, and senesce. Seasonal variability in sunlight can also affect the onset of leaf flush in tropical 'aseasonal' forests (van Schaik et al., 1993).

Evolution has taught most vegetation species not to depend on photoperiod signs alone for physiological processes. Plant response to photoperiods can be easily altered or overridden by other, more specifically, environmental variables like temperature in tropical climates. The interactions between long days and warm

temperatures are well-known triggers when deciding the flowering pathways of most plants (Wilczek et al., 2009). Flowering phenology monitors interannual air temperature changes (Miller-Rushing et al., 2007). The phenological phases can be delayed if the temperature does not drop below a certain threshold (Morin et al., 1999; Zhang et al., 2007). Precipitation variability is more likely to disrupt plant phenological phases in tropical and arid environments than temperature. Rain or drought will induce flowering in different tropical forests (Brearley et al., 2007; Kimball et al., 2012).

2.17 Ecological effects of phenology

In the past decade, scientists have given great attention to understanding the ecological implications of climate change effects on plant phenology. The pivotal role played by plant phenology in ecological relationships requires more scrutiny. Although the impacts of climate change on the phenological traits of IAPS have been widely circulated, it is still subject to debate in most ecology circles based on how different species exhibit different phenophase responses and inter-specific interactions (Lázaro et al., 2009). Thomson (2010) provides a unique example of how substantial temporal species interaction can influence pollen production in a subalpine wildflower, leading to 50 significant increases, which point to possible plant-pollinator dissociation. However, the phenomenon of plants dissociating themselves from pollinators due to changes in phenophases has not been convincingly proven (Memmott et al., 2007).

Although changes in the timing of plant reproduction are difficult to detect, they have implications that transcend beyond shifting interactions with other plants, which can affect an ecosystem's floristic and faunal compositions. Jönsson et al. (2009) state that most plant species require a minimum of one reproductive episode in an annual cycle; plant species tend to be confined to specific geographical ranges with longer growing seasons, giving them the advantage of expanding their home ranges. Process-based models like the Repackage 'phenon fit' are based on the relationship between plant phenophases and their geographical range, as described by Chuine (2010). These methods provide mechanistically informed predictions of global warming-driven changes in the range of different species, compared to what correlation-based 'climate envelope' techniques have produced. Because single pollination events may not result in successful fertilisation in some plant species, a second pollination may be required in the same season.

Lastly, growing season length can affect the soil, nutrients, and carbon cycling on an ecosystem level. In the case of carbon, it is unclear whether variations in the growing season can cause a net increase or decrease in carbon fixation because of the relationship between photosynthesis and respiration. Phenological cycles determine the time and duration of photosynthesis and increase in net primary productivity (Piao et al., 2007). Richardson et al. (2010) mention how phenophase affects ecosystem productivity, resulting in seasonal variations across tropical forest types. Extending the growing season can increase net productivity despite increased carbon loss caused by high temperatures. Thus, predicting the length of the growing season in different habitats under future climate change is necessary.

2.18 Plant phenology and species distribution modelling (SDM)

Understanding spatial variability in phenological activities is pivotal in vegetation research. RS and GIS have been used for vegetation monitoring complemented by long-term in-situ measurements of plant phenology. Over the past decades, plant phenology studies have improved the understanding of variations in lifecycle events, utilising site-species-specific information on plant growth based on phenological measurements. Ecological models focusing on climate change use phenological information at large spatial scales rather than inventory data focusing primarily on specific plant species and are mostly point observations (Scheiter et al., 2018). Using RS and GIS to infer phenological activities in vegetation increasingly becomes critical to understanding seasonal phenomena over great spatial extents. NDVI anomalies are among the most used vegetation indices to understand plant phenology and possible shifts in vegetation cover. De Beurs and Henebry (2010) allude to vegetation phenology with RS and GIS as land surface phenology (LSP).

LSP is fast emerging as a critical multi-faceted tool for monitoring Biosphere-related activities that can aid the development of phenological models and deriving land-cover maps. Myneni et al. (1997) illustrated how RS and GIS data could identify photosynthetic activity of vegetation and its effects on plant growth, leading to the lengthening of the active growing season. Tucker et al. (2001) carried out several studies using data derived from the National Oceanic and Atmospheric Administration (NOAA) satellite to calculate NDVI anomalies helpful in estimating variations in photosynthetic activity and growing season, obtaining similar results as Myneni et al.

(1990). The scope of phenology studies across time and space requires long-term research and multi-disciplinary collaborations due to their complex nature.

Models can be constructed using data collected from long-term phenological monitoring to understand the key drivers and mechanisms to simulate phenophases and predict possible future changes. These models help scientists understand possible climate-induced phenological differences in ecosystem functions, such as carbon cycling, energy flows, and environmental feedback (Richardson et al., 2013). Current approaches for modelling winter and summer phenology present considerable uncertainties in understanding the terrestrial ecosystem (Richardson et al., 2012), some of which are used in the Earth system and land surface models to forecast possible responses to climate change.

Most models present limited predictive capacity without recognising the physiological processes driving phenology at species and ecosystem levels. Only within different spatiotemporal scales may they represent correlative findings. Models based on the statistical correlation of phenology and climate variability can sometimes fail to project future phenophases into new combinations of chilling, photoperiod, and thermal forcing. Several models of plant phenology are based on known or hypothetical cause-and-effect relationships between plant physiological processes and environmental factors that rely on statistical relationships based on past observations because of the absence of dose and response functions. Such models are usually based on single or double phenophases observed before leaf unfolding, flowering, endodormancy and ecodormancy.

Insufficient observation data at the species level can lead to difficulties in creating vegetation phenology models at an ecosystem or community scale. Most existing phenology models have the same structure and functional form at the species level, and these try to explain the impact of environmental drivers (Yang et al., 2004). Vegetation types can be derived from ecosystem-scale satellite data (Botta et al., 2000). Meteorological data also drive these vegetation phenology models to simulate seasonal leafing dynamics like the Leaf Area Index (LAI) (Richardson et al., 2012). Simulations like these exhibit bias and explain only a tiny fraction of the interannual variability in observed phenophases, varying performance depending on the vegetation type, leading to weak Gross Primary Productivity (GPP) predictions

(Lafont et al.,2011). Such a model will first suffer from significant uncertainties in satellite statistical phenology data (Cong et al.,2012); this refers to non-forested tropical forest vegetation, which is difficult to capture using satellite data (Cao et al.,2015).

Another challenge for designing phenology models on an ecosystem scale is the phenology cycles of different species in the plant population. Other challenges faced by phenological modelling include but are not limited to selecting an aggregated response type, threshold temperatures, chilling periods, and forcing status. It is also essential to consider the temperature data: maximum, minimum, daytime mean temperature, critical chilling, and causing status. Different responses to different species and various environmental factors can complicate responses to the species composition of a population related to long-term climate change. Creating vegetation phenology models was challenging and appropriate by incorporating phenological responses of coexisting plant species within an ecosystem. Recent advances in monitoring methods and combined phenology data from long-term research networks have paved the way for the creation of large-scale vegetation phenology models as a critical component of earth system models (Basler, 2016).

2.18.1 Measurement of phenological data

It will take intensive measurements of phenological data to understand phenological processes, their drivers, strategies, and varying amounts of organisms that support these processes. Multi-scale spatial monitoring enables scientists to interpret observed phenological processes. Techniques used to monitor phenological activities visually include but are not limited to photography and RS (Morissette et al.,2009). Most phenology studies are overly dependent on RS data for spatial extents ranging from plots to national, continental, and global scales to detect possible phenological changes due to climate variability or ongoing global warming (Piao et al., 2015).

Digital photography and camera-based and satellite observations have become common during the last decade (Nagai et al., 2011). This assertion is supported by

the increased use of spectroradiometers to track the spectral reflections of leaves and canopies (Asner & Martin, 2008). Phenological data from camera-based measurements and spectroradiometers can be compared to satellite-based reflectance (Muraoka et al., 2013) and laboratory assays of leaf traits (Yang et al., 2014), thereby providing physiological information which is not detectable in the invisible spectra. The following overview summarises recent methodological developments in monitoring leaf and canopy phenology at multiple spatial scales. The following overview summarises recent methodological developments in monitoring leaf and canopy phenology at multiple spatial, temporal, and spatial scales based on what Homolova et al. (2013) suggested.

Commercial digital and time-lapse cameras have become the most straightforward tools widely used in monitoring landscape spatiotemporal plant changes. Terrestrial vegetation structure and function can be detected by satellites and analysed as RS and GIS data outputs. Examples of these datasets are provided by different sensor networks Nature's Notebook (https://www.usanpn.org/natures_notebook), National Phenological Network (NPN) (<https://www.usanpn.org/usa-national-phenology-network>), National Ecological Observatory Network (NEON) (<https://www.neonscience.org/>) PhenoCam, Advanced Phenology Information System (APIS) and Phenological Eyes Network (PEN) (<http://www.pheno-eye.org/>), at multiple sites in forests, grasslands, and paddy fields across the world (Nasahara & Nagai, 2015).

Phenology measurements using cameras allow scientists to observe terrestrial vegetation in diverse ecosystems worldwide directly, providing adequate data on ecosystem structure and functions. Most stations for monitoring phenology are long-term ecological and carbon flux sites worldwide, including the South African Environmental Observation Network (SAEON) in South Africa. Most sites are integrated elements measuring phenological variables, with most datasets accessible online. Most active networks play a pivotal role in providing phenological data across ecosystems these networks cover. The broad spatial distributions of phenology monitoring networks call for calibrating cameras and instruments to measure similar interoperable parameters that allow internetwork data comparisons (Wingate et al., 2015).

The availability of repeat camera-mounted digital photographs mounted on observation or flux towers in the networks enables tracking leaves, branches, canopies, and landscapes. Most of these phenology cameras can be set to collect photographs laterally or vertically that provide a fisheye view of vegetation from poles and decks (Tang et al., 2016). Fisheye images can collect hemispherical photographs of the canopy that allow the objective estimation of forest understory light (Pearcy, 1989) and the collection of forest canopy LAI (Jonckheere et al., 2004). Continuous measurements of LAI can provide canopy-level data by automating fisheye camera images. Species-level phenology observations can also be carried out using digital cameras (Nijland et al., 2014). Most digital cameras collect data in the visible part of the electromagnetic spectrum, thus allowing the segregation of the images into three specific bands Red (R), Green (G), and Blue (B). Using these bands, indices of vegetation greenness can be calculated (Nagai et al., 2014).

2.19 Phenology at leaf, plot, regional, and global scales

The scientific community requires phenological observations at different spatiotemporal scales to detect responses of plant species and ecosystems to environmental change and climate variability (Richardson et al., 2013). Phenology at the leaf scale does not necessarily translate into canopy scale measurements because the light emitted by leaves, conditions, and other territorial features varies depending on canopy height and other spurious variables (Hirose, 2005). The upscaling of canopy phenology to regional and global scales is complicated because their compositions substantially influence how they respond to changing environmental and climatic conditions. Leaf ecophysiology directly relates to the optical properties of photographs and satellite images from a single leaf to tree and forest canopies (Muraoka & Koizumi, 2009). In-situ measurements of optical data can be used to update spectral vegetation indices and estimate the net primary productivity of forest canopies in larger areas. In summary, recent technological developments have allowed the collection of fantastic data sets on plant phenology with different spatial resolutions at high temporal satellite-derived spectral resolutions (Yang et al., 2004).

2.20 Climate change and impacts of global warming on phenology and the distributions of IAPS.

Changes in climatic conditions and a rise in global temperatures can significantly affect the geographic distribution of IAPS (Parmesan, 2006). Climate change can alter and affect ecosystems' vegetative factors and biochemical processes. These factors will change species' distribution ranges, populations, and biome boundaries (Bradley et al., 2010). Changes by latitude have been observed in species and vegetation areas (Bellard et al., 2018).

The literature cites IAPS modification in plant phenology as the leading global response to climate change (Khanduri et al., 2008). Numerous scientific reports have focused on the possible effects of changes in climatic conditions on plant phenology. Significant scientific evidence focuses on seasonal changes and vital sociological significance, particularly in high-latitude countries (Fitchett, 2015). Much evidence indicates an increase in the vegetative growing season days in the Northern Hemisphere, at higher latitudes, which commonly experience high temperatures (Gordo & Sanz, 2010). Although scientists describe phenophases as a separate category from changes in species distributions, these two phenomena interact with one another and with other variables, such as photoperiod, to decide how climate change affects plant species and ecosystems (Bale et al., 2002).

2.20.1 Effects of shifts of tropical species ranges on IAPS.

Changing growing patterns are correlated with migrating tropical species into more temperate regions (Supp et al., 2015). Evidence points to the migration of vegetation species typically considered endemics in North Africa into Southern Europe, namely Spain and France. Other common migration includes recent records of species endemic to northern Africa, becoming common in east, west, south, and central Africa (Haeger, 1999).

2.20.2 Effects of elevational changes on IAPS

The variables determining biodiversity gradients in ecology are fundamental yet unresolved (Fine, 2015). The spread of most species tends to follow specific gradients as determined by temperature, water availability, productivity, area, geometric constraints, and plant diversity (Brown, 2014). Marcell et al. (2016) used a multi-taxa perspective in studying the patterns and drivers of species richness in the southern

slopes of Mt. Kilimanjaro along a 3.7 km elevational gradient (871 - 4 550 m above sea level (a.s.l.)) of natural habitat—species richness trends of different plant taxa along the same environmental gradient at Mount. Kilimanjaro in Tanzania has been unable to describe diversity gradients across various taxonomic groups convincingly. Instead, trends and predictors of elevation-driven diversity between taxa tend to be stochastic and non-uniform due to their taxonomic resource-specific requirements and environmental adaptive capacities (Marcell et al., 2016).

2.20.3 Effects of temperature variations on the phenology of IAPS

IAPS respond to temperature changes depending on the phenophase and phenological (Hatfield et al., 2011). The limits of measurable plant growth are determined by a given range of maximum and minimum temperatures (Hatfield et al., 2008). In most plant species, vegetative growth usually has a higher optimal temperature than required during the reproductive stages. The importance of temperature is evident through the impacts of climate change, which influences the structure and functioning of habitats at different altitudes (Gale, 2004). Competition between C₄ plant species and C₃ plants under various climatic conditions and carbon dioxide (CO₂) concentrations will significantly affect crop productivity (Patterson, 1993). The annual invasive C₄ weeds would benefit from an average temperature increase of 3°C, resulting in significant yield reductions in various critical C₃ plant systems (von Caemmerer & Evans, 2010).

It is essential to know how similar species have responded to temperature. A rise in air temperature usually induces plants to maintain their health by using more energy for respiration during the growing season through reduced use of the same for plant growth. With climate projections pointing to an increase in global temperatures by 1°C, a plant species' productivity levels can decrease by 5 to 10% (Lobell & Field, 2007). High mean temperatures encourage plants to complete their growing cycle rapidly (Hatfield et al., 2011). The reduction in replication time boosted by a temperature-induced acceleration of reproductive growth negatively impacts the expected plant yields (Craufurd, 2013), illustrating how C₄ plants exhibit 50% higher photosynthesis efficiency than C₃ plants.

Variations in the photoperiod will typically have more impact on temperate perennial species during the growing season than tropical species. An increase in temperature can lead to inadequate chilling, which affects plant growth and the expansion of vegetative and reproductive organs and plant fruiting cycles. Tropical plant species have a greater tolerance to high daytime temperatures during the vegetative growth phase, during which the maximum photosynthetic activity occurs at optimum temperatures ranging between 20°C and 30°C (Wahid et al., 2007). Temperatures between 30°C to 34°C can lead to a decline in yields due to the negative impacts of high daytime temperatures on the plant reproductive phase (Blackie et al., 2016). Temperatures more than 30°C can cause permanent physical damage to most plant species and lead to seed mortality during storage if the temperatures exceed 37°C. Further to this is the fact that the type of damage caused by ambient temperatures on plant species depends on the rate of temperature increase, the capacity of the plants to adapt, the type of species involved and their growth stage (Wahid et al., 2007 and Gourджи et al., 2013).

2.20.4 Effects of carbon dioxide (CO₂) shifts on phenology traits IAPS

Fluctuations or changes in atmospheric CO₂ can stress ecosystems and increase the proliferation of IAPS (Dukes & Mooney, 1999). Several scientists have noted how the changes in climatic conditions can alter habitats by affecting various parts of the invasion pathway, thus increasing the vulnerability of ecosystems to invasion either because of resource scarcity or increased competition between endemic and IAPS. Common vegetation responses to increased CO₂ levels include changes in growth rates (Poorter & Navas, 2003), resource allocation patterns (Bazza et al., 2005), water use efficiency (Steduto, 1996), and nutrient uptake rates (Jackson & Reynolds, 1996).

According to the results of Poorter's experiments (1993), an increased growth resulting from a 100% increase in the level of atmospheric CO₂ was observed to cause a proportional increase in C₃ & C₄ plants, with C₃ plants having a 41% growth increase and 22% for C₄ plants. Approximately 95% of all plants on the Earth are of type C₃, with C₄ plants constituting only 1%. The other 4% of plants use the Crassulacean Acid Metabolism (CAM) photosynthetic pathway (Lüttge., 2004), meaning any minor shift in the abundance of C₃ plants can have considerable impacts on ecosystems and carbon sequestration.

2.20.5 Effects of nitrogen (N) shifts on the phenology of IAPS

Knops et al. (2002) describe the impacts of ecosystem nitrogen cycling as exhibited in several ways. To determine the influence of Nitrogen (N) deposition on specific ecosystems, there is a need to understand the spatiotemporal patterns of deposit and the response to nitrogen deposition. Vellend et al. (2017) refer to nitrogen deposition as the primary driver of plant biodiversity loss in terrestrial ecosystems. However, in other regions, many of the most adaptive plant species are invasive and alien, likely to increase and hinder the survival of endemic species.

2.20.6 Effects of shifts in precipitation regimes on the traits of IAPS

Precipitation regime changes include variations in seasonal mean, timing, and severity of individual precipitation events, including the frequency and length of drought events. Each variable is pivotal to vegetation's productivity in any given ecosystem. The effect of precipitation changes can be amplified with temperature changes, leading to increased evaporative demands of vegetation in specific ecosystems. Based on the phenological stage the vegetation has reached, this may lead to various types of moisture stress. The impacts of changes in precipitation regimes on foliage differ significantly since about 80% of the vegetated rainfed land accounts for 95% of global biodiversity (Tubiello et al., 2007). A decline in the mean seasonal rainfall will generally result in high levels of soil degradation in most regions. Soils with lower organic carbon content hold less water.

Shifting growing seasons and weather patterns will complicate the planning and management of production for conservationists and foresters. This can be explained simply because a delayed onset of the rainy season or premature end negatively impacts the plants' phenophases, leading to heavy losses in plant productivity (Linderholm, 2005). Changes in the duration of the rainy seasons can result in alterations in plant reproductive cycles, primarily determined by day length and availability of adequate soil moisture in photosensitive species. Other anticipated impacts of climate change include increases in extreme weather events.

2.21 Conclusions

To develop a management protocol for IASs, the first consideration would be to do an in-depth review of the literature that focuses on understanding what makes species

invasive, different types of IASs and the invasion pathways. An understanding of the taxonomy, biology, ecology, and distributions of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* would also be important in understanding the local, regional, and global perspectives regarding IAPS is essential. An integrated evaluation of resource quality, ecological resources, and economic viability can guide choices regarding the best management practice suitable for predicting, monitoring, and controlling IASs at any location. Effective management of IASs improves species richness and minimises greenhouse gas concentration in the environment. This can ensure a sufficient supply of clean water and retain the protective functions of stable and self-sustaining agricultural ecosystems.

To understand the impacts of IAS proliferation, it is essential to understand how climatic variables like precipitation and temperature gradients contribute to the spatiotemporal occurrence of most plant species. Increases in precipitation can transform ecosystems, making new plant species not endemic. On the other hand, a temperature rise allows the spread of species that would have been confined in small regions due to early or delayed winter onset, thus boosting the winter survival of some invasive plant species which would otherwise not survive.

GIS and RS techniques have greatly improved the identification and mapping of invasive alien species, leading to practical assessment of possible occurrence, and spread. The combination of spatial techniques and Ecological Niche Models (ENM) and Species Distribution Models (SDM) have provided ecologists and management with reliable information for implementing legislative protocols to manage the biodiversity of endemic species. Such a conservation method involves all stakeholders, including farmers and development partnership practitioners. A system-wide capability creation strategy is suggested for a phased transition to climate-smart conservation.

It is thus essential to acknowledge that the IAPS problem relies equally on economics and ecology. The economics discipline can analyse the various market and non-market-related impacts to identify significant trade-offs in various management alternatives, enhancing the decision-making process for managing IAPS risks. After gaining insight into the IAPS problem, the study selected the best satellite platform to

identify IAPS. The image with the highest accuracy will then derive indices for modelling IAPS.

2.22 References

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Chapter 3: Evaluating the effectiveness of different platforms to map the current extent of Mauritius thorn (*Caesalpinia decapetala*) and River Red Gum (*Eucalyptus camaldulensis*) in the Vhembe Biosphere Reserve.

This chapter is based on: “Dondofema, F., Nethengwe, N., Taylor, P., & Ramoelo, A. (2023). Comparison of Satellite Platform for Mapping the Distribution of Mauritius thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) in the Vhembe Biosphere Reserve. *Remote Sensing*, 15(11), 2753.”

Abstract

Mapping and tracking invasive alien plant species (IAPS) and their invasiveness can be achieved using remote sensing (RS) and geographic information systems (GIS). Continuous monitoring using RS, GIS, and modelling are fundamental tools for informing invasion and management strategies. Using systematic comparisons, we look at three remote sensing imagery platforms and how accurately they can be classified within the Vhembe Biosphere reserve, Limpopo Province, South Africa. Supervised classification of National Geospatial Information Colour Digital Aerial Imagery, DigitalGlobe Worldview 2 and CNES SPOT 6 was performed. The Spectral Angle Mapper (SAM) algorithm was used to identify the best satellite for species-level classification. The accuracy of the classifications produced an overall accuracy (OA) of 71% with a Kappa coefficient (KC) of 0.76 for Color Digital Aerial (CDA) photographs, an OA of 81% and a KC of 0.80 for Worldview 2, and an OA of 89% with a KC of 0.86 for SPOT 6 imagery. Therefore, SPOT 6 imagery came out as the most suitable for species-level classification. The classification results from the SPOT 6 imagery were used as input data for further species distribution modelling of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR.

3.1 Introduction

3.1.1 The invasive alien species problem

Nearly all ecosystems on Earth have problems associated with invasive alien plant species (IAPS). The invasions of these species into natural systems pose a challenge to the functioning of global biodiversity, habitats, and economic costs (Clusella-Trullas, and Garcia, 2017). Invasive alien plant species detection processes are usually localised. Remote sensing (RS) and geographic information systems (GIS) thus have the potential to contribute toward high mapping accuracies for use by both the scientific and management communities (Asner, 2009). Complemented by field-based techniques, RS and GIS can simultaneously map and monitor larger scales (Issa & Saleous, 2018). RS and GIS provide potentially valuable resources for mapping and tracking IAPS and provide data inputs to models that predict areas vulnerable to

invasion (Asner, 2009 & Melesse, 2007). These technologies can be regarded as cost-effective and wide-ranging, providing the ability for long-term reporting and monitoring of IAPS are recognised as basic research needs (Asner, 2009).

Presence records derived from RS and GIS can be used to create permanent records that could easily be used as inputs into ecological models for management and control activities (Beccari et al., 2023, Pinto-Ledezma & Cavender-Bares, 20121). The availability of multitemporal RS data makes it possible to predict trends leading to efficient monitoring of abundance and distribution patterns over time (Cord et al., 2013). Using the presence data of IAPS from RS and GIS allows monitoring and mapping of areas susceptible to invasion, thus, enabling the set-up of preventive measures that can accurately deal with problematic species (Leitão et al., 2019). RS and GIS techniques can effectively map locations at risk of invasion. Alternatively, upon the establishment of IAPS, RS and GIS can be used to map potential invasion pathways.

3.2 The use of RS and GIS in identifying IAPS

For the effective use of RS and GIS in identifying and monitoring IAPS, it is essential to understand the characteristics of the IAPS at the species level and their surroundings (Pinto-Ledezma and Cavender-Bares, 2020). RS and GIS can then map and monitor IAPS based on the ability to discriminate between IAPS and surrounding species, e.g., an understory species whose direct detection is from RS and GIS (Serbin and Townsend, 2020; Bolch et al., 2020). RS and GIS detection approaches rely on plant phenological, biochemical, structural, and observable spatial patterns as IAPS proliferate in the vegetative canopy.

3.2.1 Aerial photography

When selecting imagery to map IAPS, aerial photography is accessible freely, and provides acceptable spatial resolution (0.1–2 m). The high spatial resolution of aerial photos meets most criteria for sampling IAPS to satisfy management interest, even when considering small patch sizes, albeit only for some understory species that do not form distinct patches. Aerial photography is thus considered suitable when the IAPS exhibit visual traits that separate them from surrounding vegetation.

Based on its characteristic pale-yellow flower, aerial photography was utilised to detect the *Caesalpinia decapetala* (Everitt, 1995). Many woody invasives, including blackberry (*Rubus fruticosus*), European olive (*Olea europaea*), and *Pinus* species, have previously been mapped using high-resolution colour infrared aerial photography (Crossman & Kochergen, 2002). Using visual and computer-assisted digital colour infrared photographs analysis, invasive *Vachellia* species were efficiently mapped from surrounding indigenous plants and South Africa's fynbos habitat (Stow et al., 2000).

While high spatial resolution aerial photography can be affordable, visual processing takes time, making interpretation difficult in most instances since it requires both ability and experience (Lausch et al., 2020). In addition, field measurements must be appropriately calibrated to find spectral variations in the target species rather than capturing photos of surrounding plants. Due to these restrictions, data can only be collected in relatively limited geographical areas.

3.2.2 Multispectral imagery

Multispectral imaging is based on sensors that measure reflected energy within several specific bands, varying from 3 to 10 bands across the electromagnetic spectrum. For example, SPOT images were used to identify Cogon grass (*Imperata cylindrica*) infiltrating savanna habitats (Thenkabail, 1999). In Nepal's lowland forests, Landsat ETM+ data were utilised to indirectly map IAPS in the understory based on the density of forest canopies and the intensity of light penetrating the understory (Joshi et al., 2006). Multispectral imaging outperforms aerial photography. However, some of the most common and economically important IAPS may be intermingled with other species or have thin canopies that make distinction difficult.

3.3 Trade-offs between image resolution and mapping accuracy

The mapping accuracy of IAPS-infected vegetation communities is highly influenced by spatial and spectral resolution. Even though systematic comparisons of several sensors across the same spatial region are critical for understanding temporal changes, there are few clear instances of IAPS, providing no direction to explain the selection of suitable sensors for invasion. While mapping IAPS in South African riparian habitats, researchers noticed that visual interpretation using 1:10,000

panchromatic aerial photos produced the most accurate results (Holmes et al., 2005). Landsat 8 imagery resulted in lower accuracy (Rowlinson et al., 1999). This is mainly because of the accessibility and affordability compared to hyperspectral techniques.

Research findings in South Africa indicated that Colour Infrared Red images, a form of aerial photographs with a more excellent spectral resolution, produced higher accuracy (Underwood et al., 2007). Furthermore, when comparing imagery with various spatial and spectral resolution combinations, results indicate higher mapping accuracies for IAPS with distinct features beyond the visible spectrum, with better spectral resolution than spatial resolution.

The well-known trade-off between spectral and spatial resolution and data picture processing costs complicates choosing the suitable image resolution even further (Figure 3-1). Although a comparison of analysis of multispectral (Landsat 8) with moderate resolution imagery from SPOT and aerial photos for a 100 km² study area (Hamuda et al., 2016; Hunt et al., 2011) points to Landsat ETM+, CDAI and SPOT 6 to be the cheapest as they are freely available, with DigitalGlobe Worldview 2 imagery the most expensive, there have been few systematic cost comparisons of RS and GIS in comparable research locations.

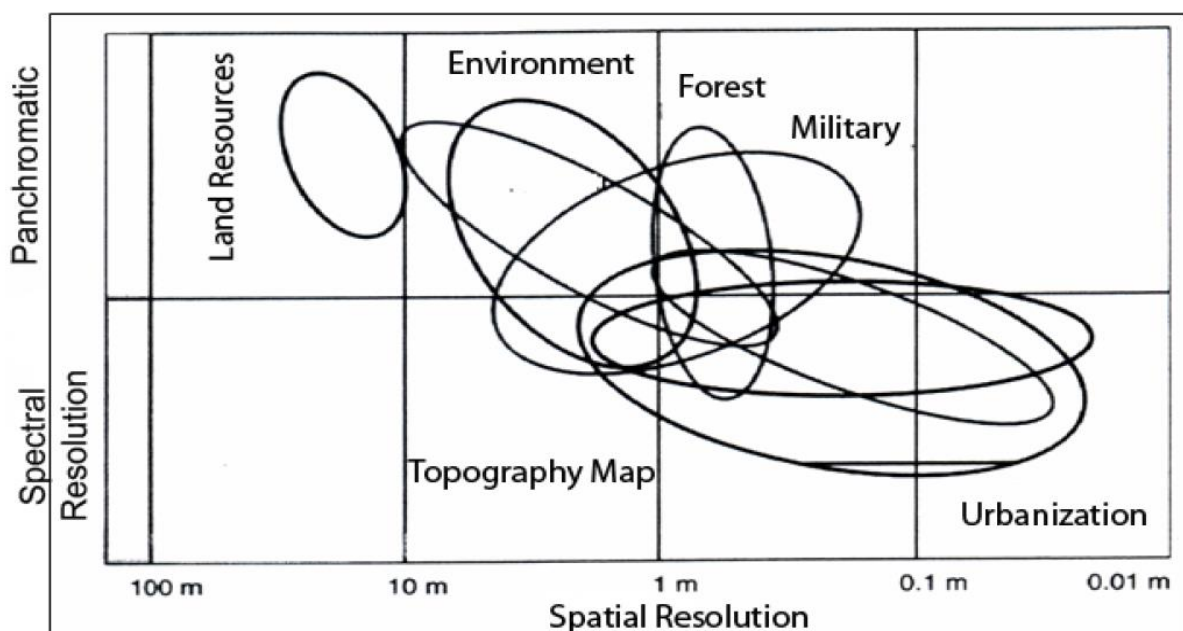


Figure 3-1: Relationship between spectral, spatial resolutions and usage type (Alavipanah et al., 2010)

3.4 Identifying the Potential Distribution of Invasive Alien Species

While not a replacement for rigorous systematic field surveys, distribution models may be a viable option for estimating IAPS distribution (Zurell et al., 2020). As a result, prioritising precious resources such as people, time and cash for control and monitoring is accelerated (Keith, 2000). The bulk of prediction models is statistical, with the presence or presence-absence data used to infer environmental circumstances that comprise most of the presence locations (Srivastava, 2019). Remotely sensed variables such as vegetation, atmosphere, soil, geomorphology, proximity to roads or pathways and knowledge of management practices may be predictors in most environmental niche models (ENM). Mechanistic models simulate physiologically limiting elements in a species' tolerance to the environment (He et al., 2015, Rocchini et al., 2015 and Truong et al., 2019). In correlative species distribution models, environmental factors are statistically linked to species occurrence or abundance (Dormann et al., 2012). On the other hand, process-based models establish a species' ecology as mathematical functions that define causation; the species' presence or abundance is an indirect, emergent result (Dormann et al., 2012). The mechanistic niche model uses comprehensive biophysical modelling tools to understand species distribution (Kearney, 2006).

The spread of IAPS presents a complex and costly problem to most countries (Rai and Singh, 2020). Typical characteristics of IAPS include fast growth, expansion, massive distribution, phenotypical plasticity, survival in different forms of foods and various environmental conditions (Roger et al., 2019). A good indicator of invasion depends on a species' success in invading a new area (Divíšek et al., 2004). Therefore, remotely sensed images should be coupled with indirect mapping methods, including the use of GIS data layers and modelling (Joshi et al., 2004). In the case of IAPS that occur in the vegetation canopy, successful detection approaches have generally capitalised on unique phenological, or biochemical properties, structural characteristics or spatial patterns created by invasions. It is thus essential to provide a brief synopsis of phenological or biochemical properties and structural features that can be used to map IAPS successfully. The potential for regional invasion in South Africa was examined locally using climatic envelope models for 71 IAPS and existing presence data collected at a geographical resolution of 25 km (Rouget et al., 2004). To identify invasion hotspots for several species, there has been a shift toward an alternate method to multiple species modelling (Schnase and Carroll, 2022).

3.4.1 Indirect identification of areas vulnerable to invasion using RS and GIS

RS and GIS can detect landscape and site features, making mapping IAPS distribution possible (Crowley et al., 2020). RS and GIS can be used to identify regions with excessive rates of deforestation that can result in plant invasions by integrating propagule transportation and micro-disruption (it should be acknowledged that defoliation due to grazing can also affect IAPS) (Xie et al., 2008). The ability to detect changes in the terrain over time may be used to define disturbance regions prone to invasion. Land degradation of the natural environment means edge ecosystems are more vulnerable to plant invasions than core ecosystems (Wellington et al., 2005). The spatial distribution of natural habitats in images and degradation indices can help identify invasion-prone locations.

3.5 Limitations of RS applications to IAPS

For more accurate species distribution and risk maps, there is a need to complement MaxEnt with Generalised Linear Mixed Models (GLMMs) to identify areas of possible spread for conservation purposes (Royle et al., 2015 and Adhikari et al., 2015) modelled hotspots of IAPS through Ecological Niche Modelling (ENM) using MaxEnt to guide the formulation of an effective policy for controlling the IAPS. The area under the curve (AUC) scores obtained for predictions can be sufficiently accurate (Elith et al., 2011). However, SDMs have some limitations, such as overestimation of the presence of species. The assumption of a random sampling of species' existence on the grid cells made by SDMs predicts each cell's significant probability of fact, which could be overestimated (Raes et al., 2018).

The high data, software and hardware costs significantly impact the uses of RS and GIS in monitoring IAPS; this is typical for contemporary high-resolution images. However, notable trends are showing declining imagery costs, such as the free access provisions being given by Landsat (Turner et al., 2003). Technical expertise is required to process images (visual interpretation) and multispectral (image processing). As indicated by comparing aquatic and terrestrial ecosystems, the ability to map IAPS and the accuracy with which they may be identified changes between environments (Elith et al., 2011; Reas et al., 2018). When spatial data and satellite images are integrated with field measurements, the best classification results are produced, giving vital inputs for classifying and validating image classifications. Because of a better

grasp of plant phenology and its implications on spectral resolution, practical awareness and familiarity with the environment enhances classification accuracy significantly.

Notwithstanding the constraints above, remote sensing remains the most significant approach for effectively gathering information across broad regional extents at high spatial resolution while allowing for the most significant percentages of spatial sampling. Developments in remote sensing, such as increased temporal image acquisition and approaches that combine passive, radar and thermal sensors and texture analysis, will almost certainly expand the resources available to map IAPS. The trade-offs between satellite image resolution continuously shift as remote sensing technologies advance and new data sources become accessible. Policies governing access to remote sensing data are evolving; a casing point is the benefit of high-resolution imagery in structured, searchable, well-documented libraries locally and globally. The South African National Space Agency (SANSA) and other governmental satellite datasets have made great strides in Earth observation data democratisation in South Africa. This study evaluated the accuracy of the NGI-CDAI, DigitalGlobe Worldview 2 and CNES SPOT 6 for species-level plant species discrimination.

3.6 Study site

The research site discussed falls within the VBR. The VBR is a member of the World's Reserve Network organised by Man and Biosphere (MAB, UNESCO), located in the northern part of South Africa, covering five local municipalities of the Limpopo Province (Blouberg, Collins Chabane, Makhado, Musina, and Thulamela). International borders to the north and east include Botswana, Zimbabwe, and Mozambique. This site was selected due to the invasion by Mauritius Thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) and the contrast in climatic conditions.

The VBR covers an area of 3,070,000 ha (30,701 km²), including part of the Kruger National Park (KNP) north of the Shingwedzi River. The Mogalakwena River forms the eastern border. The southern boundary spans from south of the Blouberg–Makgabeng and Soutpansberg Mountain range to the east, over the Luvuvhu River catchment. The VBR lies between the following coordinates (23°30'S and 22°14'S and 28°45'E and 31°29'E). Within the VBR, the altitude ranges from 2500 m above mean sea level (asl), 719 m asl (Hangklip) and 1748 m asl (Lajuma).

The extreme maximum and minimum temperatures recorded in the VBR are 43.2 °C and -3.4°C (Kruger and Shongwe, 2004). The winters in the VBR are generally mild, and frost sometimes occurs only in the southern valleys (Mpandeli, 2014). In Entabeni, the highest observation station in the region, the average seasonal rainfall surpasses 850 mm, and occasionally the total annual rainfall may exceed 2000 mm. On the other hand, stations in the mountain's rain shadow or low-lying locations, such as Pafuri and Alldays, receive barely 200 to 300 mm of seasonal rain. However, the area's poor rainfall measurement network cannot precisely assess local fluctuations.

The VBR's bushveld vegetation unit of the savanna biome is officially classified as vulnerable. The bushveld vegetation unit comprises a rainfall gradient distribution of thick deciduous woods and evergreen montane forests, with a weakly established grassy layer and open savanna in certain areas. In addition, exotic eucalyptus, and pine plantations on the Soutpansberg range further strained the Soutpansberg Mountain bushveld vegetation unit's survival. In general, vegetation groups in the Soutpansberg Mountains appear in east-west bands along the easterly moisture flow from the Indian ocean, following the direction of the mountain range's ridges.

The VBR consists of three biomes: savanna, grassland, and forest; four bioregions and twenty-three distinct plant types or biotopes. South Africa is home to eight of these biotopes. The region is also a bio-geographical node, comprising the Kalahari and Lowveld bioregions with mild to tropical temperatures. This produces zones of biologically significant interactions, which must be safeguarded for conservation to be viable. Based on a combined examination of species, ecosystems and biological processes, the South African National Spatial Biodiversity Assessment (NSBA) has designated the Blouberg and Soutpansberg complex as one of nine priority sites for conservation efforts (Van Wyk, and Smith, 2001). Additionally, the area's poor rainfall measurement network cannot precisely assess local fluctuations region as a biodiversity and endemism hotspot in South Africa.

3.6.1 Land-cover classes and IAPS

Twelve land-use/land-cover classes were classified, including two genera of invasive alien trees. The identified land-use/land-cover classes: (i) Unclassified, (ii) Water, (iii) Buildings, (iv) Bare Area, (v) Road, (vi) Plantation, (vii) Orchard, and (viii) Forest. A McNemar test was run to test the difference between the three satellite platforms used

in the land-cover classification. This was performed through a nonparametric test that compared the classification results from the three satellite platforms with binary responses for randomised complete blocks.

3.6.2 Datasets

This study used classification and accuracy assessment methods using colour digital aerial imagery (CDAI), Worldview 2 and SPOT 6 imagery. All the image analysis was performed using ENVI 5.3 and ESRI's ArcGIS 10.8.3 software. A summary of the imagery used in this study is presented in Table 3-1.

Table 3-1: Specifications of the satellite data used in this study.

Sensor	Scene	Date of Acquisition	Resolution (m)	Spectral Bands
CDAI	2329BB	2018-07-16	0.25	
SPOT 6	SPOT6_20181102_13303316qth9tssm80h_2	2018-11-02	8 m	Blue, Green, Red
		2018-11-02	8 m	Blue (0.455 μm –0.525 μm)
		2018-11-02	8 m	Green (0.530 μm –0.590 μm)
		2018-11-02	8 m	Red (0.625 μm –0.695 μm)
Worldview 2	012969746010_01_003	2017-05-12	1.8 m	Near-Infrared (0.760 μm –0.890 μm)
	012969746010_01_003	2017-05-12	1.8 m	Coastal: 400–450 nm
	012969746010_01_003	2017-05-12	1.8 m	Blue: 450–510 nm
	012969746010_01_003	2017-05-12	1.8 m	Green: 510–580 nm
	012969746010_01_003	2017-05-12	1.8 m	Yellow: 585–625 nm
	012969746010_01_003	2017-05-12	1.8 m	Red: 630–690 nm
	012969746010_01_003	2017-05-12	1.8 m	Red Edge: 705–745 nm
	012969746010_01_003	2017-05-12	1.8 m	Near-IR1: 770–895 nm Near-IR2: 860–1040 nm

3.6.3 Training data

Training data were gathered using two sources of information: (i) ecological input on target groups and (ii) field surveys (Holden et al., 202). These training data were used to produce the classifications, which were groundtruthed. In addition, a local ecological expert was engaged to provide coordinates and shapefiles of infestations of these

target invasive alien plant groups. During the field surveys, an effort was made to obtain a reasonable spatial spread of points across classes, specifically focusing on the Soutpansberg mountains and the Luvuvhu Valley (Figure 3-2). For each land-cover class, there are 7271 points for 12 classes.

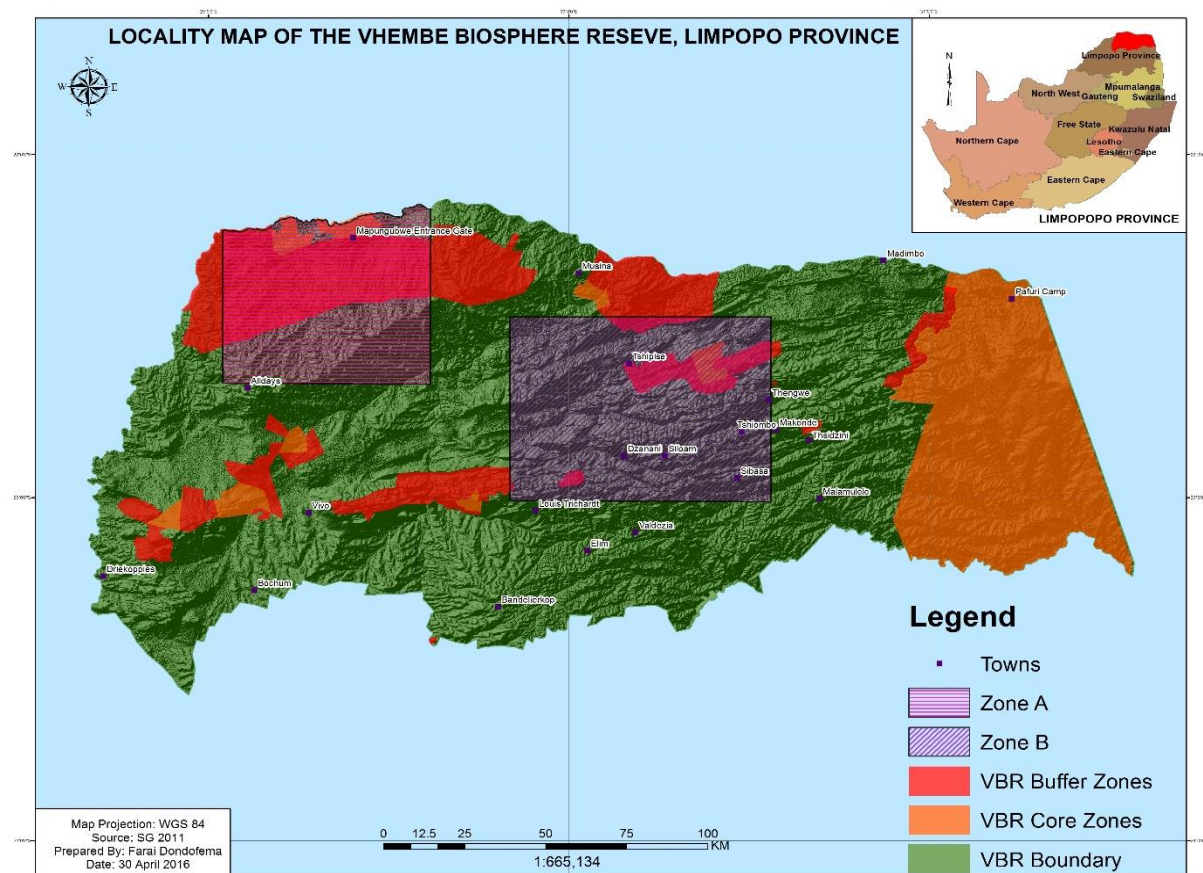


Figure 3-2: Locality Map of Vhembe Biosphere Reserve in the Limpopo province (Desmet et al., 2013)

3.7 Classification

Classification of images is a means of decryption of satellite images, identification, and delineation of any objects on the image. Classification can also be defined as a process of automatic decryption. The classification algorithms are divided into two classes according to user involvement: unsupervised (pixel-based classification and essentially computer-automated classification) and supervised (spectral signatures obtained from training samples to classify an image) classification. Supervised classification was performed on the CDAI, SPOT 6 and Worldview 2 images to differentiate the various vegetation types in the study area. Each pixel in an image is assigned to a group or class in the pixel-based classification process. Then, using

spectral pattern recognition, each pixel is allocated to a class based on its spectral properties. Object or feature-based classification methods use what is known as feature space to classify the pixels. Feature space is a scatter plot of the two bands' spectral values for all the image's pixels. Because the classes in this study are land-cover, the purpose is to map the land-cover types throughout the image. This study collected ground reference land-cover information during the three field sampling excursions in June–July 2019 and February 2020.

3.7.1 Supervised classification

Supervised classification aims to extrapolate land-cover type information from a known segment of a remotely sensed image using data acquired during fieldwork to unknown areas of the whole image. As a result, for each land-cover category, the analyst defines many 'training' regions. Based on this information, the computer develops spectral signatures using specialised spatial analysis tools. The maximum likelihood descriptor is the most common method to measure the spread of values around the mean of the class. Each image pixel is allocated to one of the groups covered by the land as far as feasible by the spectral signature. ENVI 5.3 software used for classification in this study has four different classification algorithms to choose from when running the supervised classification procedure. These include Minimum Likelihood Distance (MLD), Mahalanobis Distance and Spectral Angle Mapper (SAM). The SAM method was chosen because of its ability to compute the spectral angle between an image spectrum and a reference spectrum using vectors in n-dimensional spectral space, where n is the number of bands and reduces the influence of shading effects to emphasise the intended reflectance qualities (Kuching, 2007). SAM is also a simple and quick approach for mapping picture spectral similarity to reference spectra. Figure 3-3 shows the supervised classification process.

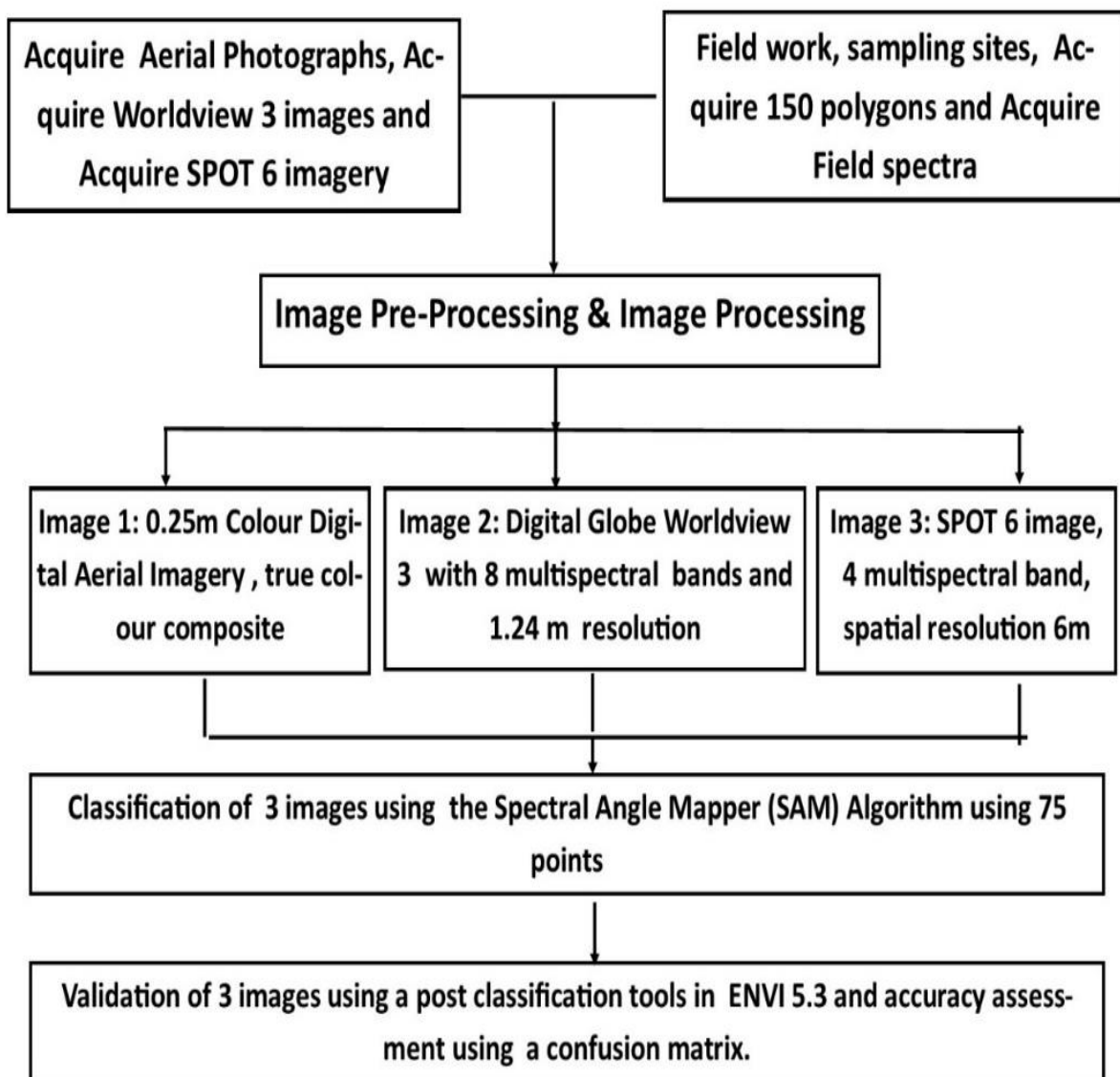


Figure 3-3: Classification of CDAI, Worldview 2 and SPOT 6 datasets.

After visually assessing many classification approaches in Environment for Visualising Images (ENVI 5.3) (Exelis Visual Information Solutions, 2013), the spectral angle mapper (SAM) classifier was chosen for our purposes because of its more remarkable ability to recognise actively photosynthetic vegetation. The SAM is a supervised machine learning approach that uses statistical learning theory to achieve classification. The SAM classifies data by extracting a hyperplane from a multidimensional feature space that optimally divides classes. This hyperplane is the ideal decision surface for class separation. The ideal hyperplane maximises the margin, which is the distance between the hyperplane and the nearest positive and negative training examples. The optimisation problem is addressed using training

samples to discover the hyperplane, resulting in a sparse solution. Even though the SAM is a binary classifier in its most basic form, the SAM classifier implementation in ENVI was enlarged to more than two classes by breaking the problem down into a series of binary class separations (De Carvalho and Meneses, 2000).

Several kernels, including the polynomial, radial basis function and sigmoid, may classify SAM in ENVI to represent more complicated forms than linear hyperplanes. The SAM was used with the radial basis function kernel for paired classification. During training, the SAM classifier can additionally implement a penalty parameter for misclassification. The penalty parameter was set to its maximum value, whereas a classification probability threshold of zero was used to classify all pixels (Exelis Visual Information Solutions, 2013). For picture classifications, the classifier's default settings were utilised. During the classification phase, the spectral subset option in ENVI was used to select only the NIR band of the NAIP imagery.

The approach taken in this study is to assess all three images (CDAI, Worldview 2 and SPOT 6) individual performance to classify land covers in the study area and evaluate their errors and accuracy to select the imagery with the highest accuracy for species-level extraction.

3.7.2 Accuracy assessment of CDAI, Worldview 2 and SPOT 6 classification

Classification accuracy was evaluated by developing an error matrix for each classified image that analyses the relationship between reference categories on the ground and matching classified categories on the image group-by-group basis. By comparing the identified classes to the ground verification data, error matrices for each classification map were constructed. To assess classification accuracy, error matrices were generated, which included overall, producer and user accuracies. Using site verification data, field validation (accuracy evaluation) was undertaken (ground control points). Verification data for 175 sites were randomly generated using the "generate random sample using ground truth image in the post-classification tool" function in ENVI 5.3 software.

The verification points were loaded into a real-time differential Trimble GeoXH Global Positioning System (Trimble Navigation Limited, Sunnyvale, CA, USA) outfitted with the ArcPad software package, a 4 m external antenna, providing submeter horizontal

accuracy (10 cm), and navigated at sites before image classification. This resulted in an unbiased field validation technique based on visited sites without prior knowledge of whether the classification method had demarcated areas for the relevant land-cover groups. Next, the land-cover type in the 175 regions was evaluated and allocated to GPS locations. Following the classification of the images, these locations were placed on the land-cover map, and a one-to-one matching was performed to create an error matrix for each site.

The error matrix was used to calculate the accuracy evaluation for classified maps, individual land-cover classes and the kappa coefficients and variances. To compare image classification at 95% confidence level sites, a two-tailed Z-test ($Z/2 = Z_{0.025}$) was used. The kappa statistic calculates the degree of agreement or accuracy between the classification map obtained from images and the ground verification data. When the row and total column estimations are considered, this is characterised by the significant diagonal and the chance agreement. For example, the Kappa values for CDAI, Worldview 2, and SPOT 6 classification vary from 0 to 1, with values more than 0.80 indicating high agreement between the categorised map and ground truth, and values less than 0.40 indicating poor agreement—scores ranging from 0.40 to 0.80 show moderate agreement with the underlying data.

3.8 Results

3.8.1 Extraction of training samples from the CDAI

The spatial coverage of the CDAI is illustrated in Figure 3-4 within the study area. Bare lands are distinguished by a lighter reddish tone on the CDAI composite image, herbaceous vegetation by a greyish response (with intermittent stream segments) and water by black or blue tones. Figure 3-4a reveals distinct spatial patterns of plantations, forests, orchards, water, bare area and other land-cover classes on each site. Image classification resulted in 3.49% Unclassified, 36.21% Buildings, 6.28% Plantations, 20.81% Forest, 2.83% Tar and 11.17% water. With a kappa value of 0.757, the overall accuracy of land-cover classifications was 70.50%.

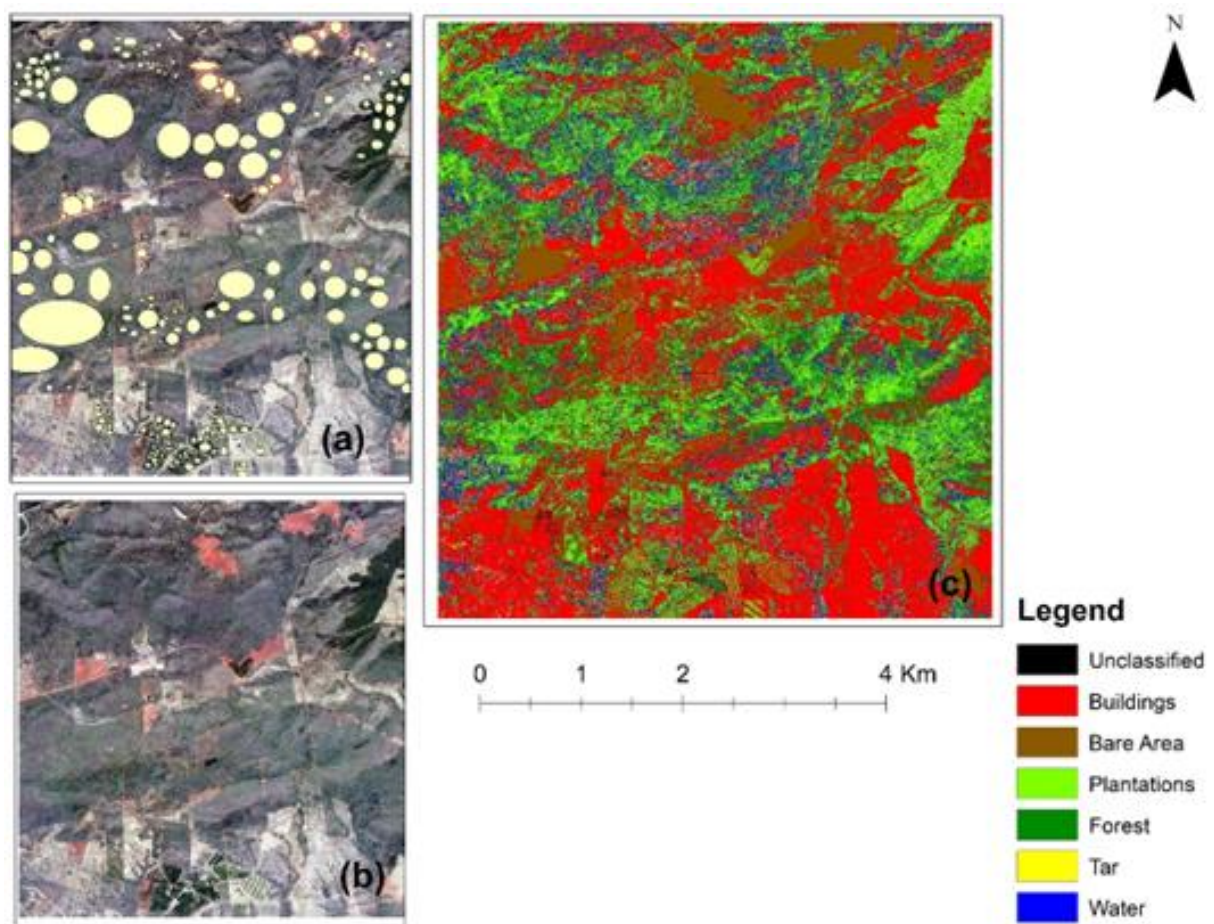


Figure 3-4: The colour digital aerial with 0.25 m spatial resolution and validation polygons represented with (a) yellow dots, while (b) is the true colour imagery, and (c) is the classified aerial imagery for the study site.

3.8.2 Extraction of training samples Digital Globe Worldview 2 Imagery

The spatial coverage of the Worldview 2 imagery is illustrated in figure 3-5 within the study area. Figure 5a shows the Digital Globe Worldview 2 Imagery with 1.24 m images for sites. The actual colour composite imagery reveals distinct spatial patterns of plantations, forests, orchards, water, bare area and other land-cover classes on each site. Plain regions are distinguished by a light greyish tone, herbaceous plants with a dark green response, and water with brown or blue tones in the actual colour composite image. Image classification resulted in 35.92% Unclassified, 0.22% BuiltUp Area, 25.51% Plantation, 34.91% Forest, 0.53% Road and 0.43% Water. Land-cover classes were identified with an overall accuracy of 80.50% with the associated kappa coefficient of 0.80.

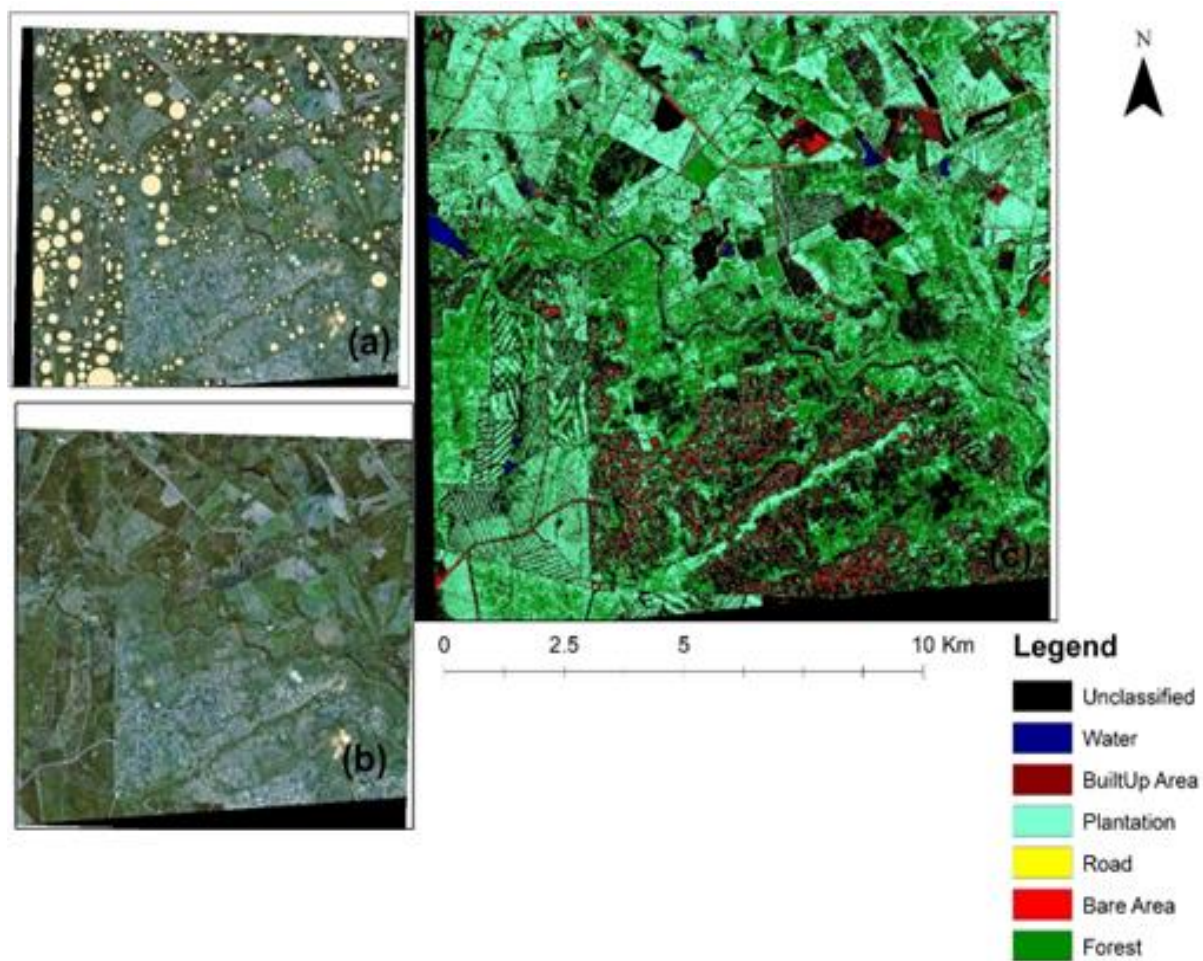


Figure 3-5: The Digital Globe Worldview 2 Imagery with 1.24 m spatial resolution and validation polygons represented with (a) yellow dots, while (b) is the colour imagery, and (c) classified Worldview 2 imagery for the study site.

3.8.3 Extraction of Training Samples SPOT 6 Imagery

The spatial coverage of the SPOT 6 imagery is illustrated in Figure 3-6 within the study area. Figure 6a shows the SPOT 6 Imagery; the true colour composite imagery reveals distinct spatial patterns of plantations, forests, orchards, water, bare area and other land-cover classes on each site. The SPOT 6 composite image shows that a brownish tone, herbaceous plants with a light green response and water with blue tones characterise bare regions. Image classification resulted in 23.39% Unclassified, 0.820378% Water, 1.50% Buildings, 13.66% Bare Area, 7.88% Road, 5.47% Plantation, 12.72% Orchard and 34.55% Forest. The associated kappa coefficient of 0.857 was used to identify land-cover classes with an overall accuracy of 88.89%.

The McNemar test is used to see if there are differences between two related groups in a dichotomous dependent variable. It is like the paired-samples t-test, except that the dependent variable is dichotomous rather than continuous. The null hypothesis cannot be rejected because the computed p-values from the McNemar test for the three remote sensing platforms are greater than the significance level $\alpha = 0.05$. The alternative hypothesis that the classification results from the three remote sensing platforms differ cannot be accepted because the computed p-values from the McNemar test are more significant than the significance level $\alpha = 0.05$.

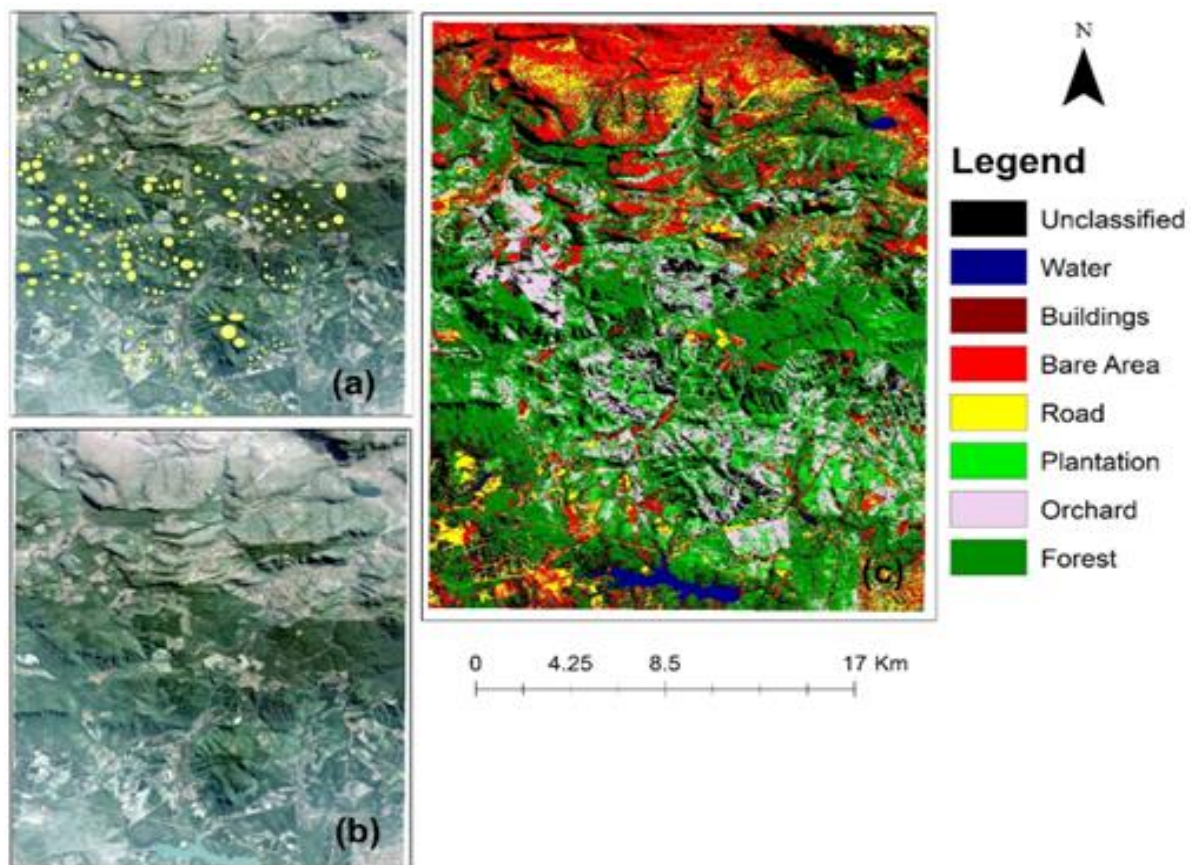


Figure 3-6: The SPOT 6 imagery with 6 m spatial resolution and validation polygons represented with (a) yellow dots, (b) is the colour imagery, and (c) is the classified SPOT 6 imagery for the study site.

3.8.4 Species-level extraction of training samples from SPOT 6 Imagery

After running classification, validation, and accuracy assessment of the three sets of images (The DigitalGlobe Worldview 2, NGI-CDAI and CNES Spot 6 images), the results indicated that the SPOT images produced the best classification with high levels of accuracy with 87.50%, 87.50% and 88.89% respectively. Given this backdrop, Spot 6 satellite images of *Caesalpinia decapetala* and *Eucalyptus*

camaldulensis were chosen for species-level classification. Furthermore, based on the spectral difference between living vegetation (forest, plantation, orchard) and senescent herbaceous or nonvegetative components, the 6 m multispectral SPOT 6 satellite images enabled unambiguous identification of all prevalent land-cover classes (paved road, shadow, exposed soil, water).

The spatial coverage of the SPOT 6 imagery is illustrated in Figure 3-6 within the study area. Figure 6 shows the SPOT 6 Imagery with 6 m spatial resolution for sites. The true colour composite imagery reveals distinct spatial patterns of plantations, forests, orchards, water, bare area and other land-cover classes on each site. For example, on the SPOT 6 composite image, bare regions are characterised by brownish tones, herbaceous plants by a light green response and water by blue tones. Table 3-2 summarises the classification analysis, while Table 3-3 shows the classification performance.

Table 3-2: Systematic comparison using the McNemar test.

	WV-NGI	SPT-NGI	WV-SPT
Q	3,200	2,250	0.500
z (Observed value)	1,789	1,500	0.707
z (Critical value)	1,960	1,960	1,960
p-value (Two-tailed)	0.074	0.134	0.480
alpha	0.05	0.05	0.05

Image classification resulted in 23.69% Unclassified, 0.82% Water, 2.91% Buildings, 17.47% Bare ground, 1.26% Shadows, 2.91% Plantation, 2.48% Orchards, 33.03% Forest, 6.60% Eucalyptus and 8.84% *Caesalpinia decapetala*. Land-cover classes were identified with an overall accuracy of 88.89% and an associated kappa coefficient of 0.8750. The producer's accuracy ranged from 50% for unclassified to 100% for water, while the user's accuracy varied from 50% for unclassified water to 100% for water (Figure 3-7). At a 95% confidence level, the Z-statistics (1.75 3.15) revealed an insignificant difference in the site classifications. A close look at the field-collected spectral, presence and absence data illustrates that, in most cases, the *Caesalpinia decapetala* occurred as mixed pixels within the natural vegetation. At the same time, the *Eucalyptus camaldulensis* grew as homogeneous assemblages close to plantations or abandoned plantations.

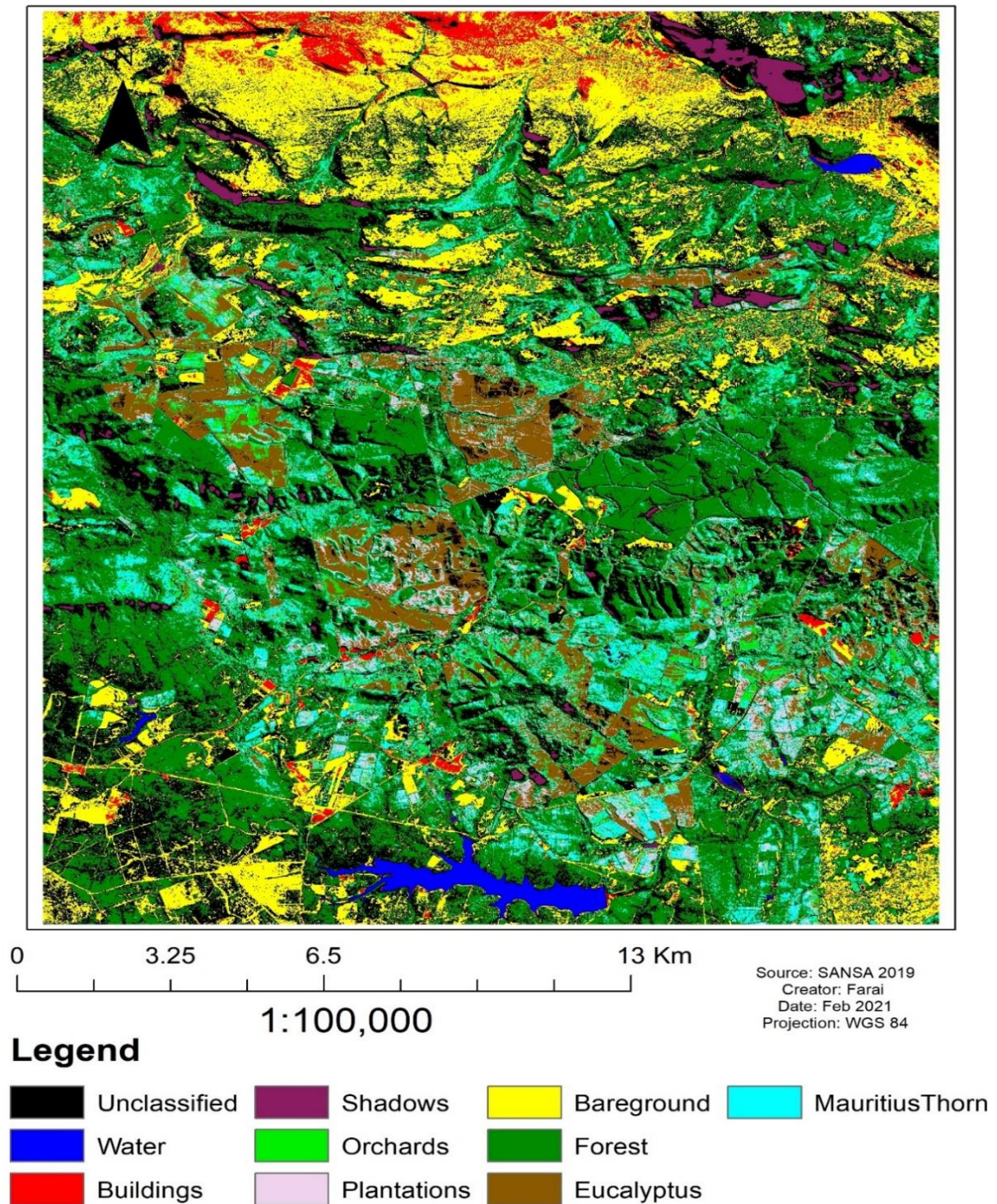


Figure 3-7: The SPOT 6 Imagery with 6 m spatial resolution and validation points represented with classified aerial imagery for the study site.

Table 3-3: The cover classification performance for the three data products.

Classification	Overall Accuracy (Percent)	Kappa Coefficient	User Accuracy (Percent)	Producer Accuracy (Percent)

NGI-CDAI	88	0.8571	100	94
DigitalGlobe-Worldview 2	88	0.8571	100	94
CNES-SPOT 6	89	0.875	100	94
Species Level CNES-SPOT 6	89	0.857	87	86

3.9 Discussion

Using a timely, low-cost method, accurate information may be obtained about the current distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* across large, challenging areas. This information can then be used in several types of rangeland ecology and management sectors. This study investigated the effectiveness of using three satellite platforms based on their spatial and spectral resolution, classification, and statistical results from the McNemar test to enable further species distribution modelling of the IAPS.

It was feasible to discern the characteristics appearing in an image in terms of the object or type of land cover these features truly represent on the ground using supervised classification, making image classification the most significant element of digital image analysis. However, the results also show that it is not the image platform with the finest spatial resolution that performs best in classification; it is also necessary to consider the spectral resolution.

Using three imagery sets in the study shows how remote sensing for IAPS detection has advanced rapidly. It progressed from CDAI, and photo interpretation approaches to digital image processing, with machine learning replacing manual interpretation to discover small characteristics the human eye cannot detect. Remote sensing technology advancements have resulted in less expensive and faster methods of managing forest resources. Nonetheless, there are still limitations to their widespread use in IAPS monitoring. Monitoring, detection and reporting on forest health concerns have constantly been prioritised by the Department of Forestry, Fisheries, and the Environment (DFFE), Endangered Wildlife Trust (EWT) and Working for Water (WfW), particularly in protected areas such as the VBR. The rate of forest area conversion inside the VBR, human-caused changes in land cover, and the threat of IAPS introduction and establishment have all heightened the demand for improved near-real-time tools and commodities.

A variety of stakeholders must be included throughout the process to maximise the usefulness of the established classification:

- Rather than just receiving letters of support, end users and other important stakeholders should be involved in the experimental design from the start.
- The researcher selected and visited practitioners in the study region at prospective field sites for data collection.
- Including stakeholders in fieldwork, learning from their experience, and instilling a feeling of ownership in the project increased the likelihood of final product identification and adoption.

This was performed to avoid the restricted cooperation required for this study among land managers, practitioners, and decision-makers. The classification results in the study region of Eastern Soutpansberg using the SPOT 6 image identified that 336 hectares were covered by *Caesalpinia decapetala* and 2629 hectares were covered by and *Eucalyptus camaldulensis*. In comparison, the SPOT 6 image covered a total area of 35,765 hectares. A notable pattern was with *Eucalyptus camaldulensis*, with which almost 30% of the identified trees were located close to plantations. In comparison, approximately 25% had escaped along watercourses, with the remainder (45%) being found all over the area of interest.

The management goals inform the spatial scales at which the classification technique can be adopted within the VBR (Sparrow et al., 2020). Field-based surveys will always obtain the most detailed and accurate information about IAPS. As a result, researchers may conduct on-site measurements of foliar chemistry, canopy structure and spectral features. Nonetheless, it is crucial to stress that the relevance of this study in advising management across the larger environment is restricted. The operational scale is also suggested for imaging with high spatial and spectral resolution, which is perfect for detecting IAPS. Unfortunately, such initiatives may be geographically constrained because of the high cost and computational requirements. The recent addition of enhanced satellite sensors (e.g., Worldview 2 and SPOT 6) has dramatically increased the capability to cover large areas at higher spatial resolutions. However, global evaluations of forest conditions often necessitate decreased spatial resolution to analyse information over enormous geographic extents. Mixed pixels, which are far more effective, frequently disguise slight changes in vegetation conditions. However,

they might be helpful in time series analysis when focusing on relative changes in vegetation indicators at continental sizes.

The scope of the inquiry determines the optimum technique for mapping and modelling the spread of IAPS, the amount of information required for the available resources, and the period if the research was to be upscaled from the VDM to the Limpopo area of South Africa. In that case, the assessment criterion may have to sacrifice spatial and spectral resolution (as well as predictive detail and accuracy) to attain the needed geographic coverage. On the other hand, a municipality worried about the propagation of a freshly identified IAPS may forego broad regional coverage to maximise the spatial and spectral resolution required to identify specific, newly developed IAPS. As with this study, some typical constraints are accessible images, time and financial resources. Gathering high-resolution pictures after September 2012 using the SPOT 6 satellite data is difficult. However, historical broadband satellite images (SPOT 1, 2, 3, 4 and 5) may provide a general evaluation of former circumstances dating back to 1986.

The comparison of CDAI, Worldview 2, and SPOT 6 imagery demonstrated that, even when not adequately suited to the user's demands, diverse satellite images may give insight that traditional monitoring cannot. The results from this study have also raised that the most comprehensive approach to detecting novel IAPS issues can only be achieved by combining several methods. One good example is the harmonisation of the SPOT 6 and Worldview 2 images to improve the resolution of the resultant output. In investigating the three satellite platforms, the best method was to investigate the relationship between spectral characteristics from higher-resolution imagery that might be utilised to train coarser-resolution data for a larger-scale review. The key is to recognise that there is no single correct strategy and that various remote sensing technologies may be employed to meet goals. According to the classification findings, SPOT 6 images performed better than aerial and Worldview images.

Many factors influence the capacity of SPOT 6 images to assess trends and patterns in woody plant cover. The spatial, spectral, and radiometric resolutions, as well as the image scale, image processing methods, atmospheric haze, shadow, terrain effects, the angle between the sensor and the vegetative layers, the relative contrast between the vegetative layers and the background, canopy architecture, crown size and height

and plant density, all have a significant impact on the detection capabilities of remotely sensed images. When canopies of individuals of the same or different plants overlap, it is impossible to discern whether a particular image shows one giant plant, numerous plants of the same species or various plants of different species from a top-down perspective.

3.10 Conclusions

Remote sensing and GIS techniques provide unique methods for recognising and mapping plant species. They can characterise the scope of an invasion by differentiating the invading species from the rest of the vegetation mosaic in a timely and spatially specific manner. The SAM classifier detected the two IAPS: *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. Given these woody plant invasions' economic and ecological ramifications, the results show that SPOT 6 imagery has the best accuracy when mapping the extent of various vegetation types and invasions.

Except for little mapping plants with less than 1 m diameter canopies, the 6 m scale level of precision proved appropriate in mapping both *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. A higher-resolution photograph of these plants may be required. This might be significant if the aim is to identify the early phases of invasion with juvenile plants. These maps may be used to monitor and plan management efforts for both under study. The SAM classifier's capacity to correctly identify diverse plant species has advantages in assessing biomass levels of each species and determining the quantity and kind of treatments necessary for woody invasion mitigation, which might differ for different shrub species. This study demonstrates how to use SPOT 6 images with a spatial resolution of 6 m to evaluate infestation by undesired rangeland species. This approach and technology should be explored when high-scale maps are required for study or land management.

The SPOT 6 archive has been operational since September 2012, providing nine years of historical analysis. The CDAI images have great promise; unfortunately, the restricted spectral resolution prevents precise classification from being used to its full potential. Nevertheless, when comparing the classification accuracy of the three images, it was clear that the CDAI photographs had a Kappa coefficient of 0.757 (substantial strength of agreement), Worldview 2 had a Kappa coefficient of 0.80 (substantial strength of agreement), and SPOT 6 imagery had a Kappa coefficient of

0.857 (almost perfect strength of agreement). This is confirmed further by the findings of a thorough comparison of the three remote sensing platform classification results, which reveal considerable variances between the platforms for remote sensing.

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Chapter 4: Species distribution models in invasive alien plant species

This chapter is based on: “Dondofema, F., Nethengwe, N., Taylor, P., & Ramoelo, A. (2023). “Using species distribution models to predict and monitor the distributions of Mauritius Thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) in the Vhembe Biosphere Reserve (VBR)” under preparation.

Abstract

Biomes in the global south are under increasing pressure from multiple stressors associated with climate change. Continuous remote sensing is a fundamental tool for monitoring plant invasions and informing management strategies. Here, we examine how environmental, habitat, climatic and phenological parameters affect invasive alien plant species (IAPS) establishment and distribution in Vhembe Biosphere reserve (VBR), Limpopo Province, South Africa. Twenty-one predictor variables split into environmental and remote sensing data were collected across two seasons (hot-dry, cool-dry) from seventy-four (39 presences and 35 absence sites) for river red gum (*Eucalyptus camaldulensis*) and seventy-eight (32 presences and 46 absence sites) Mauritius thorn (*Caesalpinia decapetala*) from fourteen belt transects and forty quadrants measuring 200 x 200m within the VBR. The stepwise logistic regression and maximum entropy (MaxEnt) modelling for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* using environmental, remote sensing variables produced a significantly high Akaike information criterion (AIC) and an area under the curve (AUC) values. Based on the stepwise logistic regression analysis, stepwise logistic regression analysis shows that variables accounted for significant variations in the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. The model increases suitable habitat from west to east along the Soutpansberg mountain and riparian areas. Further studies are required to assess the importance of environmental and climatic factors influencing the distribution of other invasive alien plant species under growing anthropogenic pressures. The MaxEnt modelling produced an AUC of 0.811 for *Eucalyptus camaldulensis*, the random, and 0.668 for *Caesalpinia decapetala*. The two models' high performance indicates high accuracy for the predictability of spatial distribution at the global and local levels.

4.1. Introduction to species distribution models (SDM)

This chapter aims to predict the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the Vhembe Biosphere Reserve (VBR). It focuses on two modelling approaches (stepwise logistic regression (SLR) and maximum entropy (MaxEnt)) in predicting the spatial distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR. The study used species presence and absence and environmental and remote sensing data to model the spatial distribution of *Caesalpinia*

decapetala and *Eucalyptus camaldulensis* at three scales (Global, VBR and local scale). The methods used in this chapter include:

- Stepwise logistic regression to model the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* at a local scale.
- MaxEnt to monitor and assess the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* on a global scale.

4.2. What are species distribution models?

Species distribution modelling (SDM), also referred to as ecological niche modelling (ENM) or predictive habitat distribution modelling, is a process that uses computer algorithms to predict the distribution of species in geographic space by using mathematical representations of their known distribution in environmental space (realised ecological niche) (Simoes *et al.*, 2020). The environment is, in most cases, represented by climate data, and other variables such as soil type, water depth, and land cover can also be used in the modelling process (Ninyerola *et al.*, 2000). SDMs allow interpolation between a limited number of species occurrence points and are used in conservation biology, ecology, and evolution in several other research areas (Hijmans *et al.*, 2016).

Species distribution models can help identify areas that need to be prioritised for conservation, like alien invasive species, or identify endangered species vulnerable to extinction (McPherson and Jetz, 2007). SDMs can be of great value in evaluating the potential of an invasive species to settle areas (Tikhonov *et al.*, 2020). SDMs can also assist in the determination of potential invasion pathways, making them essential for ecosystem health, public health, and safety. SDMs can also be combined with future projections of natural ecosystem changes to predict how biodiversity will be affected by the impacts of climate change or alterations in land use, as illustrated in Figure 4-1.

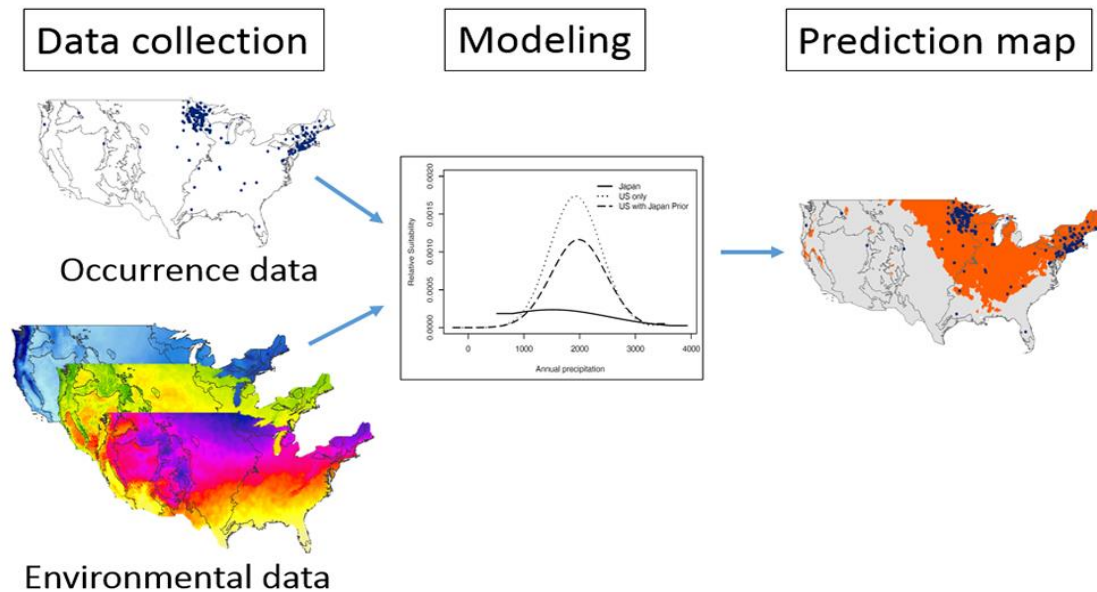


Figure 4-1: Conceptual diagram of how data are used in modelling to produce a species distribution map (Merow et al., 2016).

It is necessary to emphasise that model building is an iterative process that offers much to learn as it is executed (Guisan *et al.*, 2017). In some instances, there might be the need to revisit and improve specific modelling steps, like improving the spatial sampling design. This leads to the model-building process as a cycle rather than a workflow with a pre-defined termination point (Figure 4-2). The modelling cycle for SDMs has five distinct stages, namely: (i) conceptualisation, (ii) data preparation, (iii) model fitting, (iv) model assessment, and (v) prediction, as illustrated in Figure 4-2.

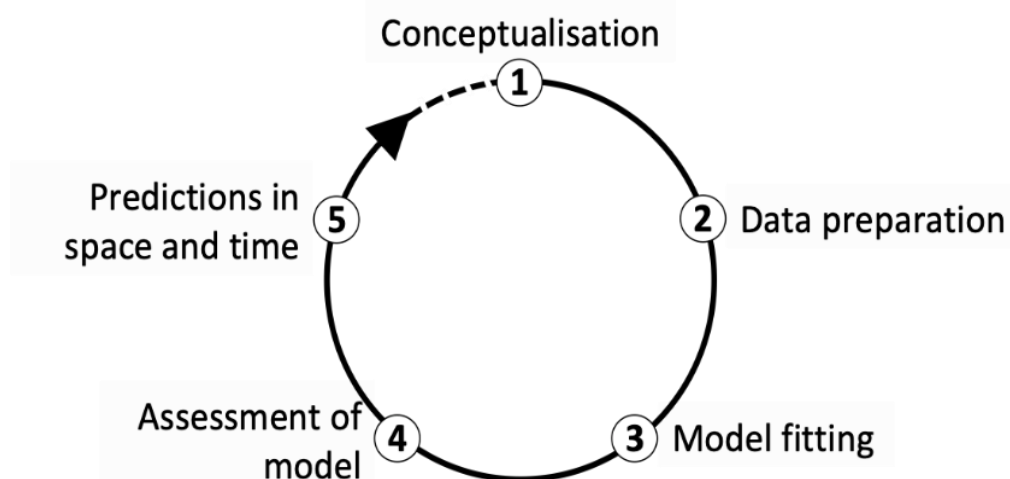


Figure 4-2: The primary modelling cycle in species distribution modelling

4.3. Species data

Species distribution data is gathered and processed to describe locations where species of interest have been observed (Gormley *et al.*, 2011 Elith *et al.*, 2020). The source of data on species distribution can be obtained by going to the field and collecting the data or using previously collected data from other researchers, if appropriate. Popular data sources include museum reports, large-scale research surveys or citizen science projects such as sightings of alien invasive species (César de Sá *et al.*, 2019; Matutini *et al.*, 2020). A growing range of online tools allows data collection on alien invasive species. These can be available to researchers for free or at a cost when accessing or downloading a specific species' occurrence dataset (Woodman *et al.*, 2019) Velásquez-Tibatá *et al.*, 2019).

The Southern African Plant Invaders Atlas (SAPIA) in South Africa provides one of the region's most comprehensive databases on invasive alien plants. Currently, it contains almost 60 000 locality records of 600 naturalised alien plant species in 1 500 quarter-degree squares, mainly in South Africa, Eswatini and Lesotho, with records spanning nearly three decades. The SAPIA dataset incorporates the roadside surveys of South Africa by Lesley Henderson from 1979 to 1993 and the SAPIA phase I project (1994–1998) (Henderson, 2007). The South African National Botanical Institute (SANBI) has an Invasive Species Programme (ISP), and Invasive Alien Plant Alert (IAPA), which aim to detect and assess the risk alien invasive species pose to South Africa and attempt eradication of high-risk species with limited distribution. SANBI ISP and IAPA are based on the guidelines provided by the National Environmental Management: Biodiversity Act (NEM: BA) category 1a listed species. Other locally based sources of datasets include the SANBI resource for GIS with interactive mapping, biodiversity data, training, and legislation BGIS (Biodiversity GIS) and Agricultural Research Council (ARC).

On a global scale, the Global Biodiversity Information Facility (GBIF) is a valuable resource with free and open access to occurrence records of more than 1.5 million species. The GBIF is an international network and research infrastructure funded by the world's governments and aimed at providing anyone, anywhere, open access to data about all types of life on Earth. Another resource available is the Global Invasive Species Database (GISD). The GISD focuses on invasive alien species that threaten

native biodiversity and natural ecosystems and covers all taxonomic groups, from micro-organisms to animals and plants in all ecosystems. Species information is either supplied by or reviewed by expert contributors worldwide. Researchers can also look at the International Union for Conservation of Nature (IUCN) Invasive Species Specialist Group (ISSG), which promotes and facilitates the exchange of information and knowledge across the globe and ensures the linkage between knowledge and practice and policy so that decision making is informed. The ISSG manages the Global Invasive Species Database (GISD) and Island Biodiversity and Invasive Species Database (IBIS).

In most SDMs, researchers can import occurrence data directly from databases like GBIF (Beck *et al.*, 2013; Peterson, 2017). However, researchers need to be aware that the outcome of an SDM is only as good as the data you put in. One must thoroughly check the species data before it can be used for modelling. As a rule of thumb, researchers need to check for outliers as they can result from typos in coordinates and might bias the model. Records can be duplicated in some datasets; thus, inspection and removal are needed. It is also required to check the recorded years to remove data collected in years unrelated to the SDM.

This is important if there is going to be the modelling of species distribution using climate data from specific years, making it essential for only occurrence records from matching years to be used for modelling. Researchers need to know the alternative names for the species working with us. There is a possibility that different datasets may present species according to the local or vernacular name; it is thus recommended to use the Latin name of the species as this is a global identity. The species occurrence data can sometimes be biased toward the accessibility of sampling locations. Because species observations might be near places where people go; thus, occurrence data can be lacking for remote areas. This may result in a non-representative sample of the environmental conditions.

Depending on the selected SDM, there might be a need for data records about where the species does not occur, usually referred to as absence data. Absence data can either be actual absence in cases where data is collected on locations where a species does not appear or can be based on pseudo-absence data, which originates from the inference that a species cannot occur in areas because of unsuitable conditions.

4.4. Factors determining species detectability.

The detectability of a species tends to be difficult depending on a series of factors. These factors include but are not limited to the following:

- The intrinsic characteristics of the species (rare or abundant, physical appearance and behaviour).
- Site characters can act as modulators, potentially inducing spatial variation in species detectability.
- Temporal variation. (Seasonal changes in behaviour or abundance).
- Detection method used, the skills of the surveyor and the amount of survey effort.

In Figure 4-3, the numbers with brackets illustrate how variables in time and space will modulate aspects determining the 'baseline' detectability. Figure 4-3 highlights vital factors affecting detectability and interactions, but it is not exhaustive. Differences in survey characteristics in space or time will induce spatial or temporal variation in detectability.

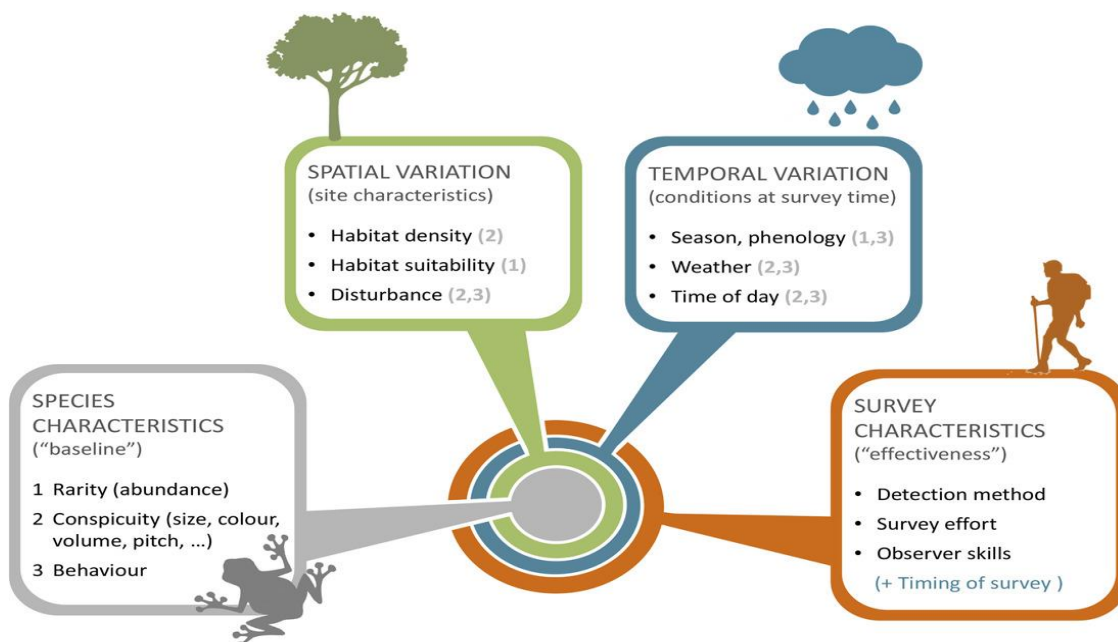


Figure 4-3: Modelling species distributions, range dynamics and communities under imperfect detection: advances, challenges, and opportunities (Guillera-Arroita, 2016).

4.5. True absence data

When it is repeatedly observed that a species is not present in a location, it can be presumed that it is truly absent (Elith *et al.*, 2020). Researchers can also use environmental conditions to determine actual absence points, as locations will be unsuitable for the species to survive. The use of comprehensive surveys can provide accurate absence data when sites have been visited one or more times (Angelov, 2019). However, it should be acknowledged that surveys for absence data make accurate absence data ever available for any given species.

4.5.1 Pseudo-absence data

In cases where accurate absence data is unavailable for species of interest, pseudo-absence data can be used. Pseudo-absence data can be derived from species absence data based on the information on the present locations of the species (Elith *et al.*, 2020; Ward *et al.*, 2008). To correctly classify the conditions of the absence locations, it is essential to generate accurate pseudo-absence data. Barbet-Massin *et al.* (2012) compared the performance of various SDM algorithms using different combinations of several pseudo-absence.

4.5.2 Number of pseudo-absence points

The number of pseudo-absence points produced must form a significant ratio to the number of presence points (Senay *et al.*, 2013). This ratio is also referred to as the prevalence, which refers to the proportion of locations occupied relative to the number of absence points. Prevalence has influenced model accuracy, highlighting the importance of selecting an appropriate ratio (Barbet-Massin *et al.*, 2012).

4.5.3 Environmental data

Environmental data describes the environmental conditions of the locations where species of interest are present or absent. Standard environmental variables used for SDM are represented as four physical environmental categories: moisture, thermal, radiation, and mineral nutrients. The moisture category is defined by rainfall and evaporation measurements, while temperature measurements are presented as thermal regimes. The radiation regime, called solar radiation or sunlight, is usually measured by photosynthetically active radiation (PAR). PAR is the spectral range of solar radiation plants can use in photosynthesis. This spectral region is the same as the range of light visible to the human eye. Factors such as soil type define the

category for mineral nutrients. Variables, such as altitude, can also influence the distribution of plant species. Most of these variables indirectly impact species, influencing environmental conditions within the primary regimes. Like in the case of the effects of altitude on temperature, thus indirectly affecting species distributions.

It is recommended that environmental variables directly affecting species survival, rather than indirect factors, be used for distribution modelling. As with species data, numerous online resources provide environmental data. Common ones include WorldClim, a set of global climate layers (climate grids) with about 1 square kilometre spatial resolution. The data can be used for mapping and spatial modelling in RS and GIS. WorldClim provides an extensive collection of global climate layers of past, current, and future climates. A global soil database like the World Soil Information - International Soil Reference and Information Centre (ISIRIC) serves the international community as repository of global soil information. These are typically soil data and other spatial data combined with analytical methods. There are also smaller-scale national Agriculture Research Council's Institute for Soil, Climate and Water (ARC-ISCW) or regional databases obtained from a country's national soil service like the Food and Agriculture Organisation's (FAO) Soil Portal.

While developing a model for species distribution, it is essential to think first about the environmental variables less likely to affect the species and then check for appropriate environmental data; raw data used for SDM would be measurements such as daily rainfall or temperature from the South African Weather Service (SAWS). This raw data usually is not very useful for SDM, as daily measurements are highly variable, and species respond to environmental conditions not so much daily but rather over longer time scales. Such raw data are then analysed to produce summary statistics, variables such as the mean annual temperature, the minimum or maximum of the warmest or coldest month or season, and the wettest or driest month.

These minimum or maximum values make much more sense in modelling species distribution because an environmental factor threshold always determines the likelihood of a species occurring in a location. Using weather data in SDMs requires the data to be initially converted to raster surfaces, allowing each cell or pixel to have a value for an environmental factor, including the cells for which no measurements of environmental factors exist. The lack of knowledge on each cell's exact value makes

it necessary for researchers to use a spatial interpolation to predict values for unknown cells from a limited number of sample data points around that cell. Spatial interpolation methods assume that cells close together tend to have similar characteristics. This can be achieved by using deterministic like Inverse Distance Weighting (IDW) and Stochastic processes like Kriging.

4.5.4 Scale

Scale is one of the essential aspects of both species and environmental data. Two components are considered when working with spatial scale: the grain, the resolution of data and the extent, which is the total study area. In other words, at what scale is occurrence data of a species or measurements of environmental factors collected? A good example is when habitat type can be defined in grid cells of 1 km² or 10 km², which we refer to as fine versus coarse resolution. On the other hand, the extent relates to the total geographic area. When selecting environmental datasets to fit your species distribution model, it is essential to think about spatial resolution data set, the appropriate resolution of a temperature dataset that is used to model the distribution of a plant species, which always remains in the same place, is different compared to one that models the issuance of a species with a daily home range of 20 or 30 km, such as large birds. Environmental variables from different regimes in models, such as temperature and soil, will likely have different resolutions among the datasets as climate data is often available at solutions of 1 or 5 km². In contrast, soil datasets have a much more satisfactory resolution, such as <100 m².

4.5.5 Attribution

Thus, researchers are encouraged to explore the different datasets available and use them in their models, bearing in mind that data collected by others needs to be appropriately referenced. It is essential to check with the data provider their terms of use and how to cite the data source. Open access (online or as documents) data were used in this case. The modellers must check whether the data is accurate when using open access. While many data providers have their process of reviewing the quality of the data, there is always the possibility that a dataset includes a few inaccurate records.

4.5.6 Predicting species distribution

Species distribution models are developed mainly from observations of species occurrences, and these are places where a species has been found. Such occurrences are often point-based and can be derived from various sources such as museum records and expert field observations. However, it should be noted that when looking at species distribution maps, the maps usually show a range rather than dots. The role of the scientist is to figure out how best to go from specific places where individuals of a species have been observed to producing a map that gives an estimate of the distribution of that species, thus giving rise to species distribution models.

Scientists typically adopt two approaches to estimate the distribution of a species (i) use mechanical methods, which incorporate known species' tolerances to environmental conditions, such as the maximum temperature in which a species can survive. This includes extensive data on the physiological response of species of interest to environmental factors. (ii) The other is the correlative when less than adequate information or data about species' tolerances to environmental variables. The correlative approach assumes that the current distribution of a species is a good indicator of its ecological requirements. The correlative approach is mainly used in species distribution models. It will be the focal method for analysing *Caesalpinia decapetala* and *Eucalyptus camaldulensis* data collected in the VBR.

4.5.7 Calibrating and mapping models

When calibrating a correlative species distribution model, there is a need for two types of input data: species occurrences and measurements of a suite of environmental variables, such as temperature and rainfall. These two data types then make the input of an algorithm to identify associations between the known occurrences of a species and the environmental conditions of targeted sites, thus aiding the identification of environmental conditions suitable for the survival of species of interest. Therefore, describing relationships between species distributions and environmental variables. This enables researchers to gather information about locations where the species can occur and, to some degree, about the environmental conditions of the sites. The algorithm uses these two types of information to estimate the likelihood that a species will occur in a place as some function of that place's environmental conditions.

After the model has been developed, it can then geographically project the predicted distribution of the species on a map. Thus, the model estimates the likelihood of a species occurring at the entry point in the landscape. The model's output can either be displayed as a binary outcome, as a presence/absence map or on a probability on a scale from 0 to 1, with darker coloured areas representing areas of the high likelihood that a species can occur. It is important to remember that species distribution maps do not display actual occurrences of a species but rather highlight areas with similar environmental conditions to areas where species of interest have been observed, therefore providing an approximation of where a species may occur. This does not necessarily mean that the species of interest exists in the area.

4.6. Overview of SDM methods

Several algorithms are distributed across four categories (profile, statistical regression, machine learning, and geographic models).

4.6.1 Profile models

Profile models only use occurrence data and focus on characterising the species-related locations' environmental conditions. In this case, multi-dimensional environmental space is bounded by the minimum and maximum variable values for all occurrences as the potential range.

4.6.2 Statistical regression models

Statistical regression models provide estimates of the influence of the different environmental variables on species distribution. These models use all available data to estimate the environmental variables parameters and construct a function that better describes the effect of those predictors on species occurrence. General assumptions of a model also determine its suitability. This category includes Flexible Discriminant Analysis (FDA), Multivariate adaptive regression splines (MARS), Generalised Linear (GL) and Generalised Linear Models (GLM).

4.6.3 Machine learning models

Machine learning models typically use one part of the dataset to 'learn' and describe the dataset (training) and the other part for the accuracy assessment of the model. These cover Artificial Neural Networks (ANN), Maximum Entropy Model (Maxent), Random Forest model (RFM) and General Boosting Models (GBM).

4.6.4 Geographical models

These models only use the geographic location of a species' documented occurrences to determine the probability of existence elsewhere and do not depend on environmental variables values. This category includes Circles, Convex hull, Geographic distance, Inverse distance weighted model and Voronoi hull.

4.7. Review of selected SDMs

This section reviews four modelling techniques (BioClim, GLM, MaxEnt, and RFM) used in this study.

4.7.1 BioClim model

BioClim is a so-called envelope-style approach that uses occurrence data only to describe a multidimensional environmental space where a species can occur. In all cases, this environmental space is built as a bounding box around the minimum and maximum values of the environmental variables, resulting in a rectilinear multidimensional frame. The resulting envelope may be reduced at defined percentiles or standard deviations to prevent the over-predictive effect of the outliers. BioClim compares the values of the environmental variables at that location with the percentile distribution of the values from known sites to estimate the likelihood of species occurrences in any given area (Appendix 4-1).

For each environmental variable, the BioClim model integrates the scores into an overall likelihood of occurrence for each location with equal weights for all environmental variables. Using the minimum across all variables, the model predicts that a species happens only at the sites ideal for the most limiting factor. The final score is subtracted from one and then multiplied by two so that the results are between 0 and 1. BioClim was the first package of modelling for species distribution to combine spatially specific species occurrence data with maps of environmental variables. It was developed in Australia. The algorithm is still commonly used, as it is simple to understand, but it is generally accepted that it does not work and specific other modelling methods.

4.7.1.1. Advantages

Some of the advantages of using BioClim include its simplicity and intuitive nature. It requires presence-only data to execute the model without absence data. It also

provides the ability for users to rank environmental predictor variables. BioClim is also helpful in teaching species distribution modelling.

4.7.1.2. Limitations

Like all models, BioClim has its shortfalls, including its susceptibility to overprediction, failure to account for interactions between predictors, inability to use categorical variables and inability to make quantitative predictions or provide confidence levels.

4.7.1.3. Assumptions

BioClim was designed primarily to model the distribution of species about climatic variables and therefore assumes that species occurrence is affected by the environment at the scale of environment variables and that these variables are normally distributed.

4.7.2 Generalised Linear Model

Generalised Linear Models can be viewed as an extension of 'simple' linear regression models, which predict the response variable as a function of multiple predictor variables. Linear regression models function on a few assumptions, such as assuming a straight line to define the response relationship with the predictor variables. A constant change in a factor causes the response variable to change constantly. This principle is often broken in ecological data; thus, these models are expanded into GLMs to manage non-normal distributed data. GLMs consider the equation for environmental variables that better predict the occurrence of a species.

The model has three essential components: the probability distribution of the response variable, linear predictor (LP), which combines all predictor variables representing an overall score for environmental suitability and linking the function by describing how the mean of the response depends on the linear predictor. Thus, the predictors are linear, but the relationship between the answer and the predictors is not linear. The connection function transforms the response such that the altered response is linearly related to the predictor. A GLM containing binomial data such as species presence/absence is called "logistic regression". In this case, the link function is thus a logit function, the log of the odds ratio (probability of presence/probability of absence).

4.8.2.1. Advantages

Some notable advantages of using GLMs include response variables having an exponential distribution type. It also can deal with categorical predictors. GLMs are relatively easy to interpret and clearly understand how each predictor influences the outcome.

4.8.2.2. Limitations

Some limitations include the large data requirement and more predictor variables, the larger the sample size required. As a rule of thumb, the number of predictor variables should be less than $N/10$ and is sensitive to outliers.

4.8.3 Maximum entropy modelling (MaxEnt)

MaxEnt predicts occurrences of organisms by identifying the most dispersed or standardised range when recognising the limits of the environmental variables in known places. The MaxEnt algorithm compares a given species to all the habitats accessible in the research area. The MaxEnt model describes certain conditions accessible by sampling many sites throughout the study area, known as background points. In some instances, background points can include locations where the species of interest is known to occur. However, background points are not the same as pseudo-absence points but define the available environment. The MaxEnt algorithm developed for species distribution modelling is a machine learning method and thus iteratively builds multiple models. It has two main components: (i) *Entropy*: The model has been calibrated to find the most widely or nearly uniform distributions in the entire region of the study. And (ii) *Constraints*: Such rules are based on values from the species' environments' environmental variables (so-called characteristics).

Maximum entropy model considers six types of characteristics, and each allows for a different possible shape of response curves and has a different impact on limitations. Maximum entropy model uses all kinds of features by default, but only a few can be used to make simple models.

Maximum entropy model first estimates two likelihood densities to determine the possible distribution. The probability density represents the conditional uncertainty in the process overall these points for all the present values. The probability density is calculated from the background points throughout the study region. The probability

density of the background points thus characterises the environment available for the study area. In contrast, the probability density of the presence points describes the environmental setting of a species found. The ratio between these two probability densities is then calculated by MaxEnt, which provides relative environmental suitability for the species present in each study area.

Maximum entropy model chooses the distribution that maximises the similarity between the environmental characteristics of the total environment and those of the locations where the species is known to be present. This is known as the raw output of MaxEnt. For a more straightforward interpretation of the results and an estimate of the probability that a species is present in each location, MaxEnt performs a logistic transformation of the raw output. The logistic output considers the prevalence of a species, which refers to the proportion of occupied areas. MaxEnt uses a default prevalence value of 0.5, implying that the species is present in half of all the possible locations. We advise caution with this default value as the exact prevalence cannot be derived from presence-only data. A value of 0.5 is, for example, inappropriate for rare species.

An essential aspect of MaxEnt is regularisation, which reduces the overfitting of the model. Regularisation is done in two ways: (i) relaxing the constraints. Instead of fitting the model using the environmental variables' exact conditions (means, variances, etc.), it considers confidence intervals around the rules. This prevents the model from being fitted too closely around the input data. (ii) penalising complexity: the model excludes feature types that do not significantly improve the model.

4.8.3.1. Advantages

These include the requirement of presence-only data and the ability to use continuous and categorical predictor variables. MaxEnt also includes interactions between predictor variables and a regularisation protocol to protect against overfitting, with a good predictive performance.

4.8.3.2. Limitations

Some limitations include the difficulty encountered when comparing output with other algorithms. MaxEnt output gives environmental suitability rather than predicted

probability of occurrence, and MaxEnt's logistic result relies on an assumption, not an estimation, of prevalence.

4.8.4 Random Forest

Random Forest (RF) is an extension of single Classification Trees in which multiple decision trees are built with random subsets of the data. All random subsets are chosen from the entire dataset and have the same data points. Used data is added to the complete dataset and picked in subsequent trees. The random subsets are chosen in RF in a process called 'bagging,' in which each data point has an equal probability of being selected for each new random subset. Each random subset contains about two-thirds of the total dataset. The other third of the data is not used to create the trees; this portion is called 'out-of-the-bag' data. This part is used later to test the pattern.

4.8.4.1. Advantages

Random Forest is one of the most accurate learning algorithms available. It can handle many predictor variables, providing estimates of the importance of different predictor variables and maintaining accuracy even when a large proportion of the data is missing.

4.8.4.2. Limitations

Some of the limitations include the tendency to overfit particularly noisy datasets. When working data including categorical predictor variables with different levels, random forests are biased in favour of those predictors with more stories. Therefore, the variable importance scores from the random forest are not always reliable for this data type.

4.8.4.3. Assumptions

No traditional distributional assumptions. Random forests are non-parametric and can accommodate distorted and multi-modal data and ordinal or non-ordinary categorical data.

4.9. Research Methods

This section outlines the methods used in the study to collect relevant data about *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. We are focusing on the field

sampling methods used in data acquisition methods. Understanding the distribution patterns of IAPS is increasingly essential to evaluating and tracking global biodiversity (Latombe *et al.*, 2017). There is a need for adequate information on the biodiversity of invasive alien species (IAS) for environmental managers and researchers to make informed decisions regarding ecosystem restoration (Gaertner *et al.*, 2012; Kumar & Singh, 2020). Invasion informatics are most helpful if they cover introductory pathways of IAPS (Foxcroft *et al.*, 2019), the ability of scientists and managers to quantify the impacts of these species (Blackburn *et al.*, 2014), or the understanding of the possible environmental impacts and subsequent ecological degradation alien invasive species might cause (Bartz and Kowarik, 2019).

Although the scientific community has made considerable progress in understanding the factors that can affect the occurrence and distribution of IAPS, parts of sub-Saharan Africa still exhibit gaps when it comes to understanding IAPS richness, which can be attributed to inadequate datasets, which show varying levels of either completeness or poor collection methodologies (Pyšek *et al.*, 2017). Such inconsistencies tend to exist at various spatial scales, but in most instances, they are linked to lower socio-economic development rates of states in sub-Saharan Africa. This is well articulated by McGeoch *et al.* (2010). They found that datasets of IAPS vary generally depending on how well-studied taxonomic groups are in various regions depending on the socio-economic development rate of the area in question (Pyšek *et al.*, 2008). Another obstacle the scientific conservation communities face is related to the difficulties in planning and inventory of IAPS, thus greatly influencing the accuracy of data on richness which in most instances is highly complex, resulting in poor distribution estimates of alien species that also require constant updates as time goes on (Seebens *et al.*, 2017).

Given the importance of knowledge about IAPS, little research has been done to determine whether alien species can be predicted reliably for areas where significant gaps in presence data exist. In scenarios where occurrence information of IAPS can be estimated correctly, there is the potential of using the datasets to cover geographic locations with inadequate data, thus extending available data on trends of biodiversity to help decisions on the protection and management of biodiversity in areas not surveyed. In addition, the high reliability of predictive models will allow for the application of predictive modelling in mapping IAPS.

They are two common modelling approaches used to predict IAPS distribution. The first involves using species distribution models, as Bertelsmeier *et al.* (2015) discussed. In this instance, IAPS distributions can be modelled individually as a function of environmental factors, and the predictions can be converted into binary maps of species presence/absence. Thus, predictions of the abundance of IAPS in various regions can be obtained by stacking the different maps. The second method includes using statistical analysis to estimate IAPS abundance as a function of existing environmental factors, an approach used by Jarnevich *et al.* (2006) and Nobis *et al.* (2009). The context for this approach is close to that of descriptive models that attribute the distribution of IAPS to spatial factors (Capinha *et al.*, 2017). Still, it goes a step further to use identified relationships to make predictions of species occurrence.

4.9.1 Data acquisition methods

This section focuses on data collection of the two IAPS of interest within the VBR. The data collected was predominantly presence and absence of the two species, using a Global Positioning System unit (GPS) to collect coordinates, with the spectral signature collected using an Analytical Spectral Devices (ASD) FieldSpec 4 Standard-Res Spectroradiometer (Analytical Spectral Devices Inc 5335 Sterling Drive, Suite A, Boulder, Colorado 80301, USA). The study site was divided into two zones [Zone A (Soutpansberg mountains) and Zone B (Luvuvhu catchment)]. Ten parallel 5Km altitudinal line transects, 1Km apart, oriented parallel with the slope's contour, were randomly placed throughout the hillside (Figure 4-4).

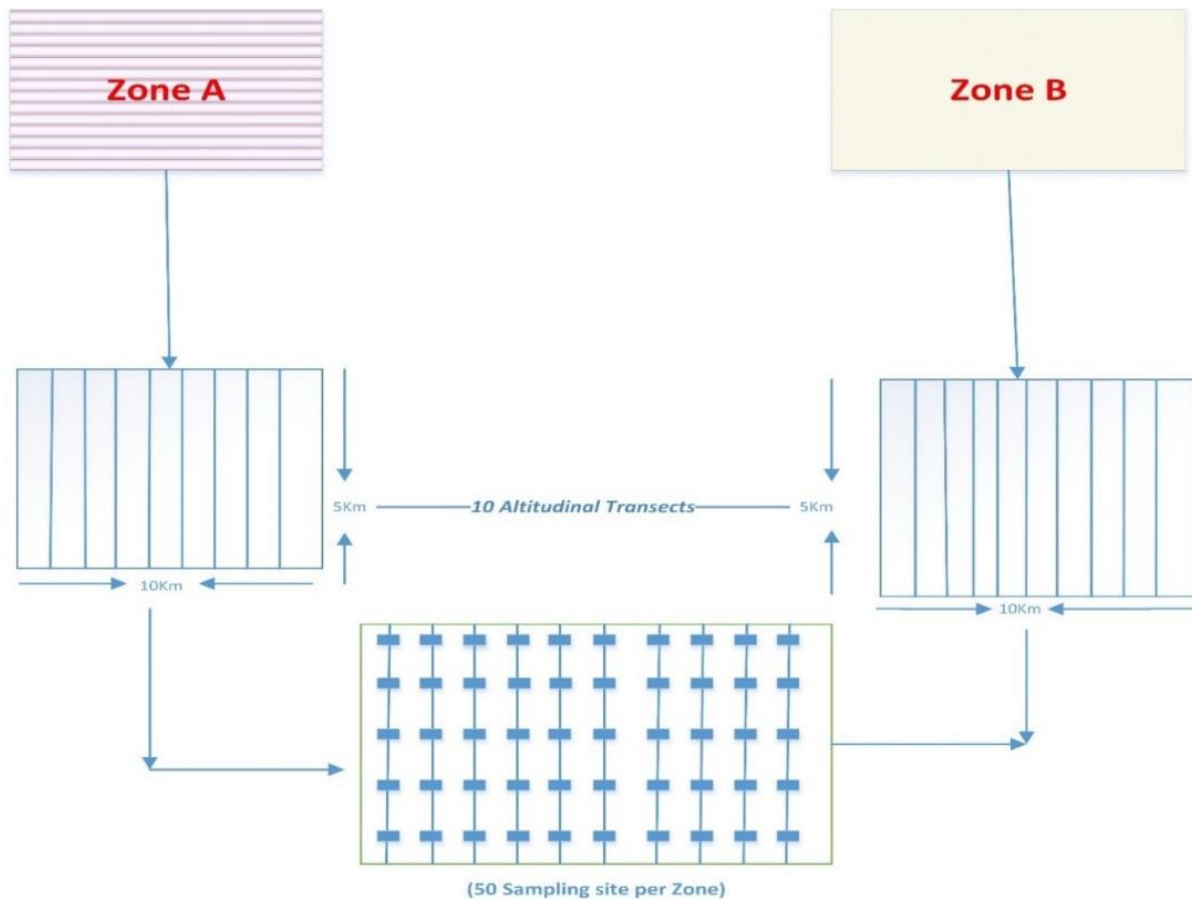


Figure 4-4: Depiction of the sampling zones with the 10 transects, 5Km long line transects used for point-line intercept and 100 sampling quadrats used for the two zones (Figure not drawn to scale).

Hundred and forty-eight (148) sampling sites in the VBR (Soutpansberg mountain and Luvuvhu areas) were used for sampling. The belt transect line is laid out across the area to be surveyed, and a quadrat is placed on the first marked point on the line. The plants inside the quadrat are then identified, and their abundance is estimated. The cover is the quadrat area occupied by the above-ground parts of a species when viewed from above. Quadrats will be sampled down the transect line at each marked point on the line. A hundred quadrats measuring 200m x 200m will be established along each transect line.

To satisfy the logistic regression requirements to analyse presence and absence data accurately, the study site was first subdivided into quadrats using a handheld GPS (Trimble® GeoXH™ handheld from the GeoExplorer® 2008) location. We recorded only the presence/absence of the target species for each sampling site to provide an

attractive alternative to enumerative selection. The number of species in each sampling site can be recorded.

4.9.2 Field sampling

The field campaigns took place in winter and summer. During the winter sampling, GPS points of areas where the two IAPS occurred, and spectral signatures were collected using an ASD which registered reflected radiation within the spectral range of 350–2500 nm with a nominal bandwidth of 3 nm between 350 nm and 1000 nm and 10 nm between 1000 and 2500 nm. The narrow field of view (FOV) of the instrument is 25°. A calibrated Spectralon white reference panel (0.25 m × 0.25 m) was mounted on a tripod and adjusted horizontally using a bubble-level measured incident irradiance. The winter sampling was done in June and July on the following dates (15th, 16th, 17th, 18th June and 10th, 11th, 12th, and 13th July 2019). While the summer sampling, which mainly focused on the collection of absence locational data, was done on the 3rd, 4th, 5th, 6th, 7th and 8th of February 2020,

Trees were identified during the two sampling periods, and their location was captured using a GPS. The winter sampling in 2019 included ASD measurements, while the 2020 summer sampling focused on collecting GPS coordinates of areas where two IAPS were absent. Winter sampling identified 39 *Eucalyptus camaldulensis* sites, 35 sites with *Caesalpinia decapetala* (Appendix 4.2). The same area was used in the summer field sampling focusing on identifying absence points of the two IAPS utilising a GPS. During the summer sampling, 46 absence sites for *Eucalyptus camaldulensis* and 32 absence sites for *Caesalpinia decapetala* were identified (Appendix 4.3).

4.9.3 Spectroradiometer data collection

During the data collection process, the spectroradiometer was used to extract the spectral signature of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. The spectral signature was used to identify areas that exhibit the reflectance signature associated with the two IAPS of interest. Spectral readings were obtained during the winter sampling campaigns using the ASD FieldSpec 4 Standard-Res Spectroradiometer's ASD Contact Probe for non-destructive data collection from live vegetation and other heat-sensitive targets. Reflectance and transreflectance were measured for leaf disks using an ASD.

The full range of the spectrometer used for data collection was (350 to 2,500 nm); on loan from the University of Limpopo (UL), it was used for optical field measurements. In cases where foliar could not be analysed onsite, the material was transported to a local site in brown paper bags. Only fully expanded mature leaves with no damage by herbivores or pathogens were selected for analysis. The ASD measurements were conducted for all *Caesalpinia decapetala* and *Eucalyptus camaldulensis* trees identified during the fieldwork. Once a tree species had been located, the ASD spectra were collected. For easy detection by most satellites, samples around the tree species were collected, considering their orientation and exposure. Figure 4.5 shows the process followed when collecting data using the ASD spectrophotometer.

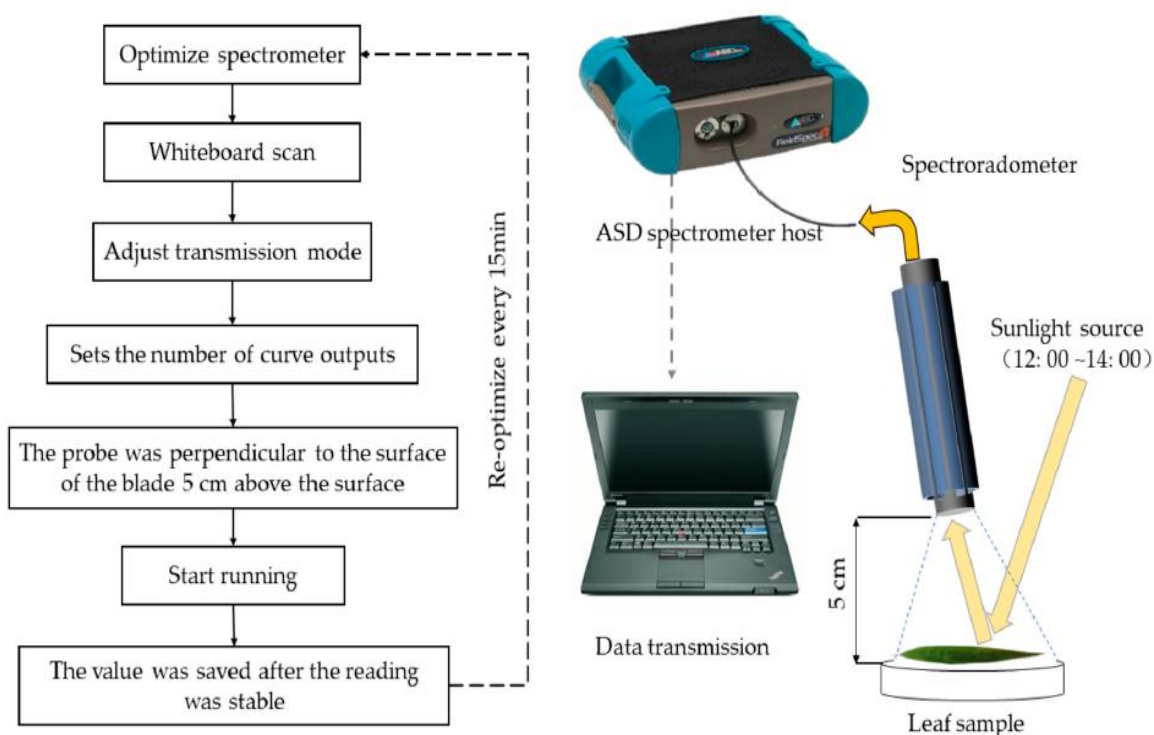
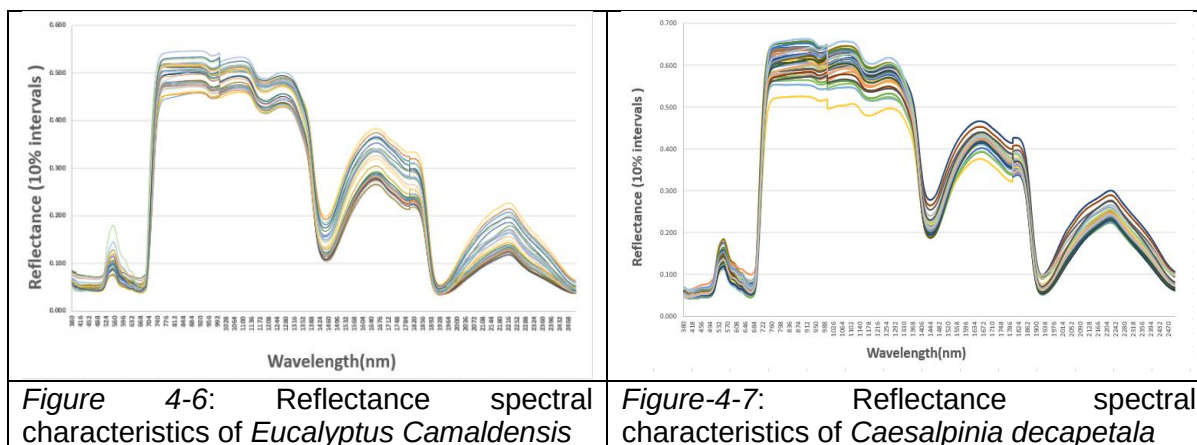


Figure 4-5:Flow chart of leaf spectrum measurement based on ASD spectrometer (Zhu et al. 2020)

Using a plant probe with the ASD leaf clip, reflectance of the leaves was collected from five branches at different sides of the IAPS. 25 leaves or leaf clusters were sampled from each branch at a 22-degree FOV with a plant probe with the ASD leaf clip. All spectral measurements were collected within 2 hours of local solar noon under clear-sky conditions. Five measurements were taken for each grass canopy, and the average of the five replicates was reported. These spectra were standardised to a

Spectralon (Labsphere, Inc, North Sutton) reference surface measured at approximately 10-minute intervals and converted into reflectance. The curves from the ASD measurements for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* are shown in Figures 4-6 and 4-7.



4.10. Stepwise Logistic Regression (SLR)

The first task will involve building an SLR model to show the habitat factors that are “most influential”. 21 predictor variables were split into environmental and remote sensing factors in a stepwise logistic regression model to best describe the relationship between the variables.. The model-building process allows you to choose the “best” variable to add to the current regression model. The data comes from a survey of two IAPS (*Caesalpinia decapetala* and *Eucalyptus camaldulensis*) in the VBR. For both *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, presence and absence data were collected in 2019 and 2020. Appendix 4.2 presents the presence, while Appendix 4.3 shows the absence of both *Caesalpinia decapetala* and *Eucalyptus camaldulensis* as a binary variable (0 = absence, 1= presence). The researcher used standard survey methods to detect the presence (or otherwise) of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* at 150 sites. The other variables are categorised into environmental and remote sensing factors, summarised in Table 4-1.

The various habitat factors are converted to an index; the indices are combined to make a final HSI (habitat suitability index). The HSI makes it easier to assess sites for their potential to support populations of the great *Caesalpinia decapetala* and *Eucalyptus camaldulensis* providing a measure of reproducibility to surveys.

Table 4-1: The other variables are categorised into environmental and Remote sensing factors.

4.10.1 Creating a Stepwise logistic regression model

SiteID -Code assigned to the site	Latitude – Line of Latitude	Longitude – Line of longitude	Altitude (MASL) – Height above sea level	Species – Species of interest (<i>Caesalpinia decapetala</i> and <i>Eucalyptus camaldulensis</i>)	Aspect - compass direction in which the slope of a mountain faces
Soil – Soil type	Soil depth (mm) – Soil depth	LandType – Land type	Landform – Landform type	Geology - geological classification	SoilStb (%) – Soil stability
GBWP (kg/m ³) - Gross Biomass Water Productivity	Anl Prp(mm) – Annual Precipitation	AETI (mm) - Actual Evapotranspiration and Interception	Pot Evap (mm) – Potential Evapotranspiration	Rel hum(%RH) – Relative Humidity	Intercept(I) (mm) - Interception
Sol Rdn – Solar Radiation	BioClim 1 - Annual mean temperature (°C)	BioClim 4 - Temperature seasonality (C of V) Cover - Type of cover on site	Addnl – Additional variables	BioClim 15 - Precipitation seasonality (C of V)	

The data collected from the *Caesalpinia decapetala* and *Eucalyptus camaldulensis* field was loaded for analysis on the regression model in R-studio software. They considered that the study was done for each species for environmental, remote, and combined environmental and remote sensing variables. Six scripts were developed for the complete analysis.

4.10.1.1. Importing data

The collected field data was captured in Microsoft Excel, as illustrated by Appendix 4.4 and Appendix 4.5. Once data are captured in Microsoft Excel, it becomes easier to import them into R-Studio, allowing the needed data extraction, manipulation, and modelling.

4.10.1.2. Data examination

For an effective Stepwise logistic regression model, exploration of the data and simple processing like examining the data summary were done to quickly illustrate the

strength and contribution some variables might have on *Caesalpinia decapetala* and *Eucalyptus camaldulensis*.

4.10.1.3. Plot coordinates

The field points were exported to a Shapefile, so they could be appropriately viewed in GIS, a medium that provides the ability to inspect the issues adequately. Appendix 4.4 and Appendix 4.5 show the number of points within the confines of the survey boundary.

4.10.1.4. Extracting spatial data

Before the spatial analysis or modelling, a suite of geodata files intersected with field data locations was created. All the geodata files were set to the same projection, extent, and cell size. After the two processes above were successfully run, a list was created in R-Studio of the file names and paths to read the geodata into R-Studio , and then the geodata values could be extracted.

4.10.1.5. Examine spatial data

After successfully extracting the spatial information and identifying if any of the variables can be used to separate the presence/absence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, as a requirement to run R-Studio, the variables were converted to numeric values, with all categorical variables being coded to equivalent numerical representation for analysis.

4.10.1.6. Modeling

Modelling is an iterative process that cycles between fitting and evaluating alternative models. It is worth noting that tree and forest models and linear and generalised models all require more input from the user. Predictive variables can confuse the model selection process; thus, automated model selection processes are not generally recommended. In addition, the order in which the variables are included or excluded from the model affects the significance of the others. Thus, several weak predictors might mask the effect of one strong predictor. Therefore, selecting helpful predictors and growing the model incrementally is best.

4.10.1.7. Variable selection

Model selection for this study was made using the 'forward selection procedure. A complete model compared to a null model to assess the different predictors' importance (or contribution). Akaike's Information Criterion (AIC) was used to test alternative models. When using AIC to assess predictor significance, a smaller number was better. Appendix 4.7 to 4.11 shows the distribution data analysis of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the Vhembe Biosphere Reserve using presence and absence points.

4.10.1.8. Examine the model

The examination was done after the model was saturated and all the significant variables; the resultant scripts are presented in Appendix 4.12 to Appendix 4.17.

4.10.1.9. Residual plots

The stepwise logistic regression was run until it was evident that no additional variables would improve the fit, and then its residuals, collinearity, accuracy, and model coefficients were evaluated.

4.10.1.10. Multicollinearity

The variance inflation factor (VIF) was used to assess collinearity amongst the predictors. Its square root indicates the increase in the predictor coefficients' standard error. A VIF value greater than two indicates a doubling of the standard error. The rules of thumb vary, but a square root of VIF more significant than 2 or 3 means an unacceptable value.

4.10.1.11. Accuracy assessment

The fact that SLRM presents a classification problem, there is thus a need to consider both errors of commission (Type I) and omission (Type II) or their corresponding accuracies of sensitivity (producer's accuracy) and positive predicted value (user's accuracy or precision) respectively. However, we must select a probability threshold before assessing the error.

- **Sensitivity** and **specificity** examine how well the ground truth or reference data compares to the predictions.

- **Positive** and **negative** predicted values (user's accuracy) examine the inverse concept of how well the predictions match the reference data.

4.10.2 Plotting prediction maps using ESRI ArcGIS

After the stepwise logistic regression, there is a need to visualise the output of the analysis. To visualise the logistic regression results dasymetric mapping technique in ArcGIS will be used to create a species distribution map. Dasymetric mapping entails the redistribution of areal enumeration data using sets of ancillary information, including but not limited to remotely sensed data, to accurately portray an underlying statistical surface (Wright, 1936, Holloway *et al.*, 1996). Figure 4.8 is a flow chart illustrating the statistical analysis of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distribution in the R-studio and mapping the results in ESRI ArcGIS 10.8.3.

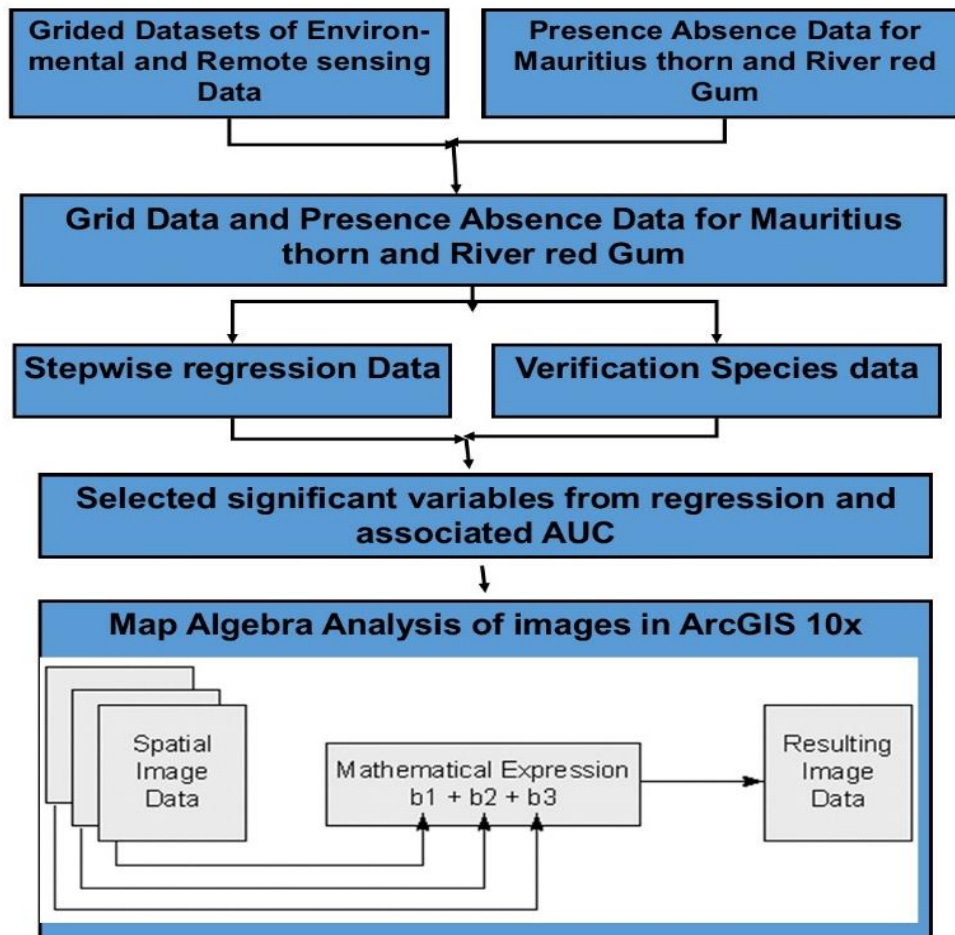


Figure 4-8: Flow chart carrying out regression in R-Studio and mapping results using ArcGIS 10.8.3.

Once the raster layers (Spatial Image Data) covering environmental, GIS remote sensing, and combined Environmental and GIS variables have been derived from the stepwise regression analysis using R-Studio software, Equation 4.1 is used as the mathematical expression for creating the resultant image data in ArcGIS 10.8.3 software.

Equation 4-1:
$$P(Y_i) = \frac{1}{1 + e^{-(\beta_0 + x\beta_1)}}$$

$P(Y_i)$ is the predicted probability that Y is true for case i ;
 i is a mathematical constant of roughly 2.72;
 β_0 is a constant estimated from the data;
 β_1 is a b-coefficient cal from the data;
 x_i is the observed score on variable X for case i .

Using Equation 4-1, the ArcGIS software's raster calculator was used to transform the statistical results obtained from the stepwise regression analysis carried out in R-Studio. Equation 4-2 shows the environmental variable with an AIC of 80.168 and AUC of 0.8851902. For this analysis, Altitude, BioClim 4, eeology, soil stability and potential evapotranspiration were the significant variables affecting the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR.

4.11. Maximum entropy modelling (Maxent)

The MaxEnt model, in this case, uses presence-only (PO) location data for selected species as input and a set of environmental predictors (e.g., precipitation, temperature) across a user-defined landscape divided into grid cells. MaxEnt extracts a sample of background locations from this landscape that contrasts against the presence locations. Presence is unknown at background locations. The data comes from a survey of two IAPS (*Caesalpinia decapetala* and *Eucalyptus camaldulensis*) in the VBR. Presence data were collected during the two sampling periods for both species of interest. 39 bioclimatic and 21 variables were split into environmental and remote sensing selected variables to describe the best relationship between the variables. The data comes from a survey of two invasive alien plants (*Caesalpinia decapetala* and *Eucalyptus camaldulensis*) in the VBR. All the presence data collected during the sampling activities and environmental Covariate and remote sensing data were used to train and test the MaxEnt model for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR (Figure 4-9).

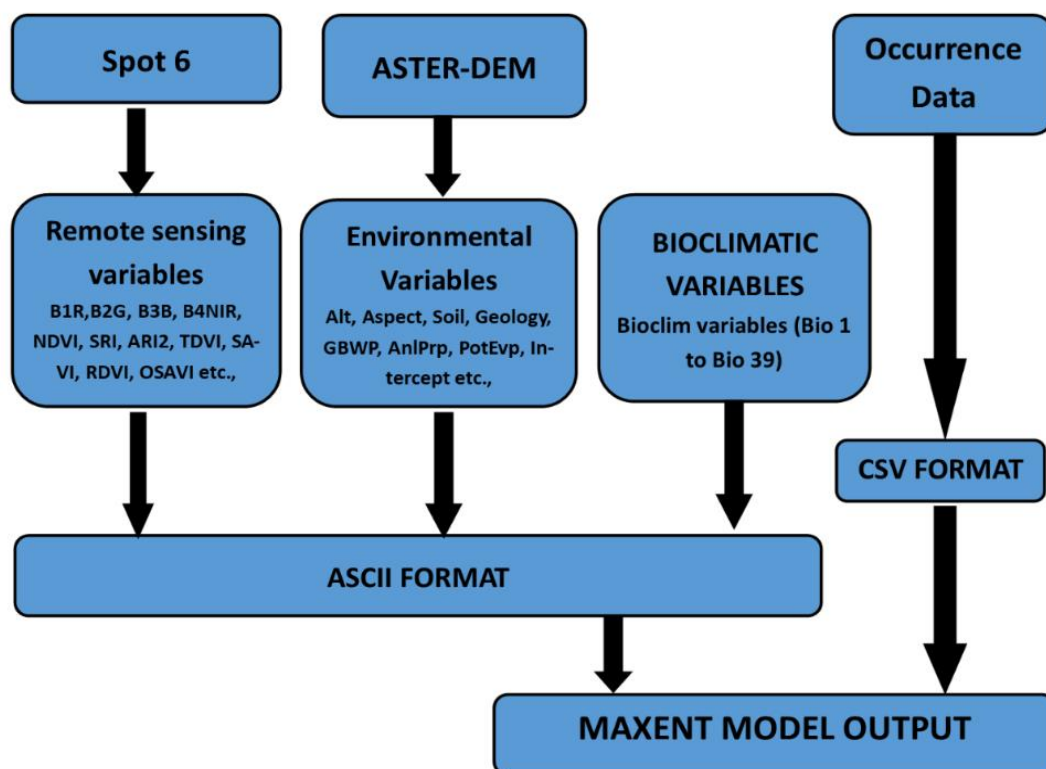


Figure 4-9: Flow chart of data collection and processing in the MaxEnt model

4.11.1 Running the MaxEnt model

In this study, the MaxEnt model was set up to aid in understanding the spatial distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR. The analysis was done in two parts, with part 1: Running MaxEnt using the R-Studio software (R Core Team 2020). Running MaxEnt in R-Studio requires several packages. Specifically, the "dismo" package, which contains a MaxEnt function that calls maxent.jar in R-Studio, the "raster" package, which provides functions for analysing gridded data, and the "rgeos" package, which provides functions for analysing spatial data. The initial analysis focused on understanding the global distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. In contrast, further research focuses on the downscaling understanding of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distribution in the VBR.

4.11.2 Projecting the spatial distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* globally using MaxEnt in R studio.

The steps involved when running the MaxEnt model can easily be summarised using ten (10) steps. The first step is to import the data into R-Studio to draw a neater map and subsequent analysis. After completing the analysis, an output directory ASCII grid file was created using the R-Studio software. The first step is to install the packages needed for carrying out MaxEnt modelling in R-Studio.

4.11.2.1. Step 1: Set up the MaxEnt path.

For Maxent to work correctly in R, the *maxent.jar* file must be accessible by the *dismo* package. This includes downloading maxent.jar 3.4.1 and placing the file in the desired folder.

4.11.2.2. Step 2: Prepare data input load environmental layers.

The bioclimatic variables (downloaded from worldclim.org) were used as input environmental layers in this study. The environmental layers were stacked so that they could be processed simultaneously.

4.11.2.3. Step 3: Picking predictive variables.

Selecting environmental parameters that impact the distribution of a species is a significant challenge to SDM methods. Altitude, bioclim4, bioclim15, Interception, Landform, Land type, Potevpotranspiration, RDVI and Soilstability were used. These are *not* necessarily the best climate parameters for your species and may require tweaking.

4.11.2.4. Step 4: Occurrence data download occurrence data

In this study, the global occurrence data of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* were downloaded from the <https://www.gbif.org> website, known as the Global Biodiversity Information Facility (GBIF).

4.11.2.5. Step 5: Clean occurrence data

The *Caesalpinia decapetala* and *Eucalyptus camaldulensis* occurrence data downloaded from the GIBF was cleaned. The cleaning process is essential as some records did not have appropriate coordinates, and some had to miss locational data as we needed to remove them from our dataset. Most of the occurrence data

downloaded from the GBIF website formed a data frame without a spatial relationship with environmental layers. Thus, there was a need to make the data spatial. Once the two datasets were spatial, the *plot* function in R-studio software was used to visualise the occurrence data allowing the checking of data points that appeared to be erroneous.

4.11.2.6. Step 6: Set up a study area.

A buffer around the occurrence locations was created and defined as the study region, which avoided sampling from a broad background like oceans and water bodies. A four-decimal-degree buffer was built around the occurrence points. This was done to ensure that the buffer encompasses the appropriate area and plots the occurrence points, the first environmental layer, and the buffer polygon. With a defined study area and the environmental layers stacked, the layers were clipped to the extent of our study area. However, this was done in two steps rather than one for ease of processing.

The first step involved the creation of a coarse rectangular-shaped study area around the study area in reducing the size of environmental data and then extracting by *mask* using the buffer we created to clip environmental layers more accurately. This approach allowed faster processing of the datasets than directly masking. The cropped environmental layers were saved as American Standard Code for Information Interchange (ascii files -.asc) as input for MaxEnt. The next step involved selecting 10,000 random background points from the study area. A static seed via set makes our experiment reproducible (i.e., determining the points' exact location). The seed (1) function was used. Then, background points were plotted together with the study area and occurrence data for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*.

4.11.2.7. Step 7: Split occurrence data into training and testing

This study randomly selected 25% of the occurrence data for model training and used the remaining for model testing. To make this experiment reproducible (i.e., select the same set of points), a static seed via *setting*. The seed (1) function was used.

4.11.2.8. Step 8: Format data for MaxEnt

The data input for the MaxEnt model was either spatial or tabular. We use the tabular format in our example, which can be more flexible. There was the extraction of environmental conditions for background, training, and testing points in a data frame format. The MaxEnt software reads a "1" as presence and "0" as pseudo-absence. The study values were assigned a "1" for the environmental training conditions and a "0" for the background. A set of rows were created with the same number as the training and testing data and put the value of "1" for each cell and a "0" for the background. A combination of the "1"s and "0"s into a vector was added to the data frame containing the environmental conditions associated with the testing and background conditions.

4.11.2.9. Step 9: Predict function running.

MaxEnt in R-studio software requires using the parameter *projection layers* as the layers will not automatically project in a GIS unless specified. However, the datasets could make projections (to data frames or raster layers) post hoc using the *predict* function.

4.11.2.10. Step 10: Model evaluation

The evaluate function from the "dismo" package was used to achieve model evaluation. Joint evaluation indices used included AUC, TSS, Sensitivity, and Specificity. The threshold function of the "dismo" package was adopted to convert the continuous suitability predictions into binary predictions. There was a need to plan the larger projections than the threshold to plot the binary prediction.

4.12.1 Projecting distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR using MaxEnt software

To perform a model run using the MaxEnt.jar Graphic User Interface (GUI), there was a need to supply a file containing species occurrence localities for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* ('samples'), a directory containing environmental variables, and an output directory. The environmental layers and clipped BioClim layers of the Vhembe Biosphere Reserve (VBR) region was converted to the American Standard Code for Information Interchange (ASCII). In the analysis,

environmental variables, and remote sensing products of the VBR were also used. All layers were converted to ASCII grid format with the same header information. When working with the MaxEnt GUI interface, the Browse button under 'Environmental layers' was used to locate your ASCII grids. For this study, the logistic output format in MaxEnt was used by checking the dropdown menu under 'output format' is set to logistic, and pictures of predictions will be created if all the option boxes are checked. Other parts of the interface were left as default.

MaxEnt software generated a probability distribution over pixels in the grid, starting from the uniform distribution and repeatedly improving the fit to the data. The probability assigned to each pixel was small, as the values must sum to 1 over all the pixels in the grid. The run produced multiple output files, of which the most important for analysing the model were HTML files called "*Caesalpinia_decapetala.html*" and "*Eucalyptus_camaldulensis.html*". By pressing the "Make pictures of predictions" button, clicking on "Settings", and typing "25" in the "Random test percentage" entry.

The MaxEnt software supports three output formats for model values: Raw (raw output is just the MaxEnt exponential model itself), Cumulative (value corresponding to a fundamental value of r was the percentage of the MaxEnt distribution with raw value at most r), Cumulative output was best interpreted in terms of predicted omission rate: if we set a cumulative threshold of the resulting binary prediction would have an omission rate $c\%$ on samples drawn from the MaxEnt distribution itself, allowing the prediction of similar omission rate for examples drawn from the species distribution and the Logistic. In the Logistic, c is the exponential of the entropy of the maxEnt distribution, then the logistic value corresponding to a raw value of r is Equation 4-2:

Equation 4-2:
$$r = \frac{c * r}{(1 + c * r)}$$

This is a logistic function because the raw value is an exponential function of the environmental variables. The three output formats are all monotonically related but are scaled differently and have different interpretations. The default output is logistic, which is the easiest to conceptualise: it estimates between 0 and 1 of the probability of presence. It is worthwhile to note that the possibility of existence depends on details of the sampling design, such as the plot size and (for vagile organisms) observation time; logistic output estimates the likelihood of presence, assuming that the sampling design is such that specific presence localities have a possibility of the existence of about 0.5.

The “25” entered for “random test percentage” told the program to randomly set aside 25% of the sample records for training. This allows the program to do some simple statistical analysis. Much of the analysis used a threshold to make a binary prediction, with suitable conditions predicted above the threshold and unsuitable below the area under the ROC curve (AUC) (Figures 4-17 and 4-18).

Upon finalising the MaxEnt model run, the output files usually contain the model results, plotted in HyperText Markup Language (HTML) files, imported into R, ArcGIS 10.8.3. This means mapping the spatial outputs can be done in GIS. Other related layers in the same projections or spatial extent can be overlaid to understand the MaxEnt model results better.

4.12. Results

The study of IAPS requires models capable of capturing the essence of an ecosystem; this can be achieved through methods that explain observed IAPS distribution, thus permitting prediction (McCullagh & Nelder 1989). The initial step focused on collecting data on IAPS, coupled with data on variables that might significantly impact the distribution of the IAPS (Burnham & Anderson 2002). Stepwise linear regression and Maximum entropy modelling (MaxEnt) are commonly used to determine the relationships between remotely sensed data and ground-surveyed vegetation variables (Mutanga & Rugege 2006). In this study, stepwise linear regression and MaxEnt models have performed on the best twenty-one (21) variables that yielded significant correlation (significance level: $p < 0.05$) with the two IAPS (*Caesalpinia decapetala* and *Eucalyptus camaldulensis*).

Given specified criteria for the best-fit model, stepwise linear regression analysis can be used to find subsets of the predictor variables that best predict responses on a dependent variable by a regression equation (Wang and Chen, 2006). However, to avoid overfitting a given stepwise regression model, the rule of thumb, as suggested by several authors (Whittingham et al. 2006), is that: (1) the number of predictor variables to enter the model be less than 1/3 of the number of observations and (2) the number of steps in the stepwise linear regression analysis is 10 to 20 times less than the training data set. The number of steps selected for this study was set at six on a training dataset of 75 samples. The authors recommended that this ratio would circumvent the problem of predictions (regression line) being very unstable.

When it comes to SDM, these tools are commonly used to understand where a species can occur based on a presence-only correlative model of where a species was known to occur. SDMs can infer niche overlap between species, assess conservation risk, identify past ranges, or study invasive potential. MaxEnt is one model commonly used to evaluate the distribution of organisms within a particular geographical area (Fourcade *et al.*, 2014) by finding the highest entropy in distribution based on environmental conditions at observed locations for occurrences. The model constraints in MaxEnt differ from environmental variables and essential functions such as quadratic terms. Each feature's mean must be consistent with the sample mean.

4.13 Stepwise logistic regression for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distribution in the VBR.

4.13.1 Using environmental variables to predict the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR.

Figure 4-10 illustrates *Caesalpinia decapetala*'s possible distribution; calculated Figure 4-11 shows the potential distribution of *Eucalyptus camaldulensis* from the stepwise linear regression and raster calculator analysis. The stepwise logistic regression analysis using the environmental variable only for both *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, the resultant images illustrate that environmental factors are used to determine the possible distribution of *Caesalpinia decapetala* (Figure 4-11) in the VBR. The distribution is skewed to the Southern boundaries of the VBR, with high densities in and around the slopes of the Soutpansberg mountain ranges. However, the *Eucalyptus camaldulensis* (Figure 4-11 analysis using environmental factors did not produce a clear distribution map. This might have been because the stepwise linear regression process resulted in too few variables to deal with in the final analytical process. This led to an output of the *Eucalyptus camaldulensis* analysis, like the geology parameters used in the analysis. The obtained results for using environmental variables to project the spatial distribution of *Caesalpinia decapetala* (AIC: 80 and AUC 0.89) and *Eucalyptus camaldulensis* (AIC: 40 and AUC 0.45).

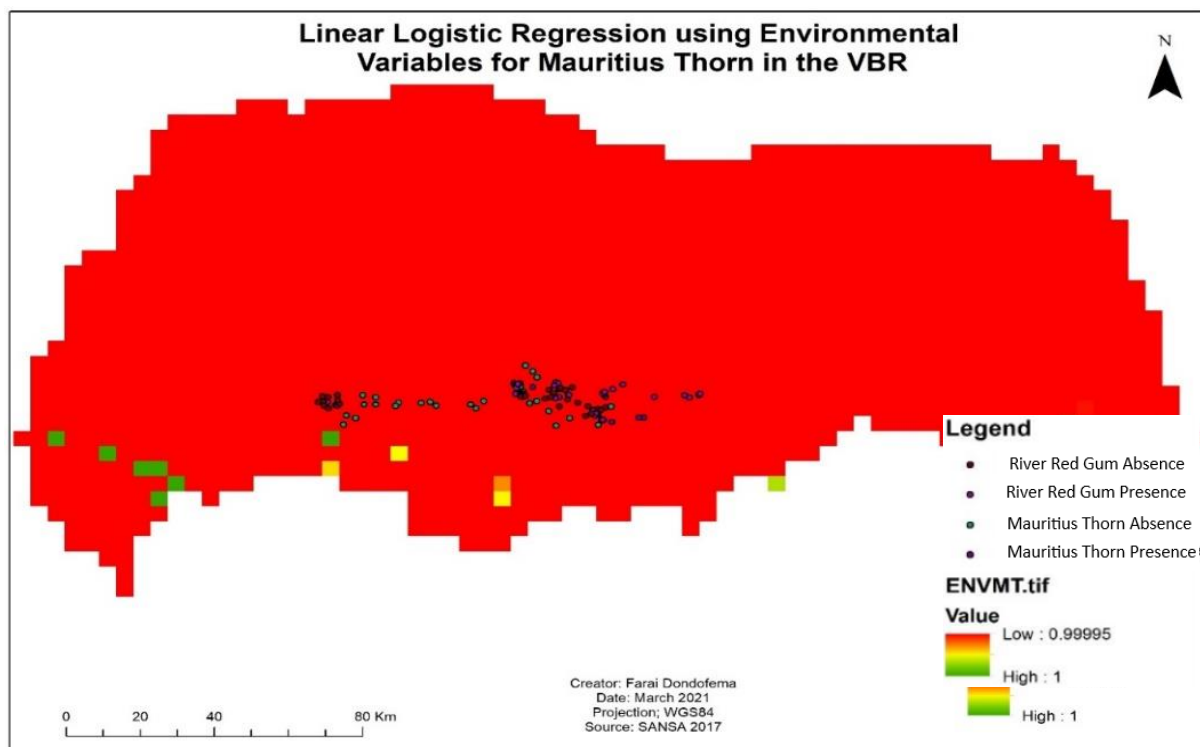


Figure 4-10: Mapping the distribution of *Caesalpinia decapetala* using statistically environmental variables in the VBR.

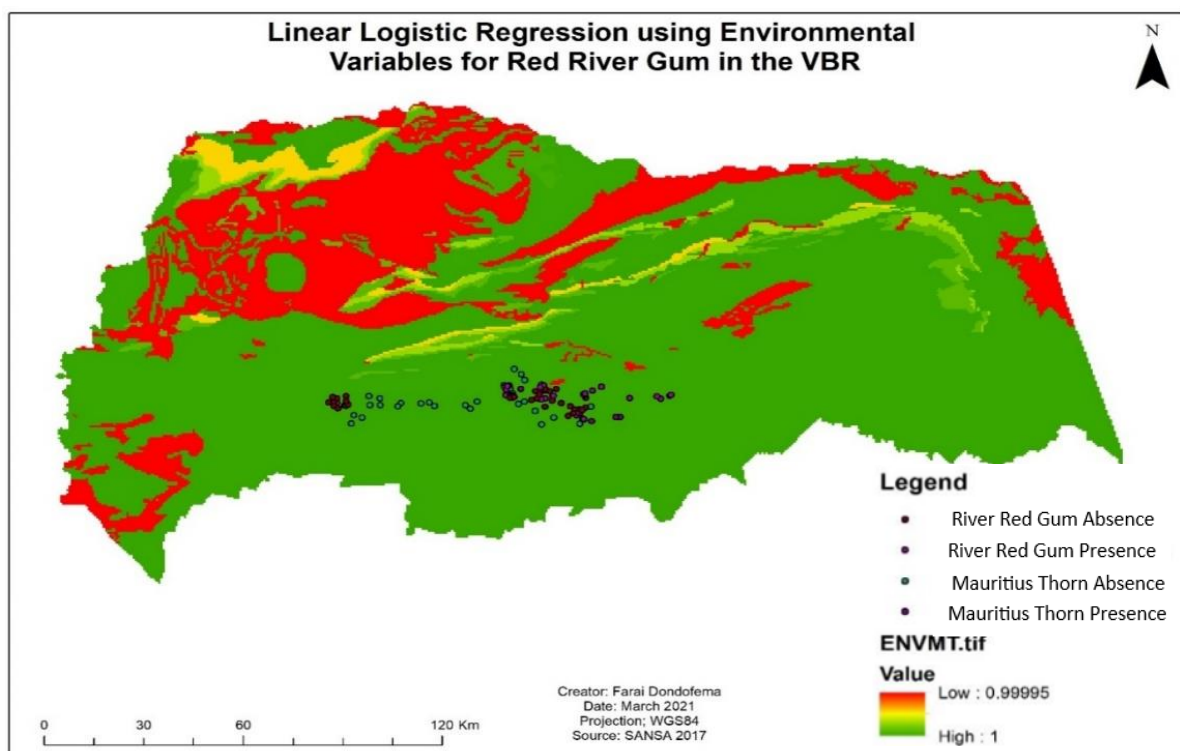


Figure 4-11: Mapping the distribution of *Eucalyptus camaldulensis* using statistically environmental variables in the VBR.

4.13.2 Using remote sensing variables to predict the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR.

Figure 4-12 illustrates *Caesalpinia decapetala*'s possible distribution, and Figure 4-13 illustrates the potential distribution of *Eucalyptus camaldulensis* from the stepwise linear regression and raster calculator analysis. The remote sensing variables show an increase in the probability of *Caesalpinia decapetala*'s occurrence along with the Soutpansberg mountain range and surrounding areas. The results also show an increased likelihood of events following rivers and valleys. The distribution of *Eucalyptus camaldulensis* shows a pattern concentrated in and around the confines of the Soutpansberg mountain range. There is also evidence of distribution following rivers and valleys. A notable difference between the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* based on the remote sensing variables is the increase of *Eucalyptus camaldulensis* as one moves from west to east in the Biosphere Reserve. The results obtained using environmental variables to project the spatial distribution of *Caesalpinia decapetala* showed (AIC: 75 and AUC 0.86) and *Eucalyptus camaldulensis* showed (AIC 84 and AUC 0.79).

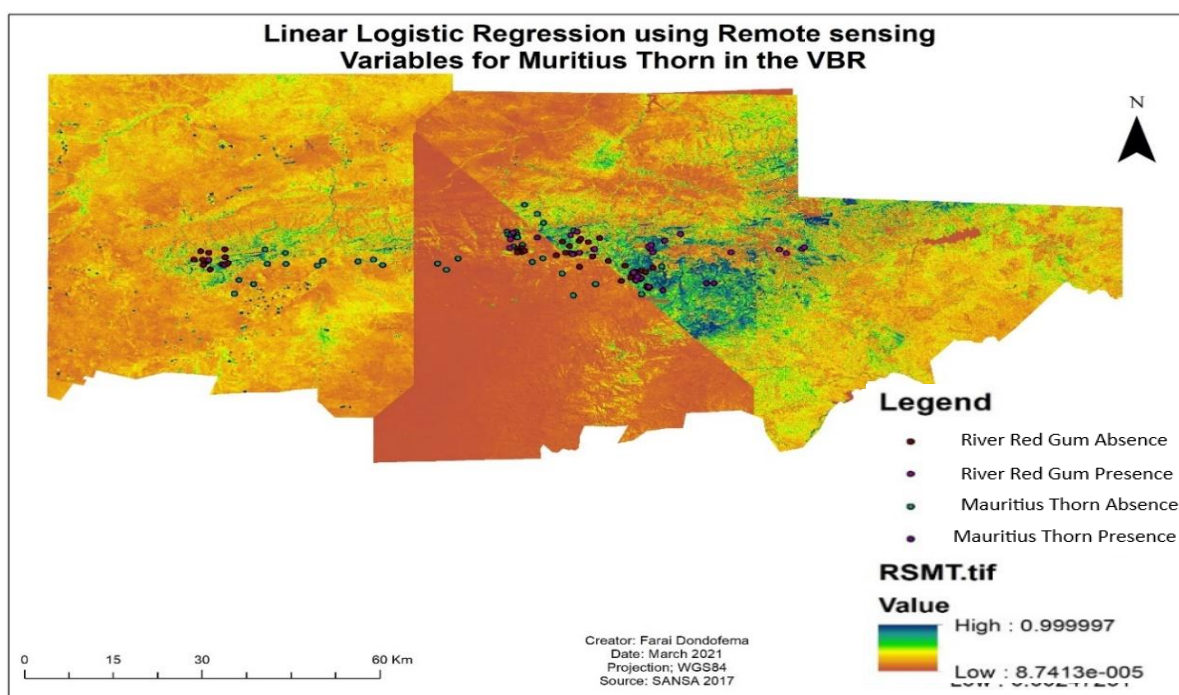


Figure 4-12: Mapping the distribution of *Caesalpinia decapetala* using statistically remote sensing variables in the VBR.

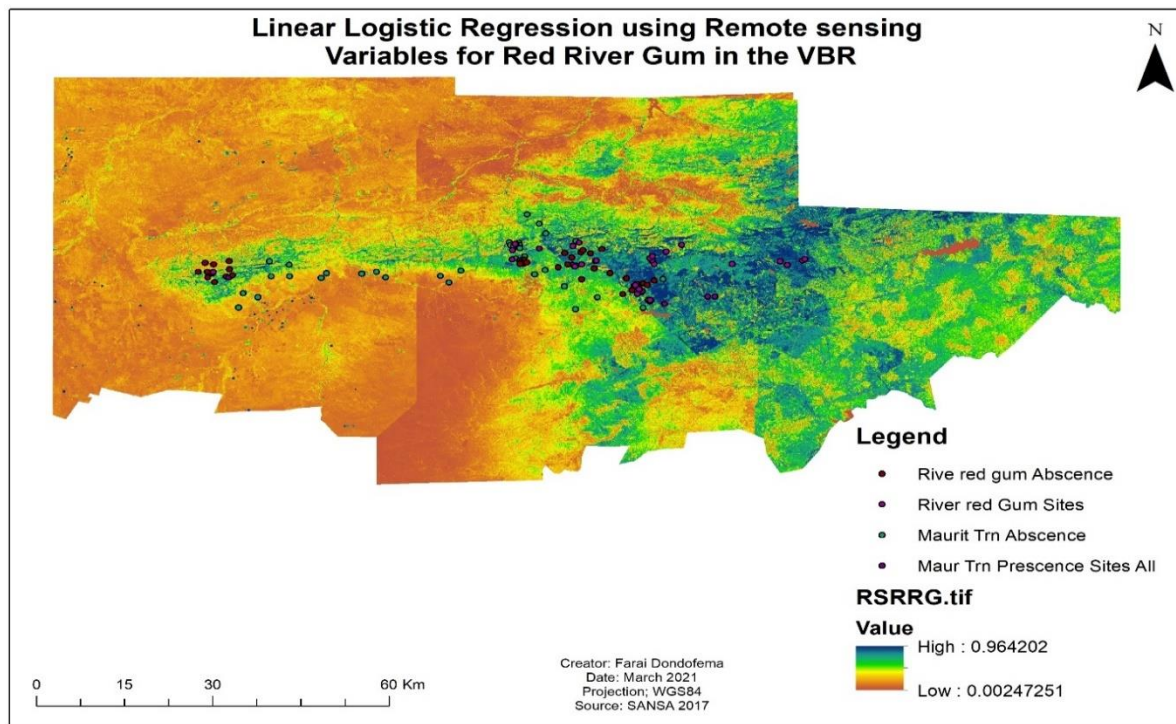


Figure 4-13: Mapping the distribution of *Eucalyptus camaldulensis* using statistically remote sensing variables in the VBR.

4.13.3 Using combined environmental and remote sensing variables to predict the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR.

Figure 4.-14 illustrates *Caesalpinia decapetala*'s possible distribution, and Figure 4-15 shows the potential distribution of *Eucalyptus camaldulensis* from the stepwise linear regression and raster calculator analysis. A combination of environmental and remote sensing variables for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR shows an increase in habitat suitable for *Caesalpinia decapetala* from the Northern to southern parts of the VBR. An interesting observation on the potential distribution of *Caesalpinia decapetala* occurs along the foothills of the Soutpansberg mountains, where the suitable habitat suitability fluctuates between high occurrence and absence. The results also depict the Northern parts of the VBR as unsuitable for *Caesalpinia decapetala*, possibly due to the area's dry and low nutrient content of the soils. As one moves to the south, more suitable habitats present themselves. This can be attributed to the slight increase in the moisture regime and improved edaphic factors that may promote the establishment of *Caesalpinia decapetala* Figure 4.10.

The obtained results for using environmental variables to project the spatial distribution of *Caesalpinia decapetala* (AIC: 60 and AUC: 0.95).

The results show an increase in habitat suitable for *Eucalyptus camaldulensis* in the south-facing slopes of the Soutpansberg mountains, especially in the bottom central portions of the VBR. An exciting distribution occurs along the foothills of the Soutpansberg mountains, where the suitable habitat suitability fluctuates between high occurrence and absence, with no suitable habitat in the northern portions of the Biosphere reserve. However, the results also show the broader Biosphere reserve as unsuitable for establishing *Eucalyptus camaldulensis*, possibly due to the area's low moisture regime and low nutrient-rich soils. The predicted distribution of *Eucalyptus camaldulensis* shows the south foothills of the Soutpansberg mountain as suitable habitats; this can be attributed to the slight increase in the moisture regime and improved edaphic factors that may promote the establishment of *Eucalyptus camaldulensis* Figure 4-15. The obtained results for using environmental variables to project the spatial distribution of *Eucalyptus camaldulensis* (AIC: 70 and AUC: 0.90).

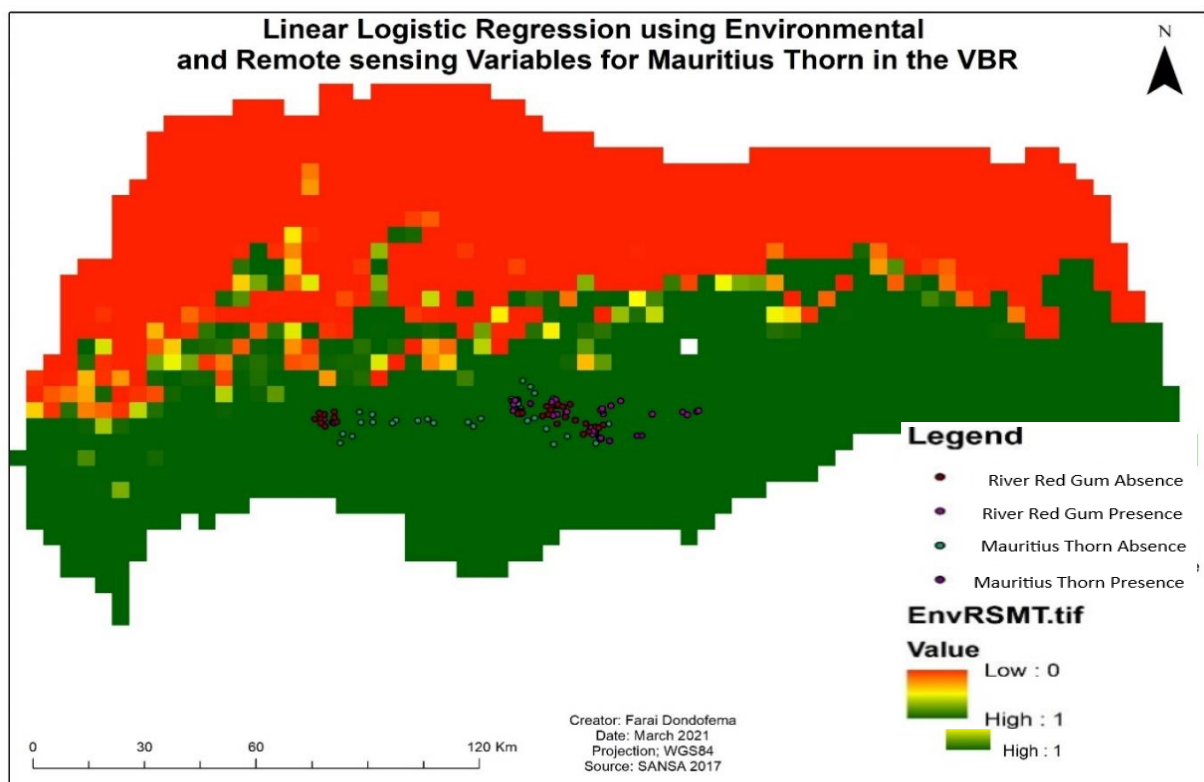


Figure 4-14: Mapping the distribution of *Caesalpinia decapetala* using statistically combined environmental and remote sensing variables in the VBR.

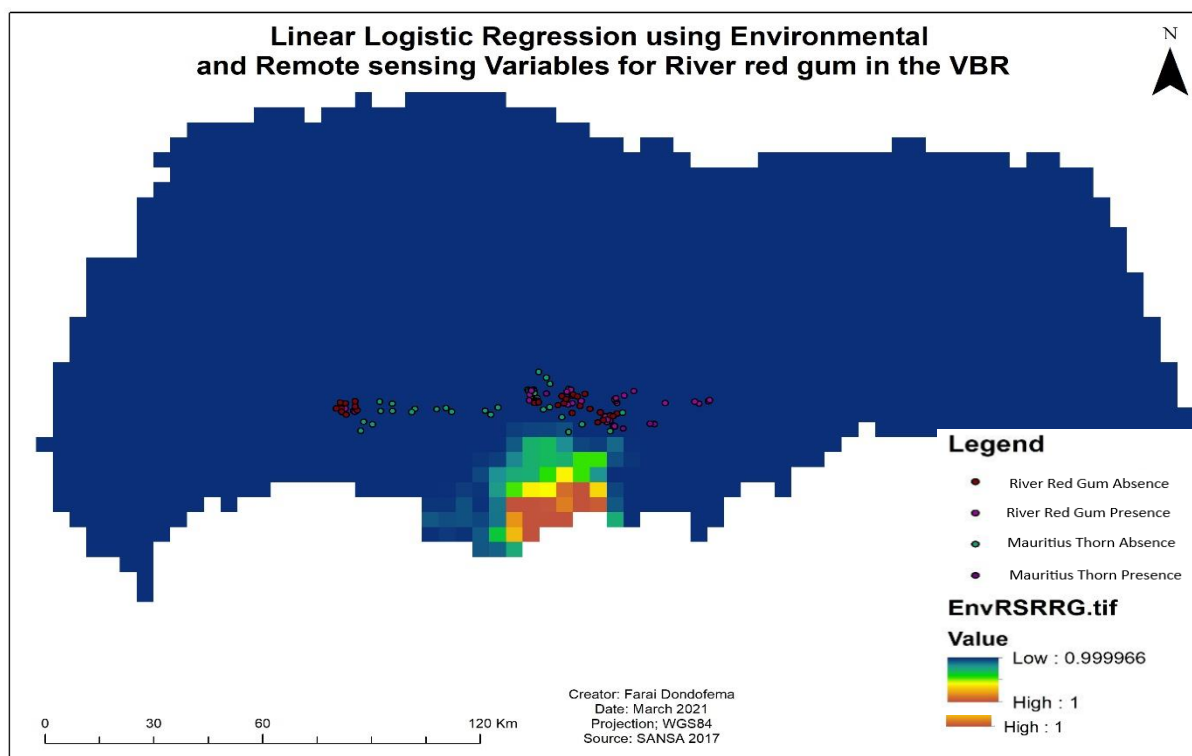


Figure 4-15: Mapping the distribution *Eucalyptus camaldulensis* using statistically combined Environmental and remote sensing variables in the VBR.

4.13.4 Using combined environmental and remote sensing variables to predict the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in Makhado and Thulamela Local municipalities.

Figure 4-16 illustrates *Caesalpinia decapetala*'s predicted distribution, while Figure 4-17 shows the expected distribution of *Eucalyptus camaldulensis* from the stepwise linear regression and raster calculator analysis. Upon considering the map outputs from the categories of variables that showed statistical significance in the study, this statistical analysis focused on the two local municipalities in the Vhembe biosphere reserve, where *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distribution showed significant distribution levels. To get a downscaled scenario of the habitat suitability for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, only the portion of the Vhembe Biosphere Reserve covering the Makhado and Thulamela local municipalities was analysed.

The results show an increased habitat suitable for *Caesalpinia decapetala* as patches within the two local municipalities. The habitat suitability increases in the west to that gradient. There is evidence of suitable habitat along with the Soutpansberg mountain range. Other notable suitable habitats included hydrological features and rainfall regimes. Moving from north to south, more unsuitable habitats start to present themselves; this can be attributed to the decline in the moisture regime and edaphic factors that may promote the establishment of *Caesalpinia decapetala* Figure 4-17. The obtained results for using environmental variables to project the spatial distribution of *Caesalpinia decapetala* (AIC: 69 and AUC: 0.90).

The results show an increase in habitat suitable for *Eucalyptus camaldulensis* as patches within the two local municipalities, the habitat suitability taking a west-to-east gradient. There is evidence of suitable habitat along with the Soutpansberg mountain range. Other notable suitable habitats included hydrological features and rainfall regimes. Movement from north to the south showing unsuitable habitats can be attributed to the decline in the moisture regime and edaphic factors that may promote the establishment of *Eucalyptus camaldulensis* Figure 4-17. The obtained results for using environmental variables to project the spatial distribution of *Eucalyptus camaldulensis* (AIC: 78 and AUC: 0.95).

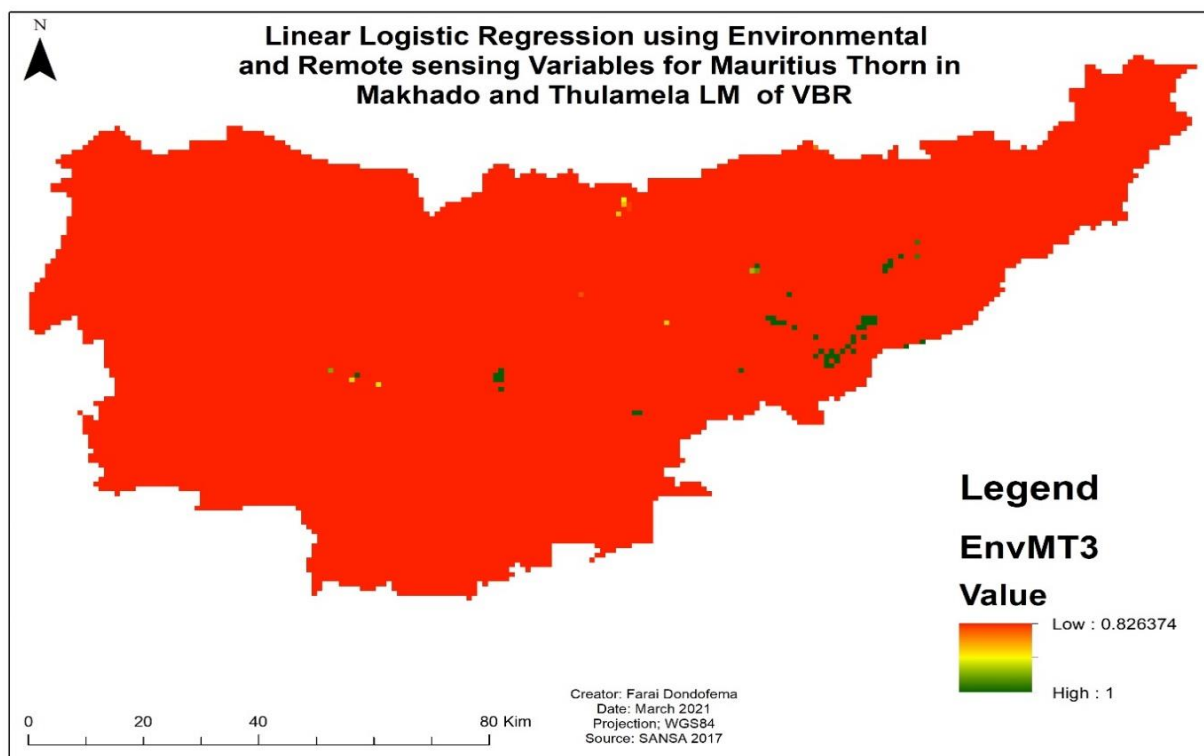


Figure 4-16: Mapping the distribution of *Caesalpinia decapetala* using statistically

combined environmental and remote sensing variables in the Makhado and Thulamela local municipalities within VBR.

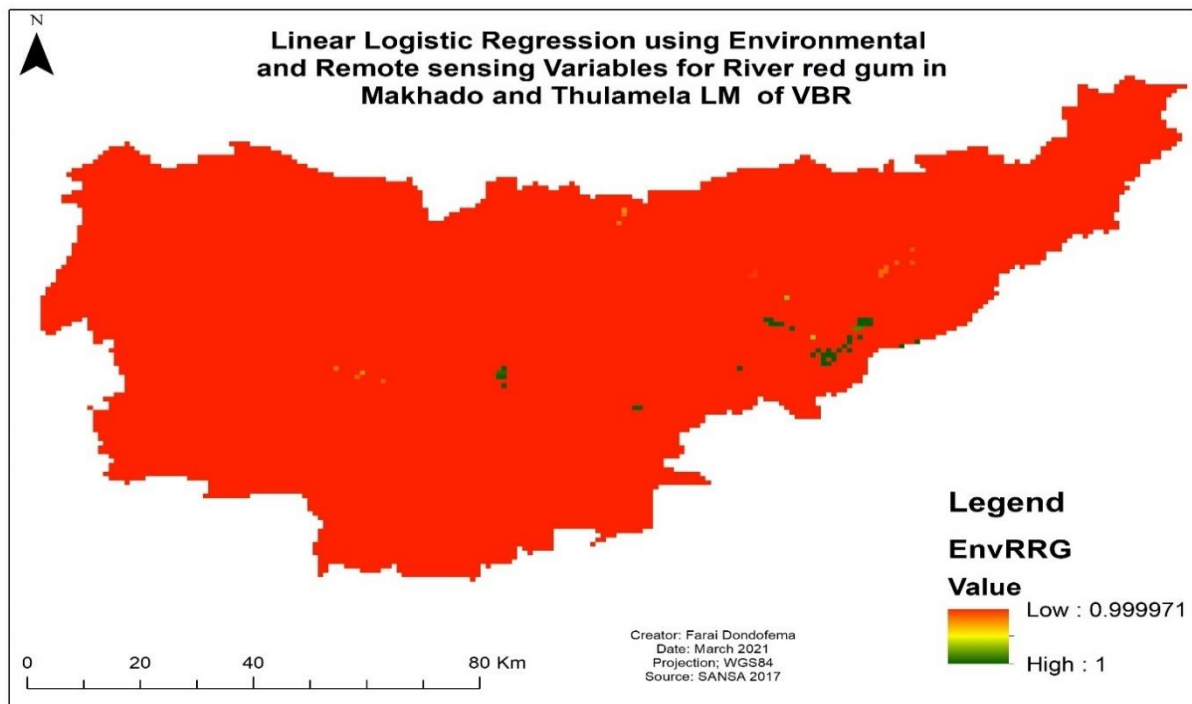


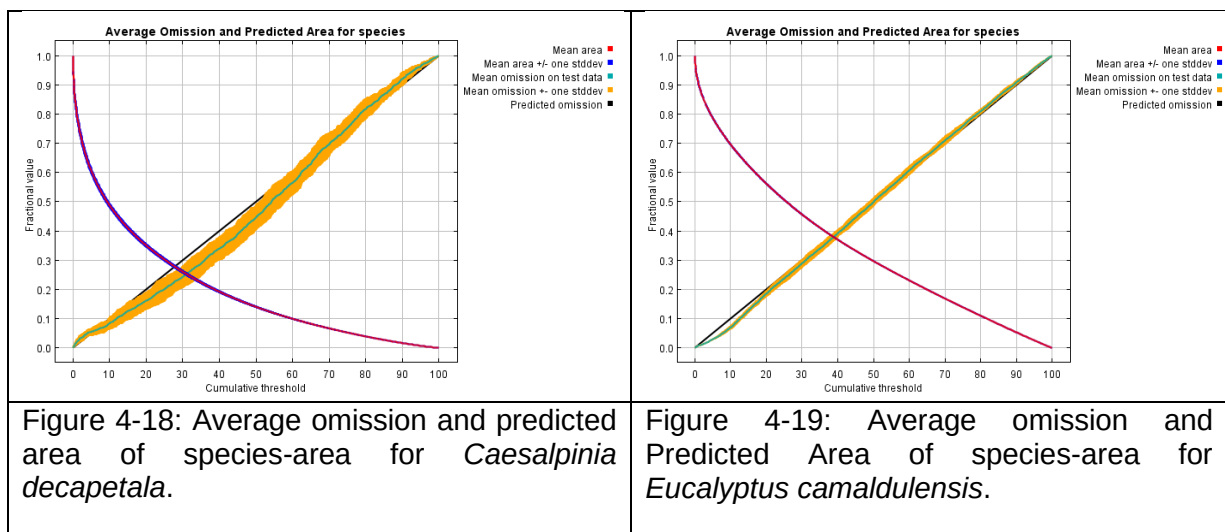
Figure 4-17: Mapping the distribution of *Eucalyptus camaldulensis* using statistically combined environmental and remote sensing variables in the Makhado and Thulamela local municipalities within VBR.

4.14 MaxEnt modelling of the spatial distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR.

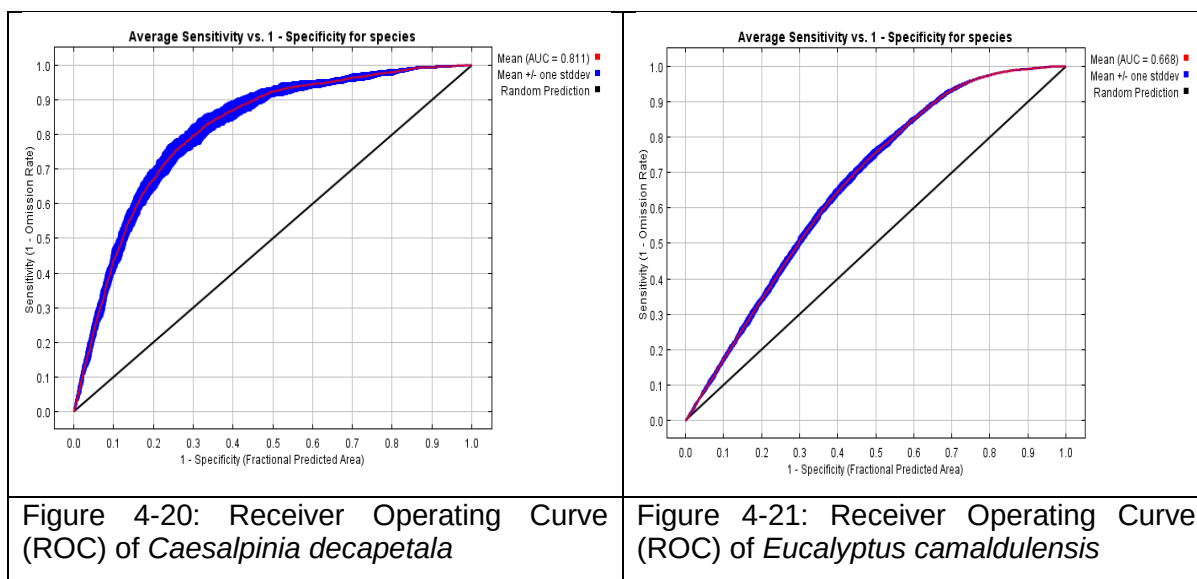
After running MaxEnt, the results are presented in this section. The analysis of the presence data for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* was carried out to understand better the global and local spatial distribution of the two IAPS of interest.

4.14.1 MaxEnt analysis in R-studio

The first plots showed how testing and training omission and predicted area varies with the cumulative threshold choice (Figure 4-18 and Figure 4-19).



The results show that the omission on both *Caesalpinia decapetala* and *Eucalyptus camaldulensis* matches the predicted omission rate for test data drawn from the MaxEnt distribution itself. The expected omission rate is a straight line of the cumulative output format, as illustrated in Figures 4-18 and 4-19. In the case of *Caesalpinia decapetala*, the test omission line lies slightly below the predicted omission line, possibly because the test and training data are not independent, familiar if derived from the same spatially autocorrelated presence data. Figures 4-20 and 4-21 present the receiver operating curve for both training and test data for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* species. Figures 4-20 and 4-21 also give the ROC curve (AUC) area.



The data for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* was split into two partitions, one for training and one for testing; both curves illustrate the red (training) line to show a higher AUC than the blue (testing) line. In this case, the red line representing the training data offers the “fit” of the model to the training data. However, the blue line represents the testing, which indicates the model's fit to the testing data and presents the real test of the model's predictive power. This analysis only uses occurrence data and no absence data, “fractional predicted area”. The fraction of the total study area predicted present is used instead of the more standard commission rate as represented by the fraction of absences predicted present. It is important to note that AUC values tend to be higher for species with narrow ranges relative to the study area described by the environmental data. This does not necessarily mean that the models are better; instead, this behaviour is an artefact of the AUC statistic.

4.14.2 The effects of variables on the prediction.

4.14.2.1. Response curves

The response curves show how each environmental variable affected the MaxEnt program prediction. The curves show how the predicted probability of presence changes for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* as each environmental variable varies, keeping all other environmental variables at their average sample value. In other words, the curves show the marginal effect of changing precisely one variable, whereas the model may take advantage of sets of variables changing together. The curves show the five replicate MaxEnt runs (red) and the mean

+/- one standard deviation (blue, two shades for categorical variables) as shown in Figure 4-22 and Figure 4-23.

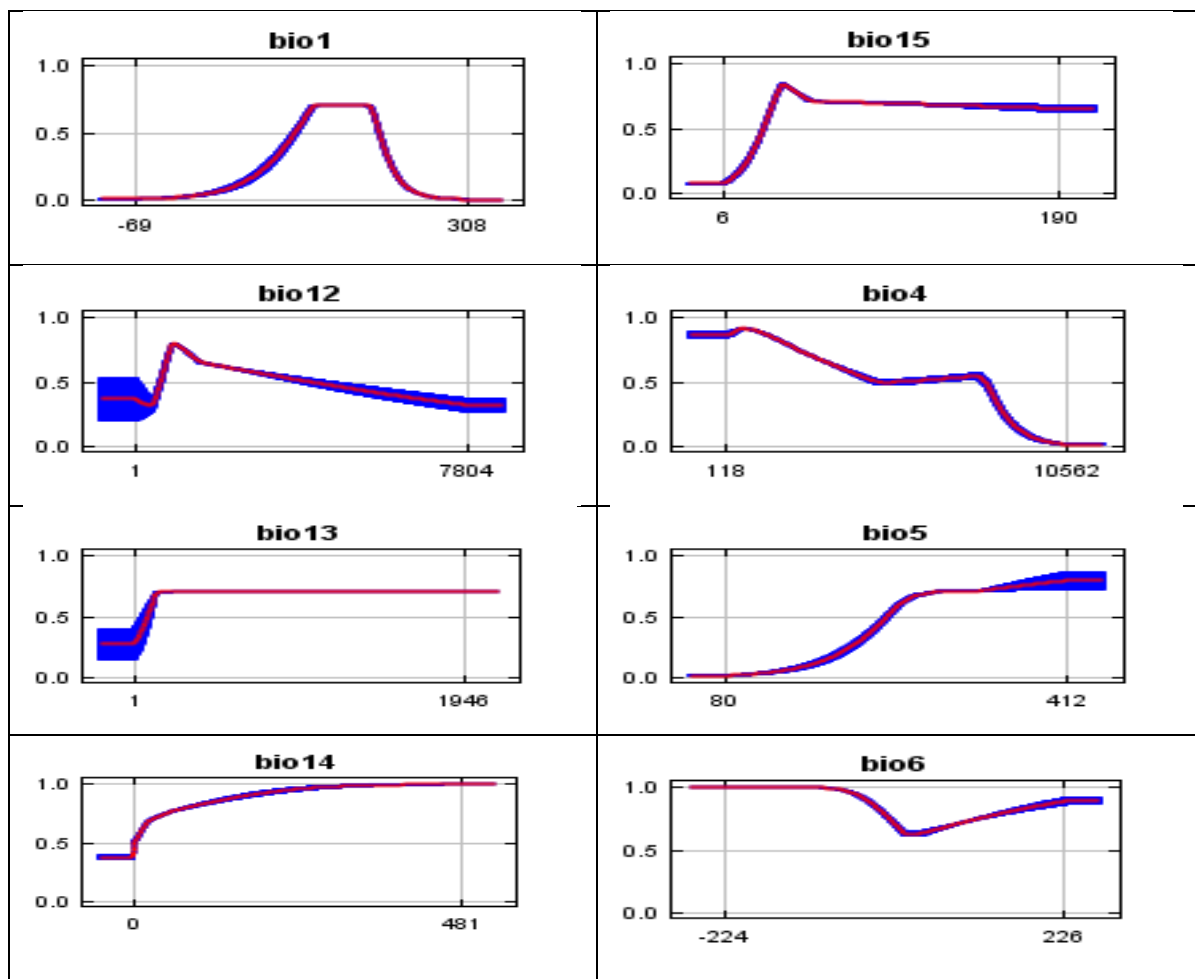
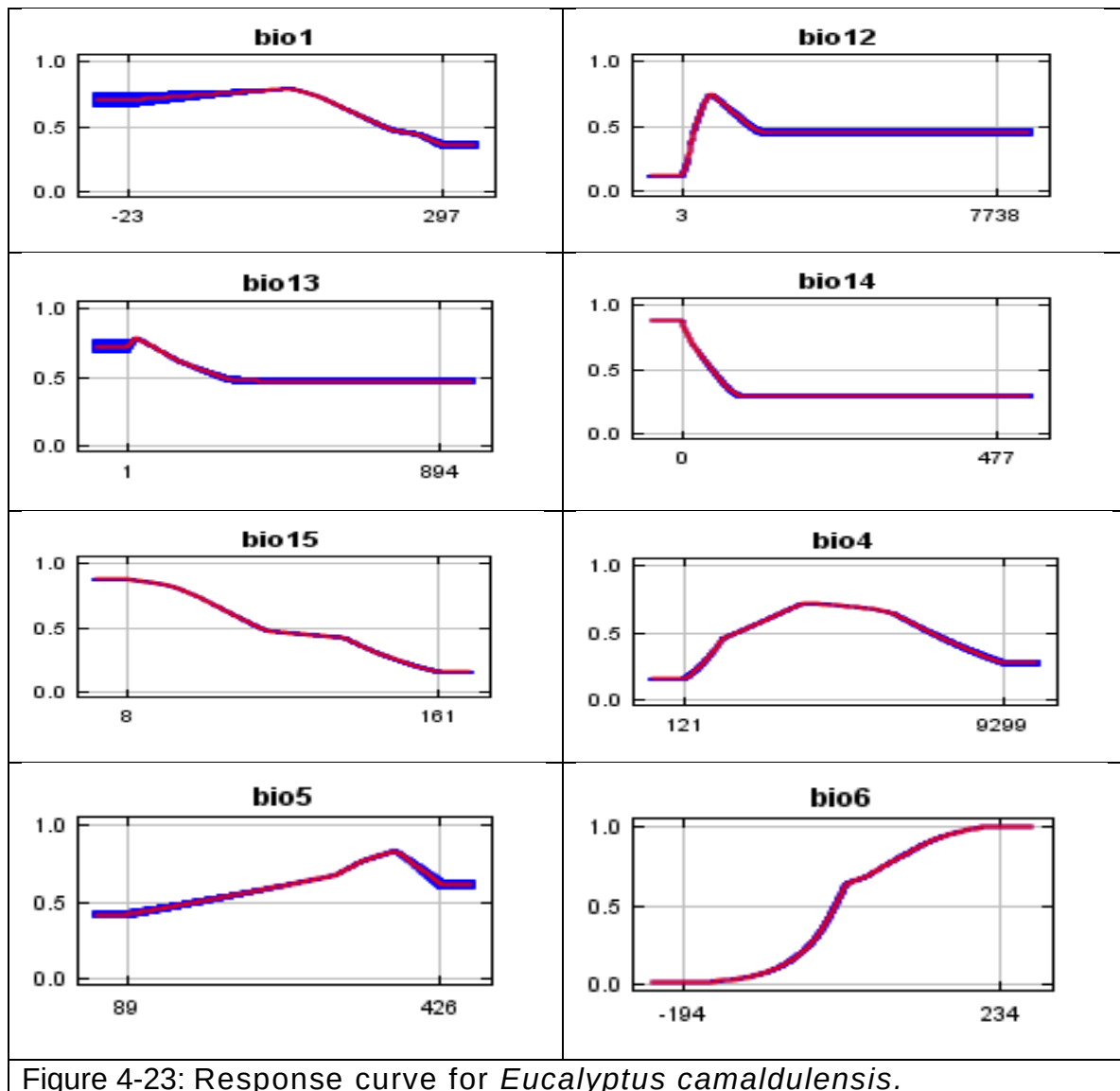


Figure 4-22: Response curve for *Caesalpinia decapetala*



4.14.3 Interactive exploration of predictions

4.14.3.1. Pictures of the model

Figure 4-24 and Figure 4-25 present a point-wise mean for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distribution globally. At the same time, Figure 4-26 and Figure 4-27 shows the standard deviation for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distribution at the global level. The point-wise mean and standard deviation are part of the five models applied to the environmental layers in Projected ASCII for the predicted global distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* globally.

The point-wise mean maps (Figure 4-22) illustrate that *Caesalpinia decapetala* favours tropical areas across the globe, with the highest concentration moving from southern, central, and east Africa. High mean distribution figures can also be noticed in South and North America, including Indo-Asia-pacific regions. At the same time, *Eucalyptus camaldulensis* plots show the concentrated distribution in Australia, India, Argentina, Brazil, USA, RSA, and more significant parts of the Sahel region.

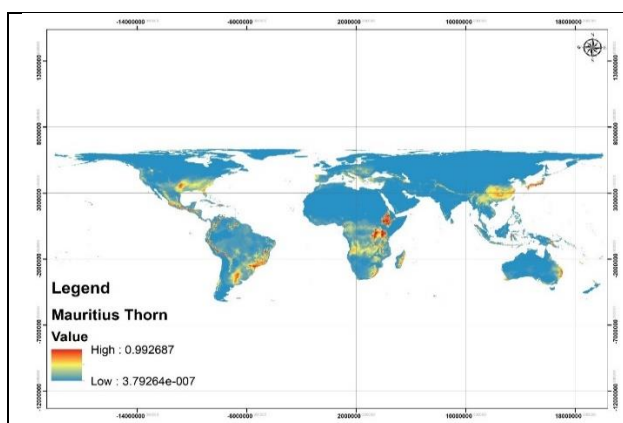


Figure 4-24: Global distribution projection of *Caesalpinia decapetala* shown as Point-wise mean

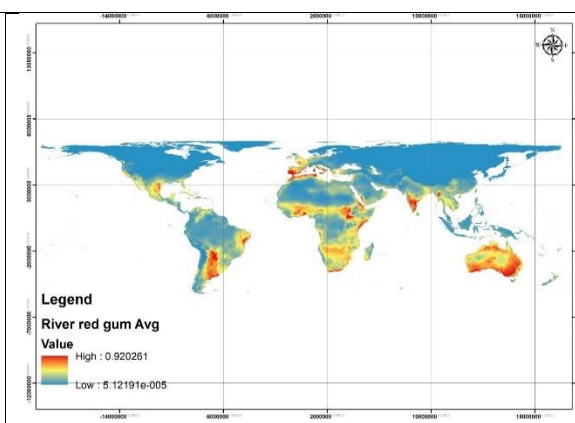


Figure 4-25: Global distribution projection of *Eucalyptus camaldulensis* shown as Point-wise mean

On the other hand, the standard deviation (Figure 4.26 and Figure 4.27) plots for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distribution at the global level illustrate that *Caesalpinia decapetala* favours tropical areas across the globe's highest concentration moving from southern, central, and east Africa. High mean distribution figures can also be noticed in South and North America, including Indo-Asia-pacific regions. At the same time, *Eucalyptus camaldulensis* plots show the concentrated distribution in South America, Indo-Asia-pacific, Central Africa and more significant parts of the Mediterranean region.

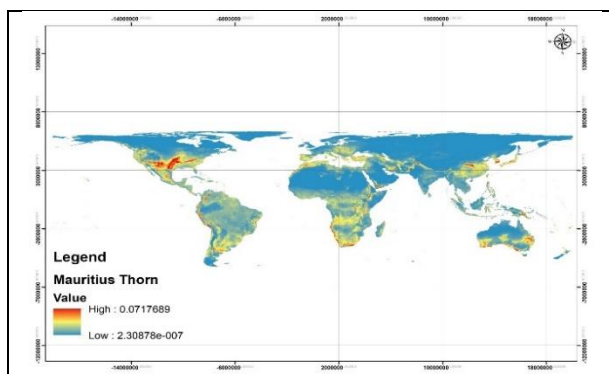


Figure 4-26: Global prediction of *Caesalpinia decapetala* shown as standard deviation

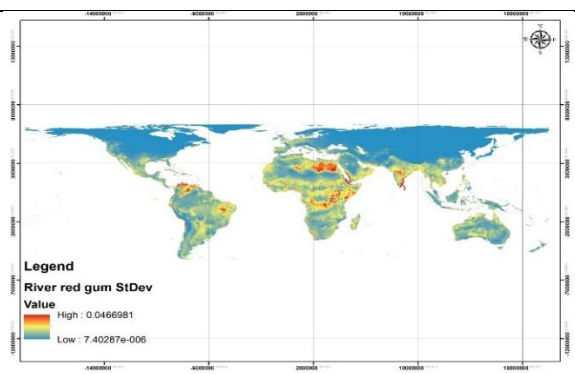
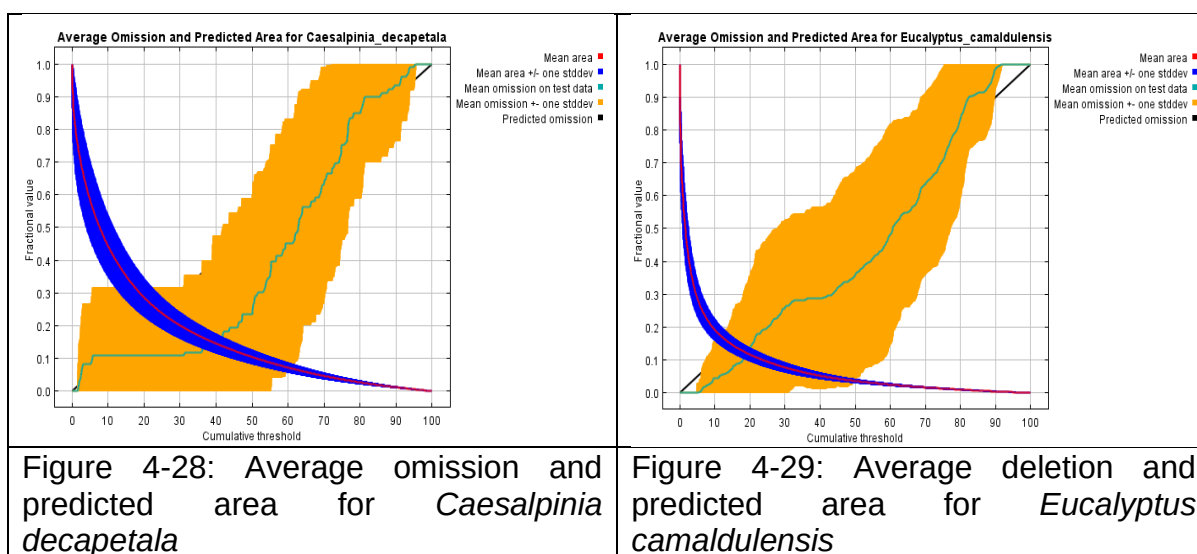


Figure 4-27: Global prediction of *Eucalyptus camaldulensis* shown as standard deviation

4.14.4 MaxEnt Analysis using the MaxEnt software.

4.14.4.1 Statistical analysis

Using 25 as a random test percentage in the MaxEnt software informs the program to randomly set aside 25% of the sample records for testing. Thus, allowing the program to do some simple statistical analysis. Much of the analysis used a threshold to make a binary prediction, with suitable conditions predicted above the threshold and unsuitable below. Figure 4-28 and Figure 4-29 show how testing and training omission and predicted area vary with the choice of cumulative point.



In the case of the *Caesalpinia decapetala* (Figure 4-30), the test omission line lies slightly below the predicted omission line. This might be caused by the test and training data not being independent, primarily if they derive from the same spatially autocorrelated presence data. The results show that the omission on both *Caesalpinia decapetala* matches the predicted omission rate for test data drawn from the MaxEnt distribution. Figure 4-30 presents the receiver operating curve for *Caesalpinia decapetala* species for both training and test data and offers the area under the ROC curve (AUC).

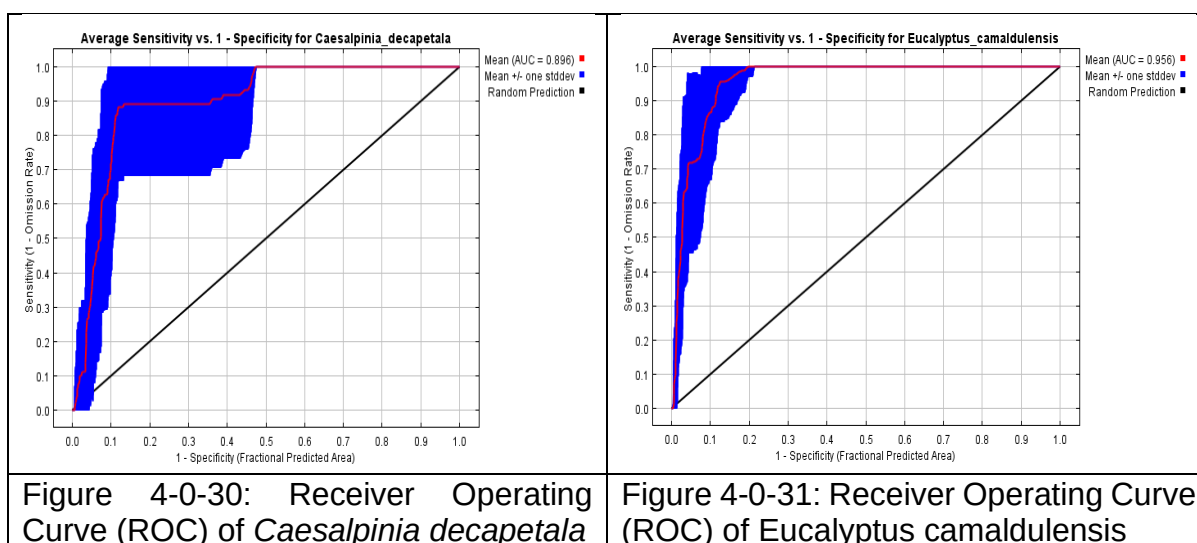
Eucalyptus camaldulensis (Figure 4-31) shows that the test omission line lies slightly above the predicted. This might be caused by the test and training data not being independent, primarily if they derive from the same spatially autocorrelated presence data. The results show that the omission on *Eucalyptus camaldulensis* matches the predicted omission rate for test data drawn from the MaxEnt distribution. Figure 4.31

presents the receiver operating curve for *Eucalyptus camaldulensis* species for training and test data and gives the area under the ROC curve (AUC).

4.14.5 Receiver operating curve (ROC)

Figure 4.26 shows the Sensitivity vs 1–Specificity for *Caesalpinia decapetala*, while Figure 4.27 shows the Sensitivity vs 1–Specificity for *Eucalyptus camaldulensis*. This is a graph of the Area Under the Receiver Operating Characteristic (ROC) Curve or AUC. The AUC values allow the comparison of the performance of one model with another and help evaluate multiple MaxEnt models. An AUC value of 0.5 indicates that the model’s performance is no better than random, while values closer to 1.0 indicate better model performance.

This analysis only uses occurrence data and no absence data, “fractional predicted area”. The fraction of the total study area predicted present is used instead of the more standard commission rate as represented by the fraction of absences predicted present. It is important to note that AUC values tend to be higher for species with narrow ranges relative to the study area described by the environmental data.



In the case of the *Caesalpinia decapetala* (Figure 4-30), the random prediction lies below the training and test data lines. The ROC curve shows the upper curve (red), signifying superior predictive ability with a mean AUC of 0.896. The random prediction of the *Eucalyptus camaldulensis* (Figure 4-31) lies below the training and test data lines. The ROC curve shows the upper curve (red), signifying superior predictive ability with a mean AUC of 0.956.

4.14.5.1 Analysis of variable contributions

Table 4-2 and Table 4-3 give estimates of the relative contributions of the environmental variables to the MaxEnt model for both *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. To determine the first estimate, in each iteration of the training algorithm, the increase in regularised gain is added to the contribution of the corresponding variable or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, the values of that variable on training presence and background data are randomly permuted for each environmental variable. The model is revaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalised to percentages. As with the jack-knife, variable contributions should be interpreted cautiously when the predictor variables are correlated. Values shown are averages over replicate runs.

Table 4-2: Estimates of relative contributions of the environmental variables to the MaxEnt model for *Caesalpinia decapetala*

Variable	Per cent contribution	Permutation importance
BioClim4_final	85.9	90.6
alt_final	5.3	1.3
Intercept_final	4	1.8
landtype_final	1.9	1.4
geology_final	1.2	1.7
bioclim15_final	0.9	0.9
landform_final	0.4	1
potevp_final	0.4	1.3
rdvi_final	0	0

The higher the contribution, the more impact that variable has on predicting the occurrence of that species. Table 4.2 illustrates that temperature seasonality (C of V) (i.e. BioClim4) had the highest predictive contribution of 85.9% for *Caesalpinia decapetala*.

Table 4-3: Estimates of relative contributions of the environmental variables to the Maxent model for *Eucalyptus camaldulensis*

Variable	Per cent contribution	Permutation importance
BioClim4_final	56.8	93.3
Intercept_final	12.1	1.1
alt_final	10.3	2.2
landform_final	6.7	0.3
rdvi_final	4	0.3
bioclim15_final	3.2	0.8
geology_final	3.2	1.4
potevp_final	2	0.4
landtype_final	1.7	0.3

The higher the contribution, the more impact that variable has on predicting the occurrence of that species. Table 4-3 illustrates that temperature seasonality (C of V) (i.e. BioClim4) had the highest predictive contribution of 56.8% for *Eucalyptus camaldulensis*.

4.14.5.2 Jackknife of regularized training gain

A jackknife test was run to get alternate estimates of which variables are most important in the model by selecting the “Do jackknife to measure variable important” checkbox. Each variable was excluded, and a model was created with the remaining variables. Then a model was created using each variable in isolation. In addition, a model is created using all variables, as before. The jackknife results appeared in three-bar charts in the “*Caesalpinia decapetala*.html and *Eucalyptus camaldulensis*.html” files.

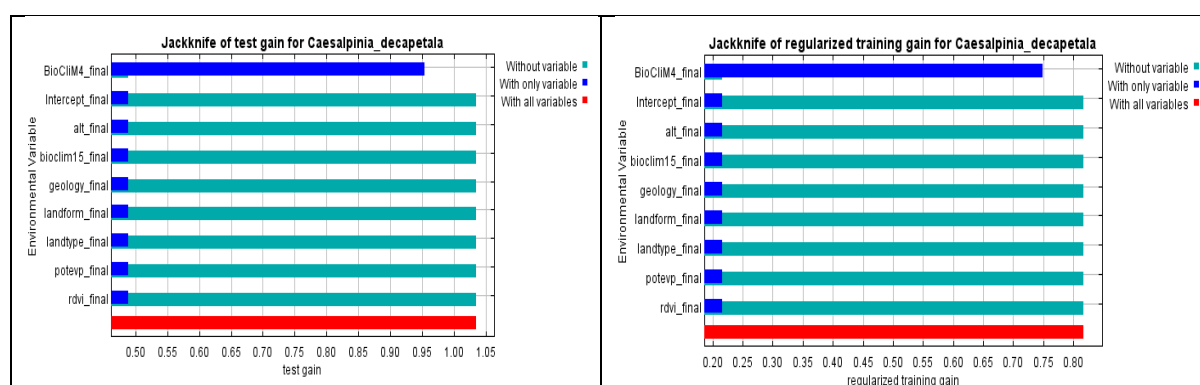


Figure 4-32: Jack-knife of regularized training and test gain for *Caesalpinia decapetala*

Figure 4.33 shows the results of the jackknife test and training gain of variable importance. When used in isolation, the environmental variable for *Caesalpinia decapetala* with the highest yield was BioClim4_final, which appears to have the most helpful information. The environmental variable that decreased the gain the most when omitted was BioClim4_final; it seems to have the most information that isn't present in the other variables, with the values shown being averages over replicate runs.

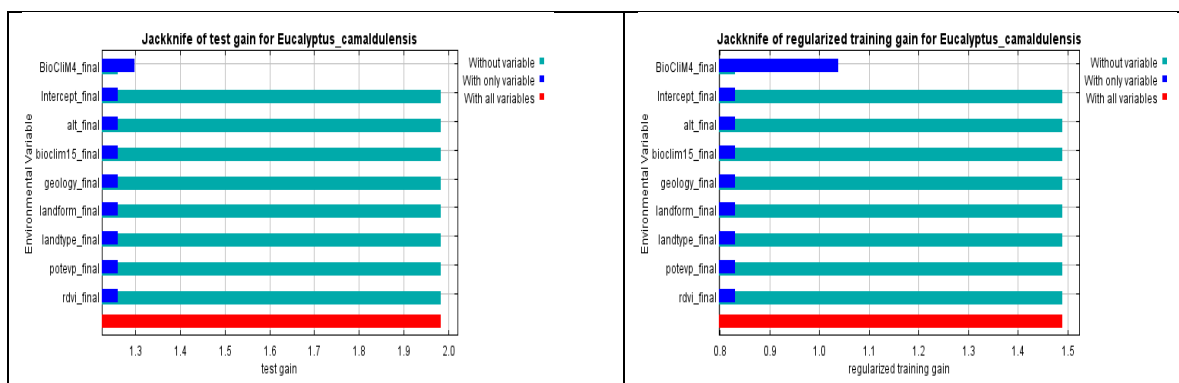


Figure 4-33: Jackknife of regularized training and test gain for *Eucalyptus camaldulensis*

Figure 4-33 shows the results of the jackknife test and training gain of variable importance. The environmental variable for *Eucalyptus camaldulensis* with the highest yield, when used in isolation, is BioClim4_final, which appears to have the most helpful information. The environmental variable that decreases the gain the most when it omits BioClim4_final; seems to have the most information that isn't present in the other variables, with the values shown being averages over replicate runs.

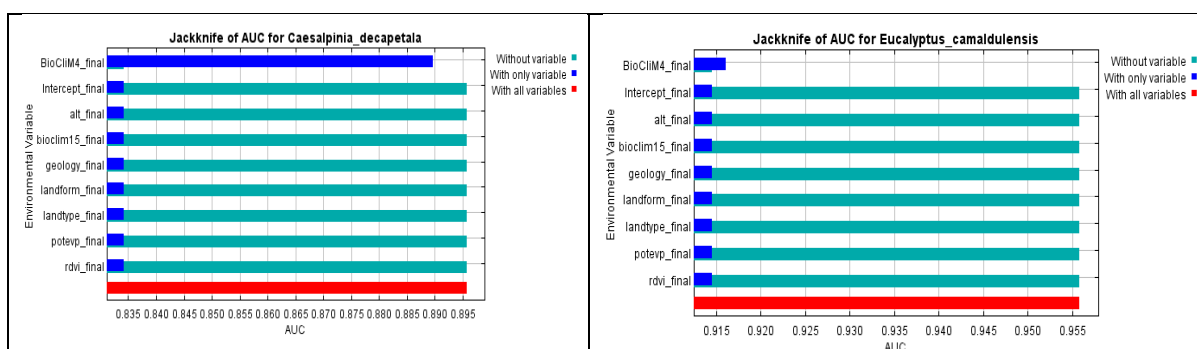


Figure 4-34: Jackknife test, using AUC on test data for *Caesalpinia decapetala*

Figure 4-35: Jackknife test, using AUC on test data for *Eucalyptus camaldulensis*

Figure 4-34 shows the results of the Jackknife test, using AUC on test data of variable importance. The environmental variable for *Eucalyptus camaldulensis* with the highest gain, when used in isolation, is BioClim4_final, which appears to have the most helpful information. The environmental variable that decreases the growth the most when omitted is BioClim4_final, which therefore seems to have the most information that isn't present in the other variables. Values shown are averages over replicate runs.

Figure 4-35 shows the results of the Jackknife test, using AUC on test data of variable importance. The environmental variable for *Eucalyptus camaldulensis* with the highest gain, when used in isolation, is BioClim4_final, which appears to have the most helpful

information. The environmental variable that decreases the growth the most when omitted is BioClim4_final; it seems to have the most information that isn't present in the other variables, with the values shown being averages over replicate runs.

A comparison of the three jackknife plots can be very informative. The AUC plot shows that annual precipitation (BioClim4_final) is the most effective single variable for predicting the distribution of the occurrence data set aside for testing when predictive performance is measured using AUC, even though it was hardly used by the model built using all variables. The relative importance of temperature seasonality also increases in the test gain plot compared to the training gain plot. In addition, in the test gain and AUC plots, some light blue bars (especially for the temperature seasonality) are slightly more extended than the red bar, showing that predictive performance improves when the corresponding variables are not used.

This tells us that monthly temperature variables are helping MaxEnt to obtain an excellent fit for the training data. Still, the temperature seasonality variable generalises better, giving comparatively better results on the set-aside test data. In other words, models made with the temperature variations over seasons variables appear less transferable. This is important if the goal is to transfer the model, for example, by applying it to future climate variables to estimate its future distribution under climate change. It makes sense that temperature seasonality values are less transferable: likely suitable conditions for both *Caesalpinia decapetala* and *Eucalyptus camaldulensis* will depend not on precise temperature values in selected seasons but on the aggregate average temperature and perhaps on temperature consistency or lack of extended cold periods. When modelling on a district scale, shifts in the precise timing of seasonal temperature patterns, affecting the monthly temperature but not suitable conditions for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, are evident.

4.14.6 The Effects of variables on the prediction.

4.14.6.1 Response curves

The response curves show how each environmental variable affected the MaxEnt program prediction. The curves show how the predicted probability of presence changes for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* as each

environmental variable varies, keeping all other environmental variables at their average sample value. In other words, the curves show the marginal effect of changing precisely one variable, whereas the model may take advantage of sets of variables changing together. The curves show the five replicate MaxEnt runs (red) and the mean $\pm$ one standard deviation (blue, two shades for categorical variables) as shown in Figure 4.36 and Figure 4.37.

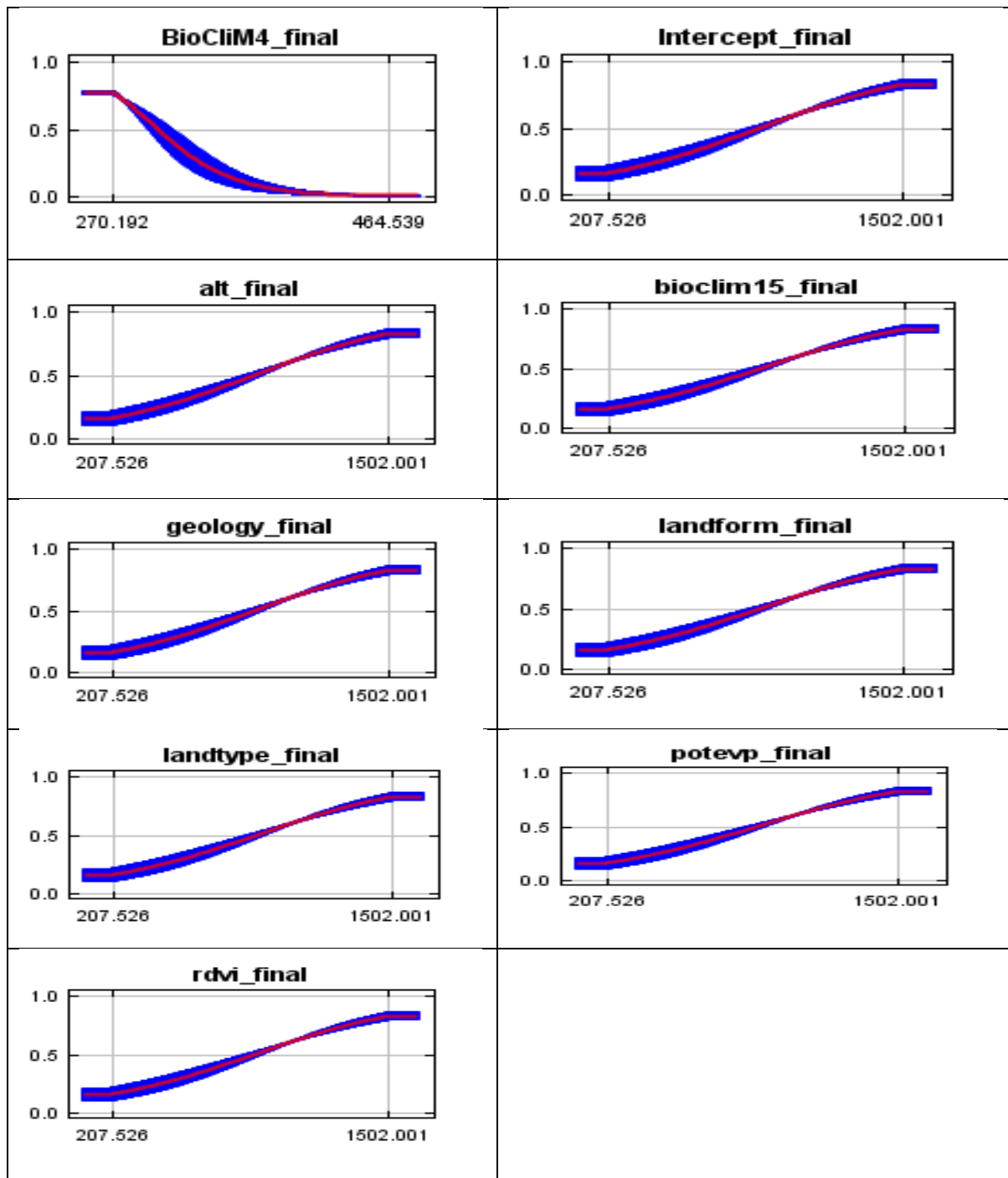


Figure 4-36: Marginal response curves for *Caesalpinia decapetala*

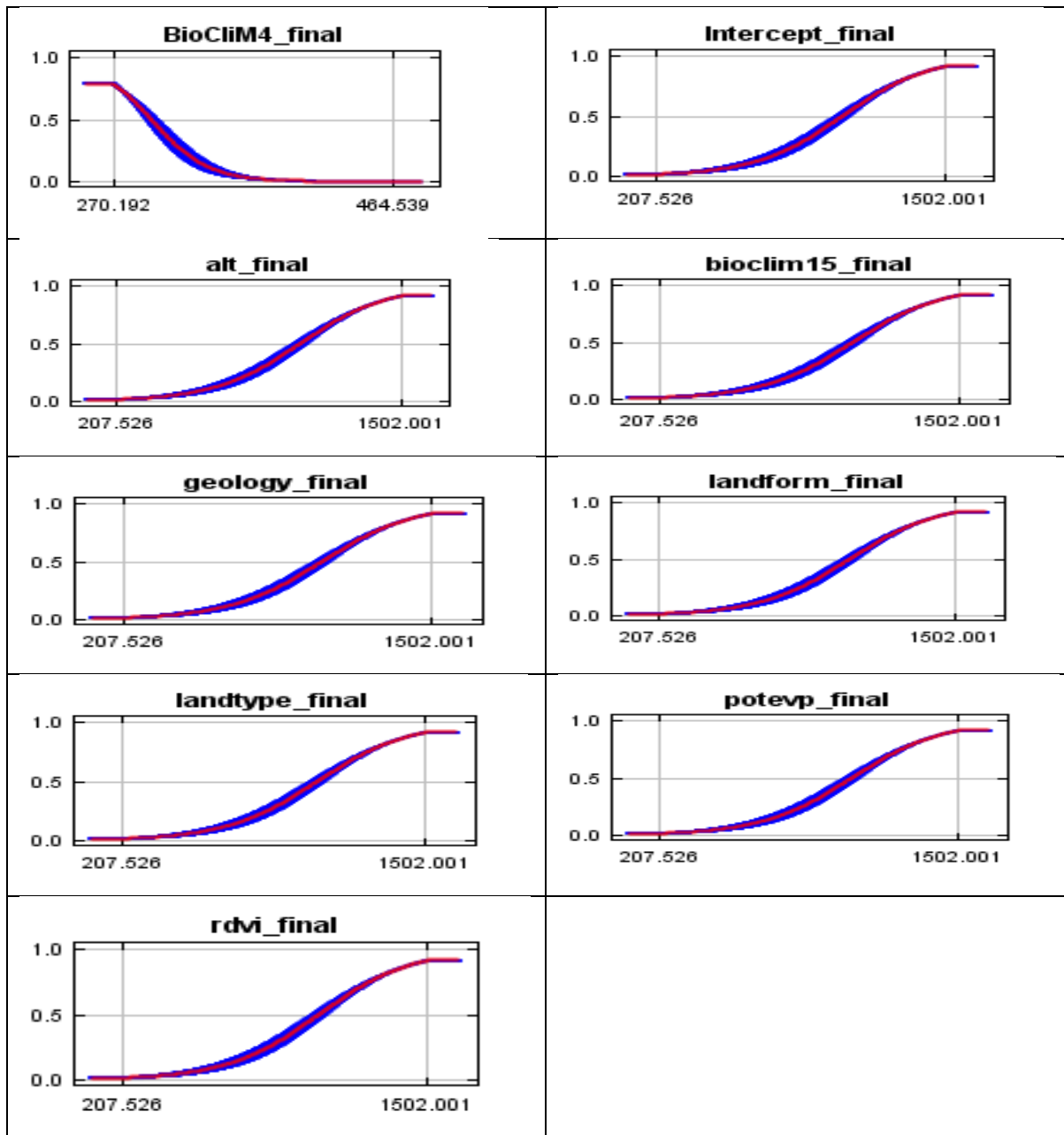


Figure 4-37: Marginal response curves for *Eucalyptus camaldulensis*

4.14.6.2 Interactive exploration of predictions

4.14.6.3 Pictures of the model

Figure 4.34 and Figure 4.35 presents a point-wise mean for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distribution in the VBR. At the same time, Figure 4-39 and Figure 4-38 shows the standard deviation for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* distribution in the VBR. The point-wise mean and standard deviation are part of the five models applied to the environmental layers in Projected ASCII for the predicted global distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* across the VBR.

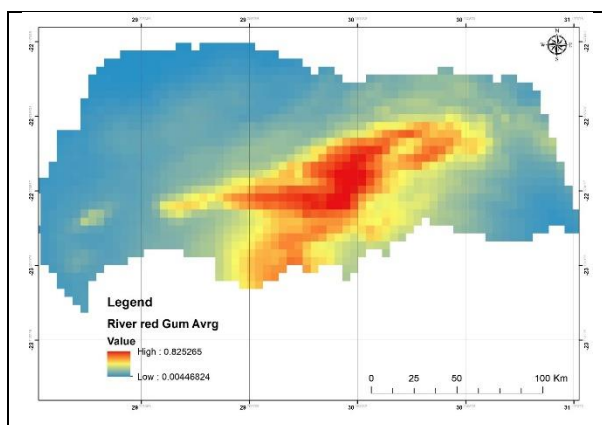


Figure 4-38: Vhembe Biosphere Reserve distribution projection of *Caesalpinia decapetala* shown as Point -wise mean

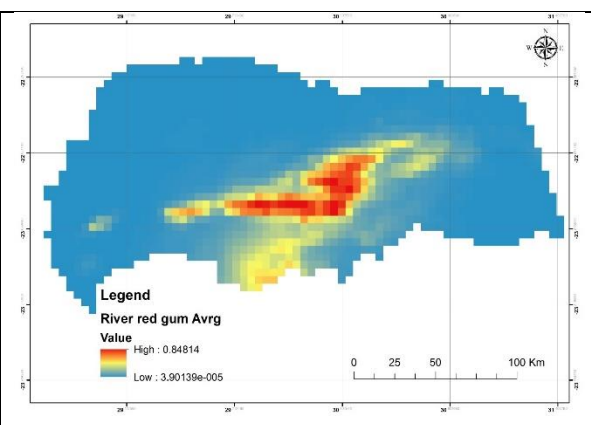


Figure 4-39: Vhembe Biosphere Reserve distribution projection of *Eucalyptus camaldulensis* shown as Point -wise mean

The point-wise mean maps (Figure 4-40) illustrate that *Caesalpinia decapetala* favours areas across the VBR with the highest concentration following the Soutpansberg mountain ranges. Notable high mean distribution figures can also be noticed in the Luvuvhu valley. The point-wise mean maps (Figure 4-41) illustrate that *Eucalyptus camaldulensis* tends to favour areas across the VBR with the highest concentration following the Soutpansberg mountain ranges. Notable high mean distribution figures can also be noticed in the Luvuvhu valley.

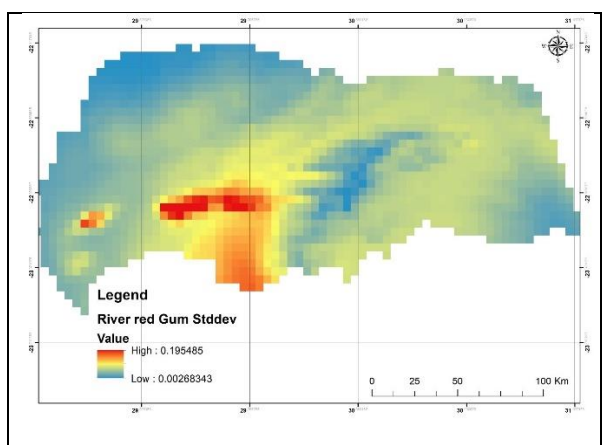


Figure 4-40: Vhembe Biosphere Reserve distribution projection of *Caesalpinia decapetala* shown as standard deviation

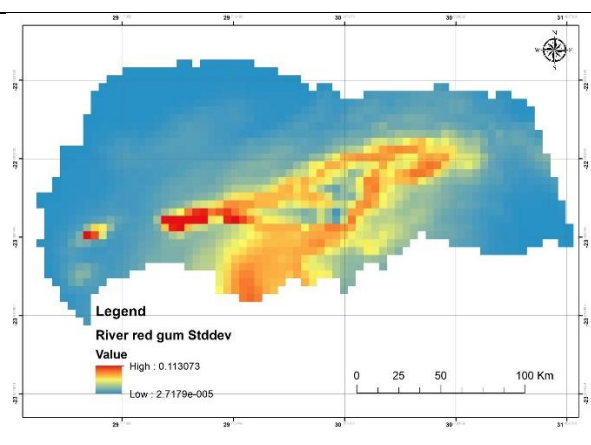


Figure 4-41: Vhembe Biosphere Reserve distribution projection of *Eucalyptus camaldulensis* shown as standard deviation

The point-wise mean maps (Figure 4-40) illustrate that *Caesalpinia decapetala* tends to favour areas across the VBR, with the highest concentration coinciding with the peaks of the Soutpansberg mountain ranges, Hangklip summit and the Lajuma summits. Notable high mean distribution figures can also be noticed southwards in the

town of Louis Trichardt. The point-wise mean maps (Figure 4-41) illustrate that *Eucalyptus camaldulensis* favours areas across the VBR with the highest concentration, following the Soutpansberg mountain ranges. Notable high mean distribution figures can also be noticed in the Luvuvhu valley.

4.15. Discussion

Field surveys within the VBR revealed that *Caesalpinia decapetala* and *Eucalyptus camaldulensis* had a detrimental influence on native plants in several ecosystems and habitats. The two IAPS were concentrated in the Soutpansberg mountains' foothills, along forest road borders and riparian habitats (mainly south of the Luvuvhu River), and along the boundaries of plantations (especially abandoned unused). Several variables influencing the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* were discovered to differ geographically. Several variables influence the distribution of IAPS (Underwood et al., 2004). These aspects involve various environmental variables that comprise the species' fundamental niche (Pysek et al., 2003). IAPS are found in disturbed environments and are influenced by abiotic variables such as past land use and management (Cowie and Werner 1993; Mack and D'Antonio 1998). (Mack et al., 2000). The explanatory variables were chosen to account for a sizable proportion of the driving elements in the current investigation.

The investigation showed that environmental and remote sensing factors could accurately predict IAPS distribution with high AUC and IAC values. The findings demonstrate how incorporating environmental factors leads to an output favouring the spread of IAPS along the VBR's foothills. However, the analysis results look skewed since the expected distribution is near the Soutpansberg mountains' foothills. A more realistic representation is obtained by combining environmental and remote sensing factors.

Considering the continuous driving factors analysed in this study, the logistic regression findings show that environmental and remote sensing predictors significantly impacted *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. On the other hand, mountains, riparian regions, and highways play an essential role in IAPS distribution. The logistic regression study reveals an unexpected finding: proximity to towns does not affect the distributions of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. *Caesalpinia decapetala* and *Eucalyptus camaldulensis* were similarly

affected by proximity to riparian habitats. Furthermore, *Caesalpinia decapetala* and *Eucalyptus camaldulensis* along riparian areas might be explained because rivers are frequently seen as natural conduits to the spread of IAPS (Fenesi et al., 2009).

4.15.1 Topographic effects

Caesalpinia decapetala and *Eucalyptus camaldulensis* were more likely to be found at elevations between 1200 and 1700 meters. Higher elevations were the central locations for the initial invasion, but successive invasions were not limited to these areas. The capacity of the *Caesalpinia decapetala* and the *Eucalyptus camaldulensis* to invade lower elevations suggests that the two IAPS are adaptable to various environmental circumstances and grow appropriately. On a north-facing slope, the likelihood of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* increased, and it was found that both IAPS were suited to relatively strong solar radiation. The presence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* on the east and southeast slopes of the Soutpansberg Mountains might be attributed to seed dispersal aided by the main wind direction (south-easterly) and rain shadow effects. Areas with topographic lows caused by hydrological channels and soil types associated with microsites for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* germination. It's conceivable that ephemeral water flow aids seed dissemination in channels or that the channels trap windblown seeds. Compared to other topographic features and human disturbance, the effect of channels was minimal.

4.15.2 Land use effects

The close link between the prevalence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* and anthropogenic disturbance characteristics, including cultivated areas, roads, and power lines, suggests that the present invasion reflects historical disturbance. Rangelands next to farmed regions are highly vulnerable to invasion. The occurrence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* is not directly linked to agriculture, as the probability of occurrence was greatest 2-3 km from agricultural activity. According to the findings, *Caesalpinia decapetala* and *Eucalyptus camaldulensis* have spread toward farming areas rather than away from them. *Caesalpinia decapetala* and *Eucalyptus camaldulensis* were found on the hillsides around various agricultural areas.

The high incidence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* is not likely related to a shift away from agriculture; nevertheless, abandoned plantations and other land uses near human inhabited areas may increase the possibility of the two IAPS to expand. Lands near roadways are likely to have *Caesalpinia decapetala* and river presence. Many studies have linked IAPS prevalence to roadways (Forman & Alexander, 1998; Trombulak & Frissell, 2000) and hypothesised invasion mechanisms such as changed ecological conditions near highways and seed dispersion by human and animal vectors. According to Gelbard and Belnap (2003), there is a positive correlation between roads and the two IAPS, with the incidence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* rising with the amount of road development. *Caesalpinia decapetala* and *Eucalyptus camaldulensis* were more likely to be found up to 1 km from any road around the Soutpansberg mountain. This is a substantially longer distance than the average roadside verge disturbance in the region. Whatever the invasion process, human activities such as farming, road and building construction all contribute significantly to the incidence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*.

4.15.3 Choice of model

A wide range of methodological techniques has been used to model habitat appropriateness. Presence/absence, presence/pseudo-absence, and presence-only models are the most often used SDMs techniques. Distribution is essential not only for the site of species present but also for the location of species absence and successful presence/absence modelling. Because of the previously noted issues about equilibrium, the lack of data on invasive plants can be problematic. The absence of a species may imply that it cannot establish itself in a specific location, but it may also infer that the species can establish itself but has not yet been introduced. As a result, presence/absence models are often applied exclusively at the landscape or local scales to answer concerns like how local disturbance impacts invasion (Bradley & Mustard, 2006). The possibility of a 'false' absence model findings is substantially higher at regional sizes because few data sets cover both presence and absence. As a result, presence/absence models are rarely used to estimate species range changes in response to climate change or to predict climatic change.

The more disturbed ecosystems and habitats are the more likely they are to be invaded by *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. As a result, forest fragmentation and clearance, transportation network expansion, and abandonment will boost the potential spread of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. Planting *Caesalpinia decapetala* and *Eucalyptus camaldulensis* for various purposes will also promote invasion inside the VBR's important habitats and ecosystems. Logistic regression using environmental variables was further used to downscale the possible spatial distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* to two local municipalities in the VBR with exceptional accuracy in the case of *Caesalpinia decapetala* (AIC- 69 and AUC- 0.90) and *Eucalyptus camaldulensis* (AIC -78 and AUC- 0.95).

As a result of global climate change, scientists have created algorithms that give essential data to understand plant dispersion better and anticipate the spatial distribution regions based on various environmental variables (Yackulic et al., 2013). The results show the MaxEnt model run to predict the possible global distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, as shown in figures 4.24 and 4.25, further downscaled to the VBR. These results hint toward a common trend in the global distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. *Caesalpinia decapetala* distribution is concentrated in tropical areas across the globe (Figure 4.38), with the highest concentration moving from southern, central, and east Africa. High mean distribution figures can also be noticed in south and north America, including Indo-Asia-pacific regions (Figure 4.39). At the same time, *Eucalyptus camaldulensis* plots show the concentrated distribution in Australia, India, Argentina, Brazil, the USA, South Africa, and more significant parts of the Sahel region.

This study modelled the spatial distribution areas for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* IAPS in the VBR using MaxEnt. The results confirmed that the highly suitable area for these species is the main areas in the foothills of the Soutpansberg mountains and along rivers and valleys in the Luvuvhu catchment. However, the predicted spatial distribution scenario for the VBR shows that *Caesalpinia decapetala* and *Eucalyptus camaldulensis* will increase if their distribution is limited to the current area of VBR. Bioclimatic variables predicting species distribution areas do not necessarily indicate the importance of topography.

Topography is critical in species dispersion regarding its influence on the microclimate (Dobrowski, 2011; Coban & Cosgun, 2020). Topology concerns are essential since the VBR's terrain varies significantly from west to east, causing minor microclimatic impacts.

This forecast was made using MaxEnt software, and the distribution regions and populations of the *Caesalpinia decapetala* and the *Eucalyptus camaldulensis* will alter. However, that shift is caused by climate change. This was evident for both *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, as illustrated by tables 4.2 and 4.3. To determine the contribution of the bioclimatic variables, the Jackknife test option in the MaxEnt modelling program was used (Figures 4.32 and 4.33). Similar research highlights that anthropogenic activities are the most critical factors impacting habitat loss, fragmentation, and the lack of biological diversity (Mantyka-pringle et al., 2012). Dislocations, population surges, and species colonisation are persistent difficulties in biogeography (Hughes, 2000).

The findings showed that the logistic regression and maximum entropy models predict the examined IAPS distribution in the VBR with comparable efficiency. Both models could predict the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. Similar studies also concur with these findings (Sahragard and Chahouki, 2015). It is important to note that all the model's input variables are not statistically significant in logistic regression.

The crucial thing to remember is that you may reduce prediction error by combining all factors. As a result, a predictive model containing a collection of significant and inconsequential variables may be constructed (Rossiter and Loza, 2010). MaxEnt, unlike logistic regression, does not consider species' absence. Based on the link between species distribution and environmental factors, MaxEnt estimates the occurrence probability of each species. (Buehler and Ungar, 2001). Furthermore, the AUC statistic may be used to independently examine each variable's influence on the model's efficiency.

As a result, to increase the model's accuracy, variables of low relevance might be omitted (Chahouki and Sahragard, 2016). Many environmental factors, including edaphic and physiographic variables, contributed to the distribution of IAPS habitats in the VBR, according to the results of logistic regression and MaxEnt. In other words,

the research area's soil physicochemical qualities and topography hold vital information regarding the distribution of IAPS habitats.

4.16. Conclusion

Using stepwise logistic regression to identify suitable habitats for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR produced varying results. When using environmental variables on their own, it is evident that the resultant suitable habitats are crude in the case of *Caesalpinia decapetala*. *Eucalyptus camaldulensis* resembled the geological formation of the VBR mainly because geology came out as the dominant variable after the stepwise logistic regression. On the other hand, the remote sensing variable produced a more pleasing and acceptable projection of suitable habitat for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*.

The stepwise logistic regression analysis points to species distribution following the Soutpansberg mountain range with a pronounced increase as one approaches the wetter and fertile Luvuvhu areas. This distribution follows the same pattern for this study's two species. When the environmental and remote sensing variables are combined and analysed using the stepwise regression model, the results for *Caesalpinia decapetala* show fluctuation of its distribution in and around the southern slopes of the Soutpansberg mountain range. On the other hand, the *Eucalyptus camaldulensis* distribution output illustrates a concentration of suitable habitats on the southern foothills of the Soutpansberg mountain range. The more significant part of the Biosphere has a low habitat suitability value. The final analysis downscaled the Region of Interest (ROI) to focus on the VBR area of the Makhado and Thulamela local municipalities. The SLR produced some exciting results with the potential distribution of both *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, showing the area along with the Soutpansberg mountain range as more suitable for establishing both species. However, the results illustrate that the distribution of *Caesalpinia decapetala* covers more area further west and east of the downscaled region of interest (ROI) than *Eucalyptus camaldulensis*.

SDM presents ecologists with powerful techniques for modelling invasive species distribution. The improved access to fine-scale spatial information on environmental variables and developments in SDMs based on presence data has enabled ecologists to define broad ecological conditions suitable or unsuitable for species over large

geographic regions. The outcomes of this study indicate that the potential distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* globally and locally VBR as facilitated by environmental conditions is vast. The study identified the environmental factors favourable to *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR. The study also established that MaxEnt has more robust predictions than stepwise linear logistic regression, as reported by other studies. The potential invasion maps developed in this study can assist in developing and implementing mitigation measures to minimise the *Caesalpinia decapetala* and *Eucalyptus camaldulensis* in the VBR.

The study on modelling the spatial distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* led to several recommendations suggesting the implementation of MaxEnt and its possible applications for methodological research. However, it is essential to note that the subsequent conclusions may also apply to similar situations; the results from this study document *Caesalpinia decapetala* and *Eucalyptus camaldulensis* at a global and local scale by considering occurrence data with few and highly biased localities. However, it is worth noting that results of SDM can vary greatly depending on the regularisation employed, leading to higher performance. In contrast, under the sample-size-independent regularisation approach, intermediate values led to the best performance, like that achieved based on the default values. The feature class selection can also contribute to model variation, thus suggesting using both feature classes with few and highly biased localities if appropriate regularisation is employed. When allowing MaxEnt to consider additional feature classes, more care must be taken to ensure that the model is not overfitting.

The results indicate that even with highly biased geographically or environmentally, variable conditions high-quality models can be made with few localities when appropriate regularisation is used. However, it is essential to note that most SDMs can be improved in certain instances by factoring more localities, with attention being given to localities that are clumped and known or suspected to result from biased sampling; inclusion of higher sample sizes can exacerbate problems associated with these issues. When clumping exists, and sampling bias is imagined as the causal agent, spatial filtering of localities before modelling may lessen its adverse effects. The findings of this study are relevant, and further support the use of ENMs in countless ecological scenarios. It should also be stressed that studies applying a model to

another temporal or spatial coverage may require high transferability. In most cases, even ecological setups that do not involve transferability desire general models that are not overfitted. Common examples of these ecological setups include conservation assessments, macroecological analyses, and applications to many other basic and applied environmental science areas. Amongst these, consideration of the effects of bias and low sample size seems especially pertinent for assessments of the conservation status of invasive alien species, for which only a few localities may exist. Although the present conclusions correspond directly to the commonly used MaxEnt, the same principles also hold relevancy for other modelling techniques.

It is possible to conclude that the logistic regression model is essentially a linear model that demonstrates a direct link between environmental factors and the probability of a species occurrence. As a result, the optimal efficiency of the Logistic and MaxEnt models is in research to investigate a linear connection between the likelihood of species occurrence and environmental factors. Meanwhile, MaxEnt provides response curves to describe the nonlinear correlations between species presence probability and environmental factors. When there is a nonlinear relationship between species presence probability and environmental factors, the MaxEnt model will produce a more accurate prediction than logistic regression. In contrast to logistic regression, the MaxEnt model requires fewer variables to build an appropriate model. After modelling the distribution of IAPS in the VBR Chapter 5 looks at the estimation of water use by IAPS focusing on the Luvuvhu valley catchment in the VBR.

4.17. References

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Chapter 5 : Assessing the effects of Mauritius thorn (*Caesalpinia decapetala*) and River Red Gum (*Eucalyptus camaldulensis*) on water availability in the Luvuvhu catchment in Vhembe Biosphere Reserve.

This chapter is based on: “Dondofema, F., Nethengwe, N., Taylor, P., & Ramoelo, A. (2023). “Assessing the effects of Mauritius thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) on water availability in the Luvuvhu catchment in Vhembe Biosphere Reserve.” Under review.

Abstract

This chapter uses existing remotely sensed Evapotranspiration (ET) products as a proxy for plant water in assessing the effects of Mauritius thorn (*Caesalpinia decapetala*) and river red gum (*Eucalyptus camaldulensis*) on water availability in the Vhembe Biosphere Reserve (VBR). This chapter is based on statistical analyses of selected Food and Agriculture Organisation (FAO) Water Productivity Open-access Portal (WaPOR) products to determine their applicability in estimating water use in the Luvuvhu catchment. The study focused on the WaPOR remote sensing-based products, such as actual Evapotranspiration and Interception (ETIa) and Gross Biomass Water Productivity (GBWP). Analysing the relationship between water loss and biomass productivity products extracted from the FAO WaPOR platform at various spatiotemporal scales shows the two parameters to be correlated. WaPOR products enabled comparing plant water to use by *Caesalpinia decapetala* and *Eucalyptus camaldulensis* within the Luvuvhu catchment. The results show significant inverse positive relationships between ETIa and GBWP in was significantly higher in the absence of *Caesalpinia decapetala* but not *Eucalyptus camaldulensis*. The correlation results indicate that plant water loss (ETIa) and plant productivity (GBWP) show a significant relationship that can be used to understand the distributions of IAPS distribution. ETIa was significantly higher in the absence of *Caesalpinia decapetala*, compared to presence sites (F (60.28) and P (<0.0001)). In contrast, ETIa and GBWP did not vary significantly between presence and absence sites (F (0.85) and P (0.359)). In the case of *Eucalyptus camaldulensis* , ETIa was significantly higher in the presence of this species compared with its absence showed (33.9) and P (<0.001),.but ETIa and GBWP did not vary significantly between the presence and absence of RRG(F=1.59, P=0.212). Establishing the relationship between vegetation's evaporation and biomass components can be broadly used to indicate how *Caesalpinia decapetala* and *Eucalyptus camaldulensis* proliferation affects the water use in the Luvuvhu river catchment. This was achieved using water use as represented by ETIa and plant biomass production in the form of GBWP. Despite temporal and spatial differences in ETIa, the study indicated that was significantly higher in the absence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* increased water use in the eastern Soutpansberg of South Africa.

5.1 Introduction

Invasive alien plants (IAPS) are generally associated with reduced runoff within catchments. Many documented cases of water gains from alien clearing show high levels of water use by these IAPS (Görgens and Van Wilgen, 2004). Similar catchment-level research findings show that IAPS use a large quantity of water, reducing streamflow (Dye & Bosch, 1999). This study uses remote sensing (RS) derived datasets to estimate the adverse impacts of IAPS on water flows across the Luvuvhu catchment in the Vhembe Biosphere Reserve (VBR). This was achieved using presence and absence data with a 250m spatial resolution for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* to extract relative water use by IAPS using RS grids as proxies to plant water use.

FAO WaPOR RS grids with spatial resolution varying from 250m to 1 km were used to estimate water use by *Caesalpinia decapetala* and *Eucalyptus camaldulensis* across the Luvuvhu catchment. The high evapotranspiration (ET) rates associated with IAPS are generally related to increased plant water use, posing significant water security threats (Le Maitre et al., 2013). However, it is crucial to disclaim possible outputs from studies like this, as the estimates are generally conservative because of common underestimations of IAPS impacts.

Riparian areas, especially wetlands, store floodwater slowly after the rain has fallen, thus regulating flows within catchments; however, invasive plants threaten these regulatory services (Rai and Singh, 2020). *Caesalpinia decapetala* and *Eucalyptus camaldulensis* are common IAPS in the Luvuvhu catchment of the VBR. There are several techniques for quantifying the effects of IAPS on water resources (Savage et al., 2004). These methods are broadly categorised as measuring techniques and modelling approaches and are often used at both the plant and catchment levels. This study used comparative spatial statistics to estimate plant water use by the IAPS derived from spatial resolution ranging from 250m to 1Km RS inputs, given the narrow size of riparian areas.

5.2 Evapotranspiration (ET) as a measure of plant water use

Approximately 99.9 per cent of the water consumed by plants is obtained via the plant roots and lost through leaf transpiration. Roughly 0.1 per cent of all water taken in by

plants is utilised to generate plant tissue. ET from plants or landscapes during an entire growing season has a unique direct link with seasonal water consumption (Hartfield & Dodd, 2019). This indicates that monitoring ET within certain geographical extents can help manage catchment water. The hypothesis for Water Use Efficiency (WUE) is based on plant growth increasing with increasing water use. Increasing WUE will require increased plant water use, as illustrated in Figure 5.1. Plant water usage and ET are based on physiological, morphological, and weather conditions (Kimball, 2007). Primary weather variables that affect ET are:

- Sunlight (solar radiation)
- Air temperature
- Relative humidity
- Wind speed

These meteorological elements determine how much energy is available to evaporate water and cause transpiration.

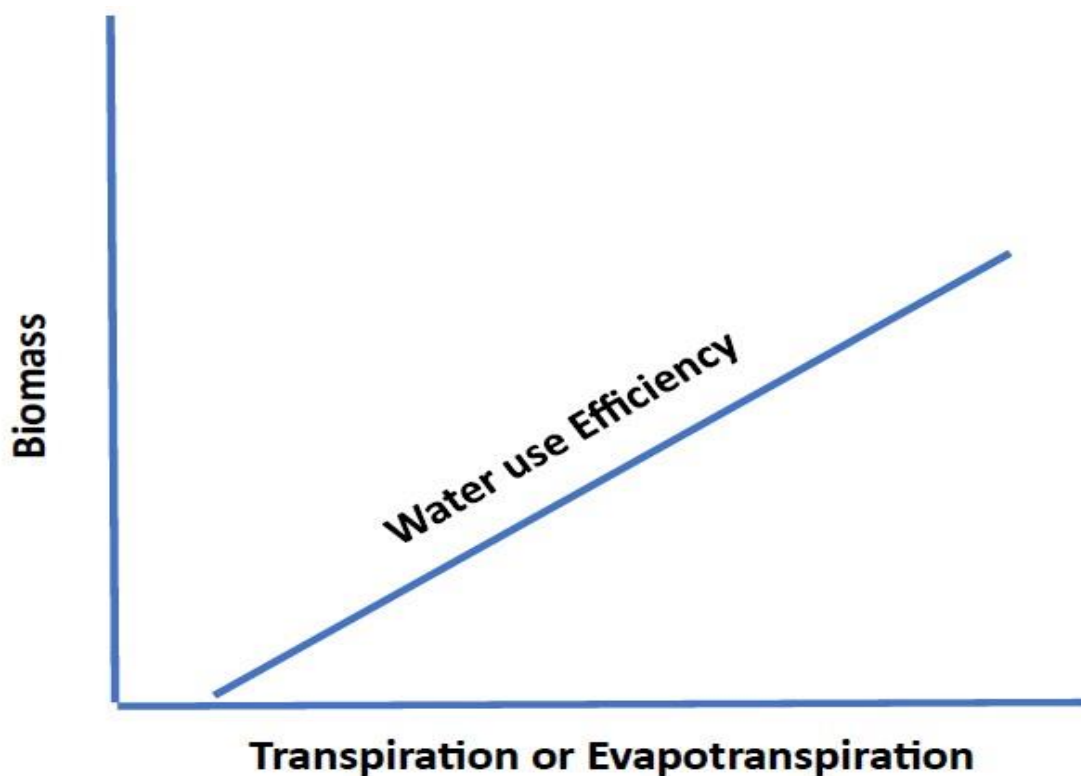


Figure 5-1: An illustration of water usage efficiency as a function of plant water use relative to biomass or grain yield (Hartfield & Dodd, 2019).

5.3 Conventional techniques used in ET estimation.

Several conventional methods exist to estimate ET at the field scale (Jarman et al., 2009). In South Africa, standard ET assessing methods, including the Bowen ratio

(BR), eddy covariance (EC), surface renewal (SR), scintillometry (Sy), and lysimeter (Ly) systems, have been evaluated and widely used (Savage et al., 2004). Of all these methods, only scintillometry integrates spatial trends in ET. These models can estimate ET at the catchment scale using point rather than grid data. However, others employ techniques to disaggregate point data for spatial representation. This study uses remote sensing data derived from the WaPOR datasets.

5.3.1 Bowen Ratio (BR)

Bowen's ratio approach partitions the energy balance by measuring vertical air temperature and humidity gradients (Bowen, 1926). The energy balance of the underlying surface is used to calculate the BR for flux measurement. The Bowen ratio method of flux determinations is usually applied to potentials averaged for half to one hour.

5.3.2 Eddy Covariance (EC)

Eddy covariance is a prominent micrometeorological approach for directly observing gas flow, energy, and momentum between the Biosphere and atmosphere. Due to the direct measurement of water vapour exchange between the atmosphere and plant canopy, the EC approach is the most trustworthy of all other methods for estimating ET.

5.3.3 Surface Renewal (SR)

Higbie (1935) created the SR theory from the discipline of chemical engineering to examine interfacial heat transfer between a liquid and a gas. Based on the scalar conservation equation (Paw et al., 1995; Castellvi, 2009), surface renewal analysis estimates scalar exchange at the vegetation-atmosphere interface, as Stull (1984) identified.

5.3.4 Scintillometry (Sy)

Scintillometer readings are based on the scintillation hypothesis; sensible heat induces atmospheric turbulence near the ground, and surface evaporation causes refractive index changes due to air temperature and humidity fluctuations (Hill et al., 1980). The strength of the refractive index variation is proportional to the sensible and latent heat fluxes.

5.3.5 Lysimeter (Ly)

Lysimeter is an instrument for measuring water content change in the soil. A lysimeter consists of an isolated soil block nearly identical to the surrounding soil in its physical and chemical properties. And momentum fluxes Lysimeters can be weighed to determine the amount of water added to them by precipitation or irrigation and removed by evapotranspiration (Jensen et al., 1990). Lysimeters are expensive devices, but since they provide the only absolute measure of mass transfer from a nearly natural part of the Earth's surface, their use is essential in micrometeorology.

5.4 Considerations when assessing water use by invasive alien species

To fully address the consequences of IAPS on available water resources requires an integrated approach. It involves many species, often occurring as mixes of variable densities throughout various temperatures and access to groundwater and surface water. One method commonly used to measure the variability in plant water use at broad geographical scales involves RS data to estimate evapotranspiration from invasive alien plants and compare it to estimates of evapotranspiration from native vegetation.

The study used the FAO WaPOR. Statistical inference was used to extrapolate annual Gross Biomass Water Productivity (GBWP) (kg/m^3 , 250m (0.00223 degrees) and 32bit Integer), annual actual Evapotranspiration and Interception (ETIa) (mm, 250m (0.00223 degrees) and 32bit Integer), monthly Precipitation (PCP) (mm, 5km (0.05 degree) and 16bit Integer) and monthly Reference Evapotranspiration (RET) (mm, 20km (0.17 degree) and 16bit Integer).

It should, however, be noted that the RS approach has some shortcomings (i.e., the impact of clouds, resolution of images in time and space, requirements for verification on the ground), but also the potential to quantify and compare the water resource impacts of a diverse range of IAPS over a vast region in a consistent manner. As spatial and temporal resolutions improve, RS applications become more robust and helpful.

5.5 The use of RS to estimate potential water use by IAPS.

In all biomes of South Africa, it is evident that IAPS do not exist in isolation but as mixed stands with natural vegetation. Several studies have been conducted on a regional and worldwide scale to monitor water usage patterns of co-occurring native vegetation to assess the water demand by IAPS compared to native vegetation (Dzikiti et al., 2016). RS data may be used to quantify ET from IAPS and compare it to current ET estimates from native vegetation, allowing for an assessment of variability at broad geographical scales. The ET algorithm based on RS has been developed in various complexity levels (Verstraeten et al., 2008).

This research consequently applied various earth observation geographical information systems (GIS) and remote sensing (RS) techniques to model actual ET-derived measurements of water use and loss (Gross Biomass Water Productivity (GBWP), actual Evapotranspiration and Interception (ETIa), Precipitation (PCP) and Reference Evapotranspiration (RET) as surrogates to water use by IAPS. RS surrogates have several limitations that include but are not limited to reduced accuracy due to clouds, effects of image resolution, both spatial and temporal, and the need for ground-truthing. However, RS provides an excellent platform for consistently estimating the water resource impacts of a wide range of IAPS over a large area and comparing them with other land cover classes (Meijninger and Jarman, 2014).

Evapotranspiration is the most challenging but necessary component to quantify in the hydrological balance cycle (Gibson et al., 2013). The global evaluation, quantifying water loss from vegetation is essential for plant growth at the local level (Nouri et al., 2015). Plant ET monitoring is becoming increasingly critical in understanding plants' complex water consumption and management. Understanding the interactions between land surfaces and the atmosphere requires estimating temporal and geographical changes in ET using RS data (Mu et al., 2007). Different RS-based ET estimation approaches have been grouped into four broad categories by several reviews: (i) parameterisation of the energy balance, (ii) Penman-Monteith formulation, (iii) water balance, and (iv) vegetation index/land surface temperature relationships which will be used for this study. Evapotranspiration algorithms based on RS have recently been developed to cover a need to estimate vegetation water use spatially

and temporally (Allen et al., 2007). The RS technique has potential (Jha and Chowdary, 2006) as it is a cost-effective option for providing frequent data on a somewhat wide scale, allowing long-term monitoring of vegetation water use at local and regional scales. Several conventional methods exist to estimate ET at the field scale, as illustrated in Table 5-1.

Table 5-1: Different methods for estimating ET. Their usefulness in vegetation water use across various spatial and temporal scales was assessed using historical and literature reviews to summarise some studies conducted in South Africa.

Type	Study focus	Parameters	Temporal scale	Spatial scale/resolution	Reference
Review	Methodology	ET, energy balance	Instantaneous, day, week, month	Field / 30 m	Jarman et al. (2009)
Historic	Catchment water use efficiency	ET	Day, 2-weekly for three years	Field, catchment / 250 m	Hellegers et al. (2011)
Historic	Natural veld water use	ET	Day, season, annual	Regional / 1 km	Palmer and Weideman (2011)
Historic	IAP, natural veld water use	ET, rain, rain-ET	Day, two-weekly for 3 years	Provincial / 250 m	Jarman and Meijninger (2012)

Various studies in South Africa have explored possible uses of RS-based approaches to improve water resource management (see Table 5-1). Table 5-1 further demonstrates how the research on ET has been done based on a literature review and how the use of historic estimations of ET can be applied to near real-time data. Notable studies include the assessment done by Jarman et al. (2009) using ET and energy balance.

Palmer and Weideman (2011) researched natural veld water use historically. Jarman and Meijninger (2012) analysed the effects of IAPS on ET, the availability of water resources in the Western Cape and KwaZulu-Natal provinces, and the clearing of IAPS by the Working for Water (WfW) Programme. Similar studies produced similar conclusions after combining spatial ET data with information about land use to determine the ET of IAPS. Higher-resolution data (>30 m) would better analyse the influence analyse IAPS on ET across a more extensive range of invasion densities

and water regimes, including riparian zone, than the medium to coarse resolution data (>250 m) data similar resolution to some WaPOR grinds used in this study.

5.6 Materials and Methods

5.6.1 Study Area

The invaded area ratio used by Bezeng et al. (2020) was adopted to put the study into context. A map showing the invasion rate in the Luvuvhu catchment was generated to highlight how invasive alien species can potentially impact the catchment, as highlighted in Figure 5-2.

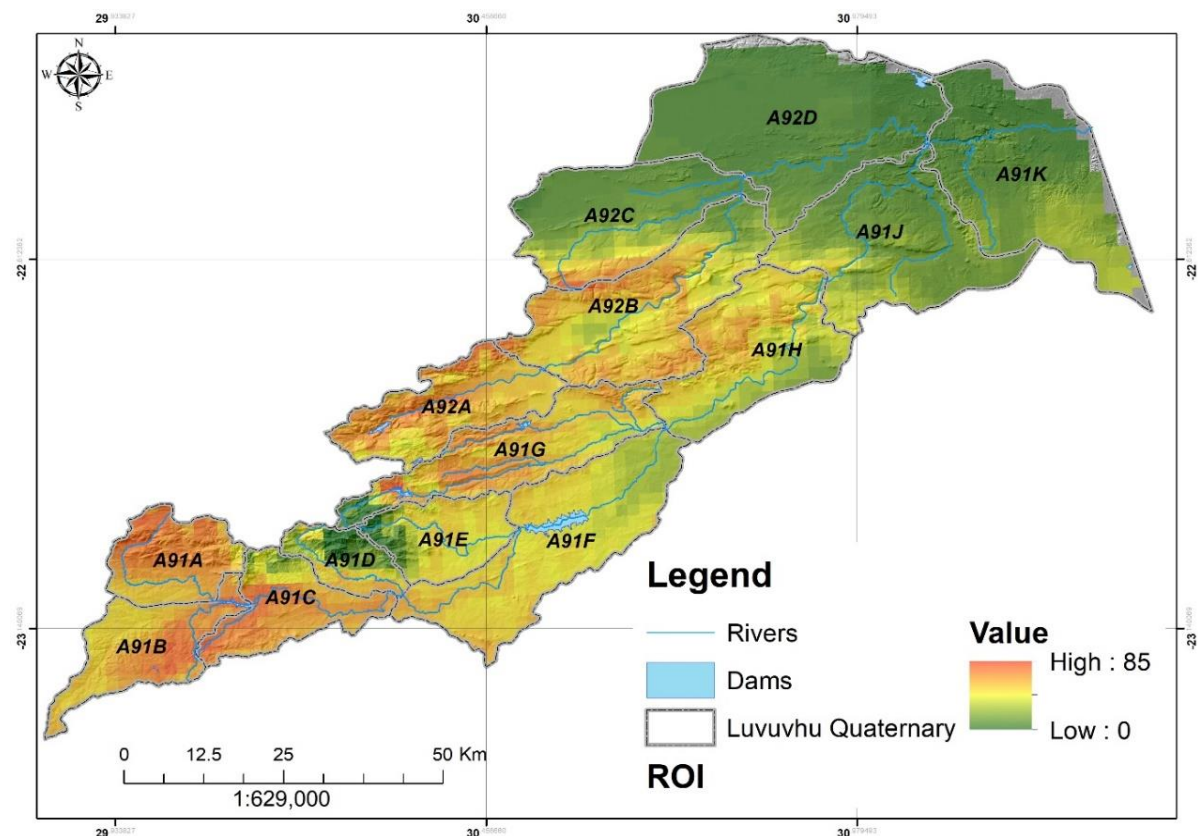


Figure 5-2: Luvuvhu catchment map showing the Risk of Invasion (ROI) (Kumschicknet al., 2020)

A map of the Normalized Difference Vegetation Index (NDVI) for the Luvuvhu catchment using the FAO's WaPOR website NDVI data product, as shown in Figure 5-3.

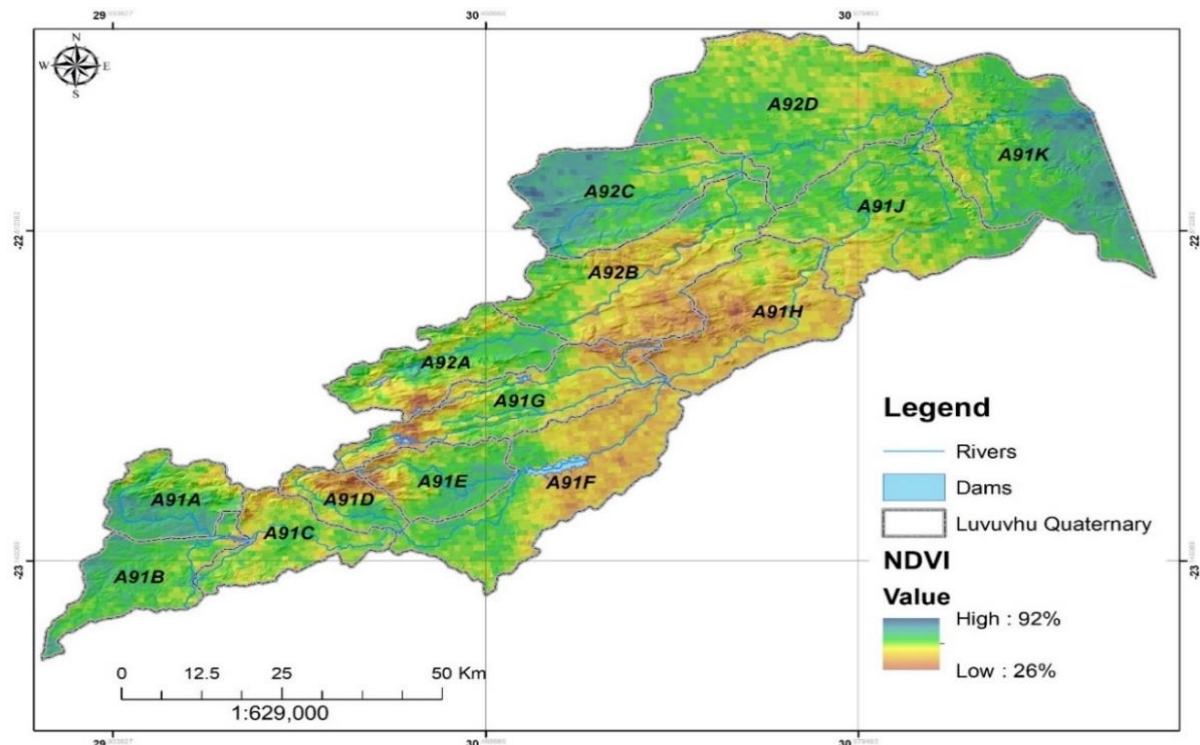


Figure 5-3: Luvuvhu catchment map showing the actual Normalized difference vegetation index (NDVI)

A map of the actual Evapotranspiration and Interception (ETI) for the Luvuvhu catchment was created using the FAO's WaPOR website ETIa data product, as shown in Figure 5-4.

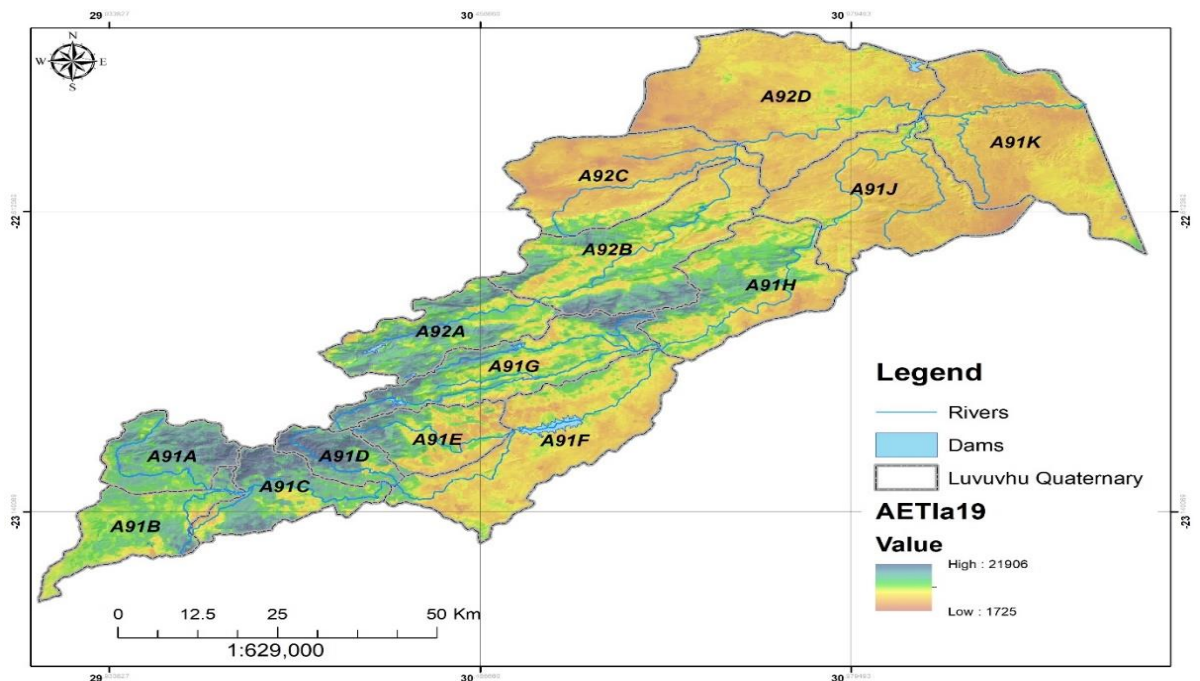


Figure 5-4: Luvuvhu catchment map showing the actual Evapotranspiration and Interception (ETIa)

A map of the Annual Precipitation (PCP) for the Luvuvhu catchment was created using the FAO's WaPOR website PCP data product, as shown in Figure 5-5.

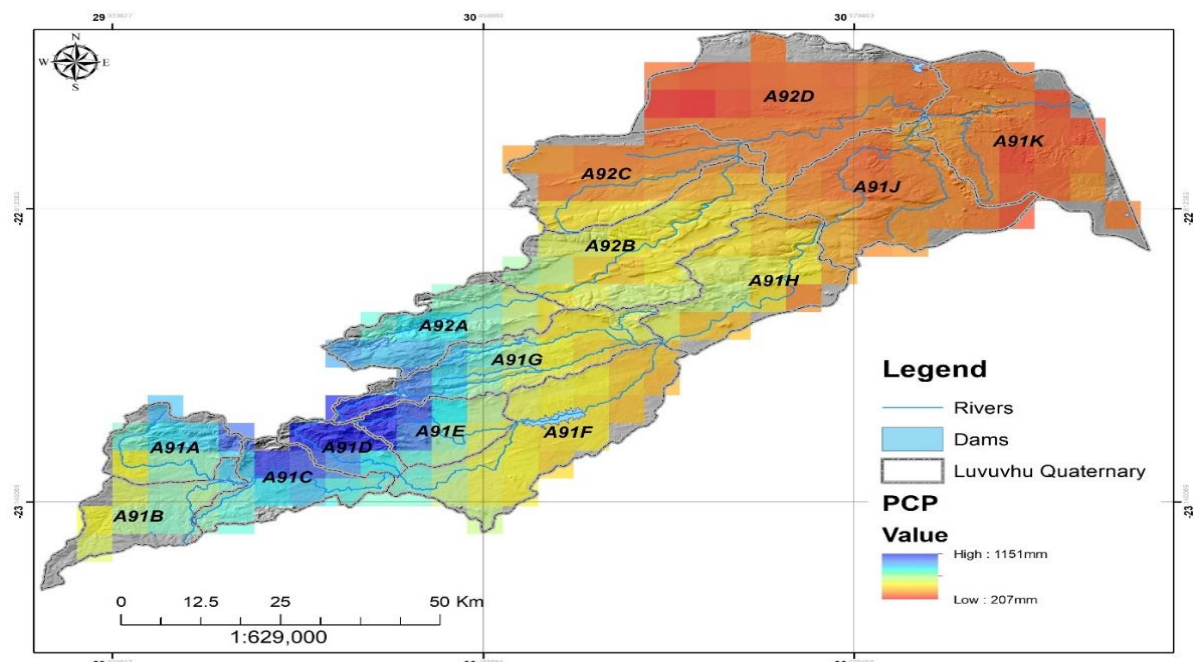


Figure 5-5: Luvuvhu catchment map showing the Annual Precipitation (PCP) for 2019.

The experimental site was selected in the Vhembe Biosphere Reserve (VBR), covering the Luvuvhu catchment in the Limpopo province Figures 5-6 and 5-7), and micrometeorological measurements were collected from the FAO WaPOR portal. The data collection focused on the quaternary catchments A91A, A91D, and A91E.

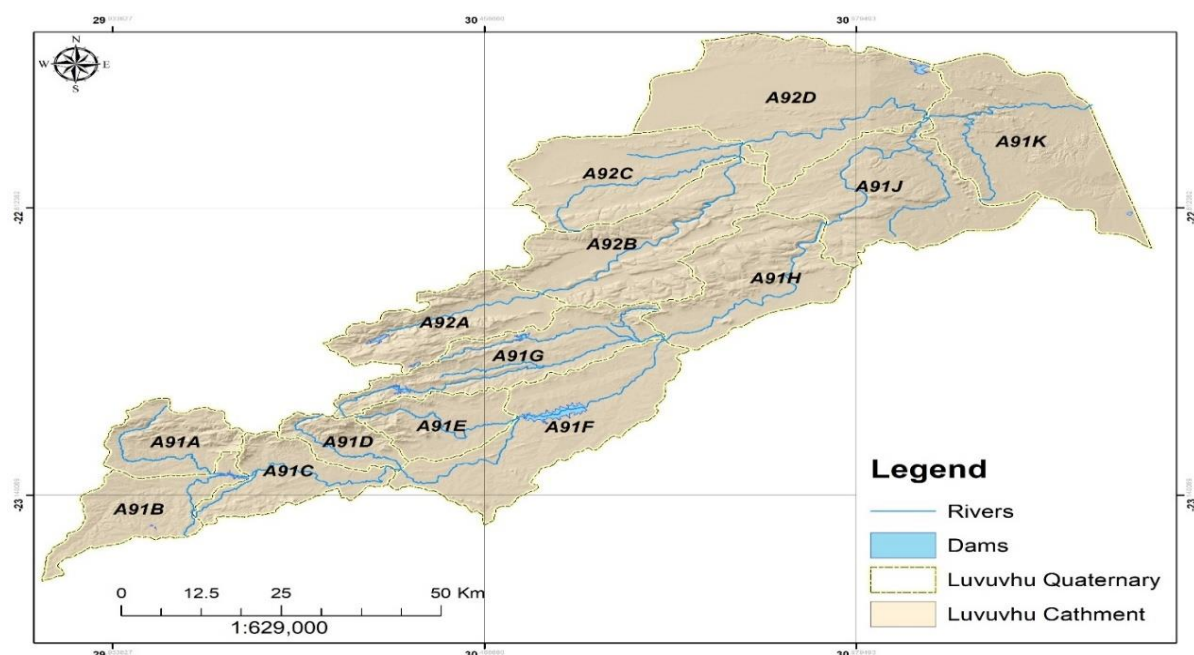


Figure 5-6: Luvuvhu catchment map showing the quaternary catchment rivers and dams.

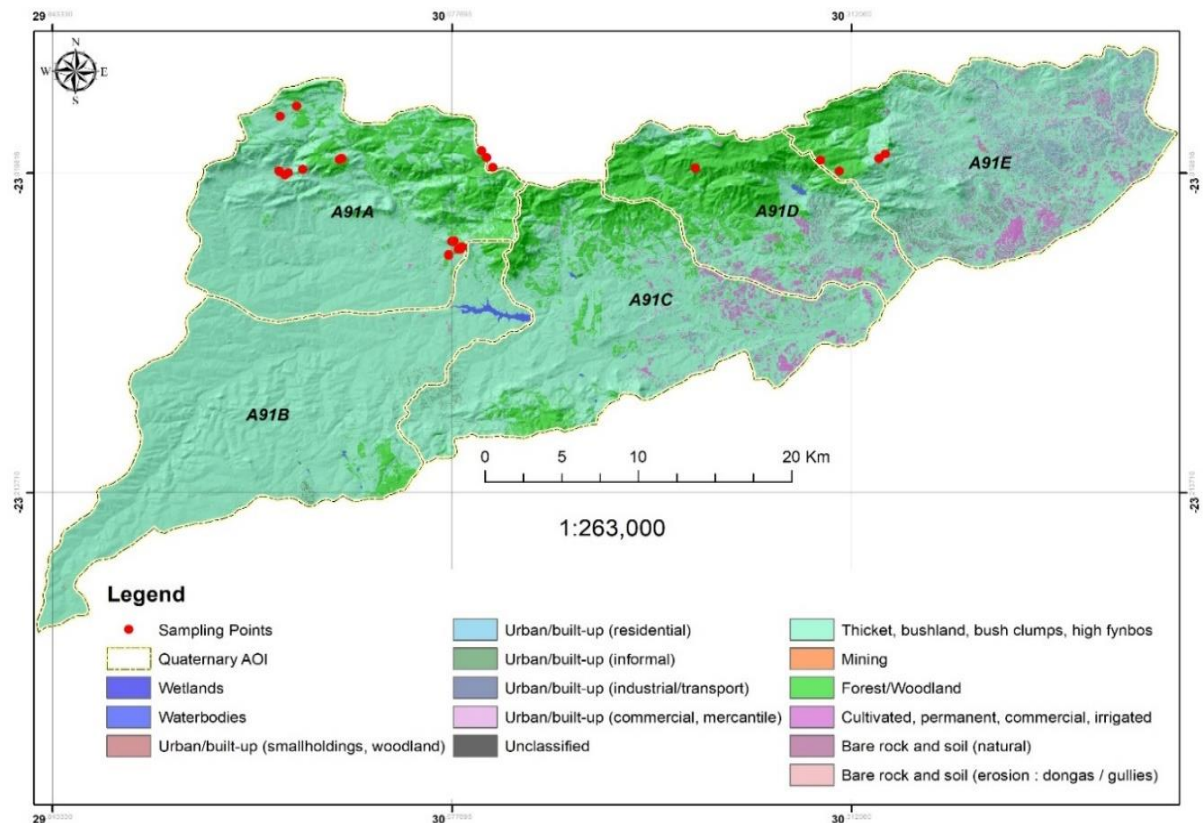


Figure 5-7: The selected area sampled in the Luvuvhu catchment (Quaternary catchment A91A, A91D, and A91E)

The study site lies in the Savanna Biome, covering the Cathedral Mopane Bushveld, Granite Lowveld, Gravelotte Rocky Bushveld, Ironwood Dry Forest, Limpopo Ridge Bushveld, Lowveld Riverine Forest, Makhado Sweet Bushveld, Mopane Basalt Shrubland, Musina Mopane Bushveld, Northern Mistbelt Forest, Nwambyia-Pumbe Sandy Bushveld, Sand Forest, Soutpansberg Mountain Bushveld, Soutpansberg Summit Sourveld, Subtropical Alluvial Vegetation, Subtropical Salt Pans, Tsende Mopaneveld, Tzaneen Sour Bushveld, and VhaVenda Miombo (Figure 5-8) (Mucina et al., 2006).

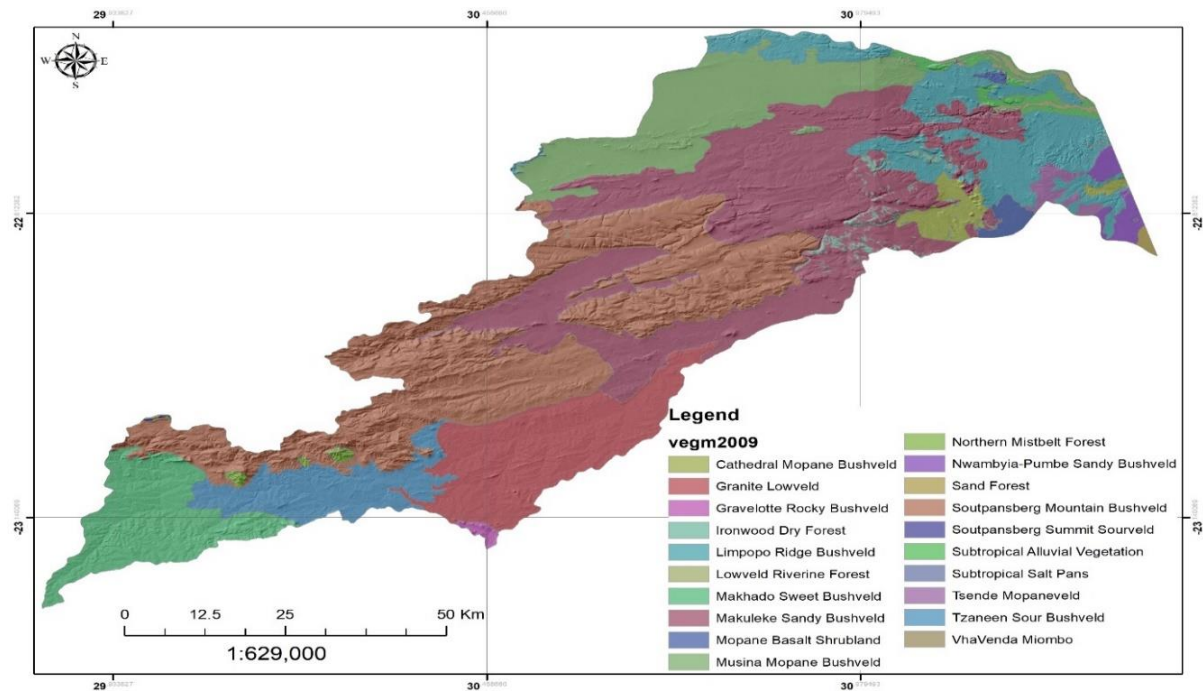


Figure 5-8: Vegetation types of the Luvuvhu catchment in the VBR (Mucina & Rutherford, 2006)

A field campaign approach was adopted, collecting presence and absence data at Seventy-two (72) sites for *Eucalyptus camaldulensis* and seventy-eight (78) sites for *Caesalpinia decapetala*.

5.7 Pixel selection

Seventy-two (72) pixels for *Eucalyptus camaldulensis* (39 presence and 33 absence points) and seventy-eight (78) pixels for Mauritius thorn (32 presence and 46 absence) over periods of five (5) years were selected and extracted from GBWP, ETIa, and RET maps. The pixels were in the centre of each presence point for each overpass, covering a period from 2009 to 2021. GWP was downloaded annually from 2009 to 2020, ETIa was downloaded quarterly from 2017 to 2021, Total Biomass Production (TBP) was available annually from 2014 to 2020, and RET was downloaded quarterly from 2015 to 2021. It was assumed that the pixels represent the entire *Eucalyptus camaldulensis* and *Caesalpinia decapetala*. The number of pixels per year is presented in Table 5-2.

Table 5-2: The year and several pixels selected throughout the years of analysis.

Year	GBWP	AETI	TBP	RET
2009	150			

2010	150			
2011	150			
2012	150			
2013	150			
2014	150		150	
2015	150		150	450
2016	150		150	450
2017	150	450	150	450
2018	150	450	150	450
2019	150	450	150	450
2020	150	450	150	450
2021		150		150

5.8 Pixel value extraction

The raster values, such as GBWP, ETIa, TBP, and RET, were extracted to point features to identify data at specific locations. For example, to determine the GBWP (kg/m^3) (Equation 5-1), at designated catchment areas. The Extract Raster values tool in ESRI ArcGIS 10.8.3 was used to extract cell values from the four raster layers at places specified in a point feature class and to save them to the point feature class's attribute table. The ESRI ArcGIS 10.8.3 Spatial Analyst extension provides numerous tools for converting raster data to points; for this study, the Extract Multi Values (EMV) to Points tool was employed.

5.9 Procedure

ESRI ArcGIS 10.8.3's Spatial Analysts Extract Multi Values was used to extract values of the multiple raster layers to the input point layer of presence and absence for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. The extracted values were converted to Microsoft Excel using the ESRI ArcGIS 10.8.3 Conversion tools.

5.10 Use of Water productivity components

This study used the water productivity components, i.e., biomass and water consumed, using ETIa. ETIa is a highly significant predictor of the net annual aboveground productivity in mature terrestrial plant communities. It is hypothesised that a positive correlation exists between ETIa and plant productivity since ETIa measures the simultaneous availability of water and solar energy and is the most critical rate-limiting resource in photosynthesis. Water consumption occurs through evapotranspiration, the sum of plant transpiration through the stomata in the leaves, evaporation from the soil surface, and intercepted water by the leaves (Squire, 2004). The equation used ET because it represents downstream users who cannot re-use the water balance component in the Luvuvhu River catchment context. As such, water productivity can be expressed as:

$$\text{Equation 5-1: GBWP [kg/m}^3\text{]} = \frac{\text{TBP [kg]}}{\text{E+T+I [m}^3\text{]}}$$

Where:

- GBWP: Gross Biomass Water Productivity
- TBP: Total biomass production
- E: Evaporation
- T: Transpiration
- I: Interception

$$\text{Equation 5-2: PSWP [kg/m}^3\text{]} = \frac{\text{PHY [kg]}}{\text{SET [m}^3\text{]}}$$

Where:

- PSWP: Plant-specific water productivity
- PHY: Plant harvestable yield
- SET: Seasonal Evapotranspiration

Therefore, this study assumed that the ETIa can be used as a proxy of plant water productivity or performance indicator to monitor changes in a catchment. In that case, plant-specific water productivity (PSWP) (Equation 5-2) could indicate the effectiveness of the interventions that positively or negatively impact the use of water or remain unchanged. In addition, spatial information on water productivity can show higher performance areas.

5.11 Food and Agriculture Organisation (FAO) programme on water productivity open access portal (WaPOR) data

The meteorological information was taken from the FAO WaPOR global data repository. The FAO WaPOR provides RS-derived data for water productivity monitoring. The WaPOR site also considers ecosystems and the equitable use of water resources, reducing total water stress. Through improved data availability to sectors, this technology delivers near-real-time pixel information, assisting conservationists in gaining more reliable production information. The WaPOR platform provides water and land productivity data at three spatial levels. For this study, Level I and II data was used:

- **At level I (continental level - 250 m ground resolution)**, water productivity is measured in biomass output per hectare per cubic meter of water consumed. Agriculture is classified as either irrigated or rainfed. Land and water production are calculated at the pixel level and aggregated to the country or river basin level.
- **At level II (national and sub-national level - 100 m ground resolution)**, The WaPOR platform monitors land and water production for a small group of nations and river basins. Land productivity is measured in yield (kg/ha) on this platform, whereas water productivity is measured in production per volume of water (kg/m³).
- **At level III (irrigation scheme and sub-basin - 30 m ground resolution)**, Land and Water productivity is calculated similarly to level II. Furthermore, water productivity is assessed for economic return per acre for diverse water applications. Indeed, water productivity is essential in evaluating irrigation performance, which serves as the foundation for irrigation modernisation. Water services given to all consumers should be more dependable, cost-effective, adaptable to increased climatic unpredictability because of climate change, and ecologically friendly. The pixel size of the WaPOR datasets at different levels is illustrated in Table 5-3.

Table 5-3: The table below shows how the pixel size (expressed in m) varies with increasing latitude.

Dataset	Degrees	Equator Lat/Lon (m)	Lat/Lon (m) at 20° n/s	Lat/Lon (m) at 40° n/s

level 1	0.00223	246.6/248.2	246.9/233.4	247.6/190.4
level 2	0.000992	109.7/110.4	109.8/103.8	110.1/84.7
level 3	0.000268	29.6/29.8	29.7/28.0	29.8/22.9

It's worth noting that the data components are general historical data from 2009 to April 2019, followed by a phase of continuous near-real-time (NRT) processing. The NRT data components should be preliminary and released five days after a dekad (6 dekads). The final version of the dekadal dataset has a higher quality since gap-filling and interpolation techniques, when necessary, were based on more data observations.

5.12 Theoretical Background

5.12.1 WaPOR data components

Three WaPOR products were used to analyse IAPS water use in this study. These are GBWP, E, T, I, TBP, and RET. The following section discusses the products to illustrate the combined metrological components to form each product.

5.12.2 Gross biomass water productivity (GBWP)

The GBWP measures the amount of biomass produced about the total amount of water utilised over a specific time (FAO, 2016). This indicator provides insights into the impact of plant growth on consumptive water use and, consequently, on the water balance in each domain by connecting biomass output to total evapotranspiration, which is the sum of soil evaporation canopy transpiration and an interception. Figure 5.9 illustrates the components of GBWP.

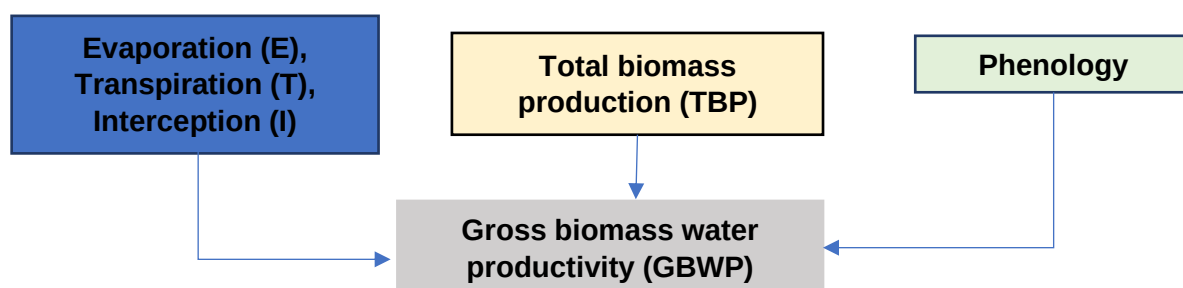


Figure 5-9: Gross biomass water productivity about other data components

TBP, E, T, and I, and phenology, when computed on a seasonal time step, are all required inputs for calculating Gross biomass water productivity (GBWP). To calculate

GBWP, no external data is necessary. This is the only data component that produces the output. The calculation of Gross Biomass Water productivity is as follows in equation 5-3:

Equation 5-3:
$$GBWP = \frac{TBP}{E+T+I}$$

Where:

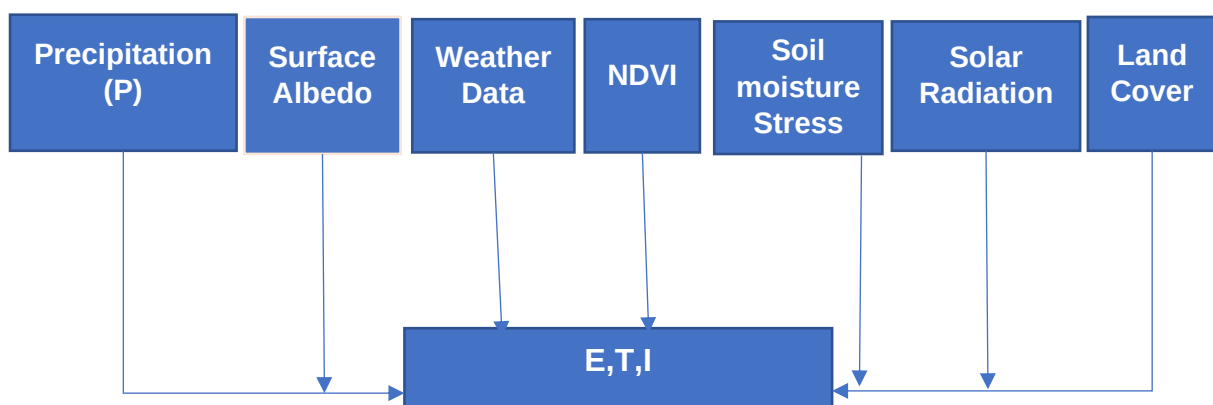
- **TBP** is total biomass production in kgDM/ha,
- **E** is evaporation,
- **T** is transpiration and
- **I** is interception, all in mm.

5.13 Evaporation, transpiration, and interception

Rainfall collected by the leaves of plants and evaporated straight from their surface is referred to as interception. Climate conditions, such as wind speed, radiation, and air temperature, limit evaporation, transpiration, and interception, while soil moisture content represents soil conditions. The sum of the three parameters, ETIa, can calculate plant water use.

Combining biomass output or yield allows for the calculation of agricultural water productivity. At all three levels, evaporation, transpiration, interception, and ETIa are supplied on a dekadal basis, with pixel values representing average daily E, T, I, and ETIa values in mm/day for that specific dekad. All external input data sources have lesser resolution than the optical satellite data, which is provided in three spatial resolutions: Level 1 (250 m), level 2 (100 m), and level 3 (30m). As a result, the spatial variability of these data sources is reduced, impacting the E and T data component.

E and T were calculated using the ETLook model supplied by Bastiaanssen et al. (2012). ETLook employs the Penman-Monteith (P-M) equation, modified to accommodate RS data. The Penman-Monteith equation (Monteith, 1965) estimates



total evaporation and transpiration using frequently recorded meteorological data. Figure 5-10 illustrates the components of E, T, and I.

Figure 5-10: Evaporation, transpiration, and an interception with other data components.

Seven data components must be entered to calculate E, T, and I. Daily inputs include sun radiation, meteorological information, and precipitation. Dekadal inputs include soil moisture stress, Normalized Difference Vegetation Index (NDVI), and surface albedo. I only require input from NDVI and Precipitation. Surface roughness and minimal stomatal resistance are calculated using land cover input. E, T, and I are calculated without any external data sources. Water productivity and land cover categorisation employ E, T, and I as inputs. E, T, and I are computed on a decadal basis.

5.14 Total biomass production (TBP)

TBP is the total amount of dry matter generated by plants throughout the growing season. As a result, TBP progressively rises between the start of the season (SOS) and the end of the season (EOS). TBP is an excellent indicator for estimating plant production because it incorporates three essential factors: present vegetation status (through fAPAR), weather effects (by Dry matter productivity (DMP)), and 'history' (via the summation throughout the season). TBP is generally measured in kgDM/ha and varies between 0 to 45; higher values are conceivable. The TBP's accuracy is directly connected to the NPP's accuracy since it integrates the DMP over time. TBP is used as an input to WaPOR when calculating the GBWP.

TBP is given on a seasonal basis for levels 2 and 3. The seasonal value indicates the accumulated biomass from SOS to EOS throughout a growing season. The reliance on phenological data limits the ability to calculate seasonal TBP, which means TBP can only be derived for locations where seasonality has been identified. For ecosystems with slight seasonal variation, such as tropical woods or deserts, the



season begins on January 1st and ends on December 31st. Figure 5-11 illustrates the components of TBP.

Figure 5-11: Total biomass production of other data components

TBP is calculated using NPP inputs for dekadal biomass production and phenology for growing season delimitation (at levels 2 and 3) using equation 5.4. There is no need for an external data source. Levels 2 and 3 produce seasonal production, whereas Level 1 has yearly output.

Equation 5-4: $TBP_s = \sum_{i=SOs}^{EOS} Nd(i) * DMP(i)$

Where:

- DMP(i) is the dry matter production at dekad i, expressed in kgDM/ha/day.
- Nd(i) is the number of days within each dekad, varying between 8 (end February) and 11.
- The first term, $\sum Nd(i)$, is needed to obtain the TBP sum in kgDM/ha. Without it, one would obtain the mean.

Table 5-4: Overview of TBP data component

Data component	Unit	Range	Use	Temporal resolution
TBP	KgdM/ha	0-20,000 for seasonal, 0-35,000 for annual	Total dry matter produced. It can derive yields if the information on phenology and crop parameters is available.	Seasonal, annual, or user defined (cumulated NPP on the period of interest)

5.15 Data extraction

The statistical analysis aimed to identify similarities and differences between the WaPOR datasets. The relative agreement (Correlation) and analysis of variance were considered. The pixels of ETIa annual data were transformed to the Luvuvhu catchment spatial pattern and resolution to compare with the GBWP of the WaPOR platform. The process was to use the Luvuvhu catchment as a cookie cutter for the WaPOR ETIa and GBWP pixel to extract the spatial mean of geographically coincident data (ESRI, 2020). The extracted annual datasets were used to show the effectiveness of using ETIa as a surrogate to estimate the potential water use by *Caesalpinia decapetala* and *Eucalyptus camaldulensis* data.

ETIa, GBWP, Precipitation, and RET estimates were aggregated at the catchment scale for each year (2017-2020) to explore the general water use behaviour at the catchment level. In this study, the GBWP represented the plant water use for the Luvuvhu catchment, a derivative of ETIa dynamics within the catchment. ETIa was extracted for the Luvuvhu catchment for the study period (4 years) to study the temporal variations between years. In addition to these variables, two ancillary variables were incorporated to aid in interpreting the material behaviour of the ETIa estimates. These variables were: WaPOR, GBWP and RET.

Due to its similarity to the NDVI, the GBWP was selected as an independent tool to analyse plant phenology and understand its role in plant water use calculation. ETIa, in this case, is treated as a proxy for vegetation water use, where higher values relate either to surface water (not occurring in the study area) or to the water captured by surface vegetation (interception). Higher ETIa represents healthier vegetation storing water in its leaves and green tissue in the latter case. A similar response to the NDVI is expected, with higher values meaning that the plant has more leaves with available water for transpiration and higher ET rates.

5.16 Data analysis

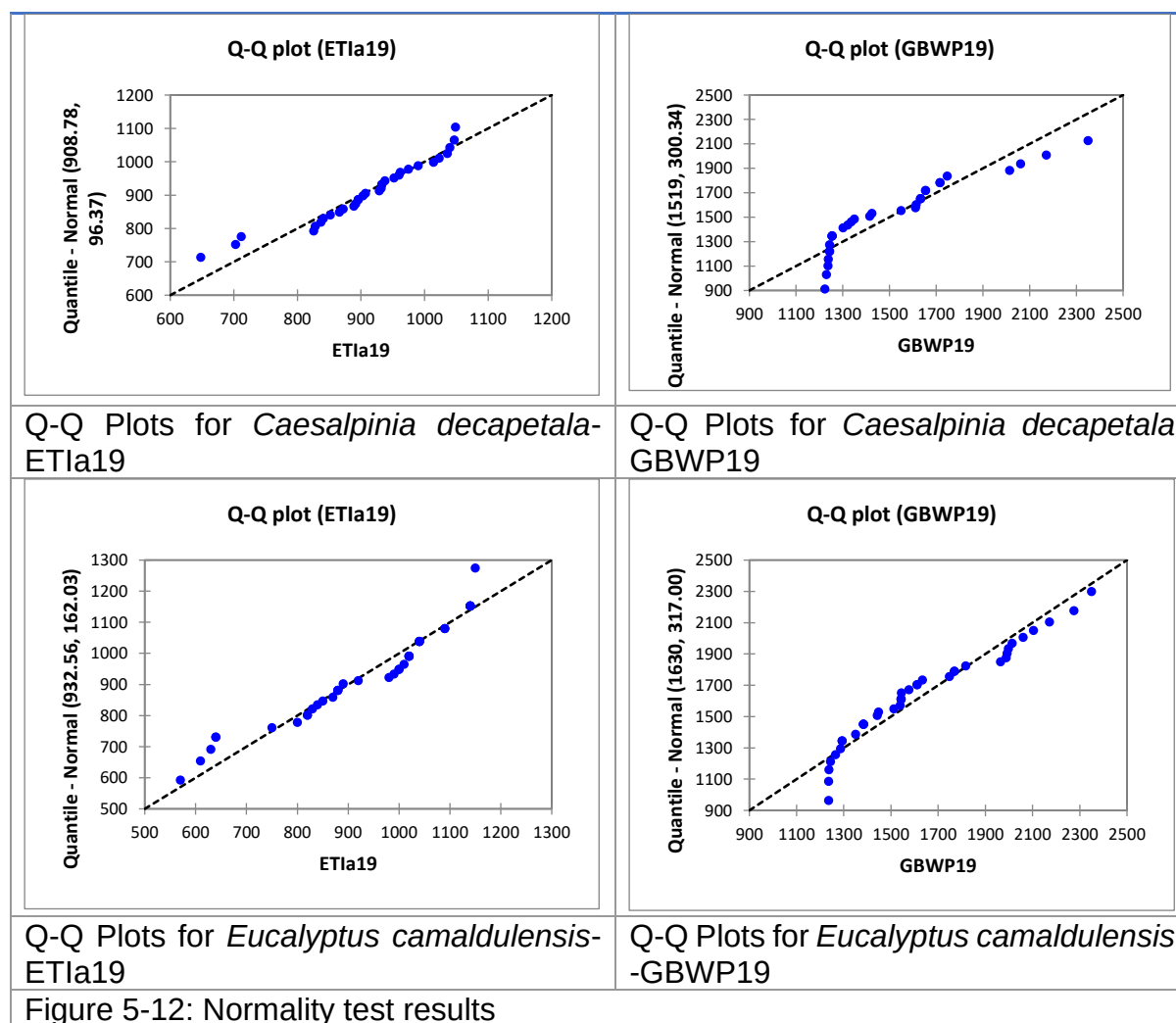
The data analysis included the following:

- Cross-correlations between WaPOR data were performed to analyse coefficients of correlation. Since observations are temporally dependent, a linear regression model was used to test the significance of simple correlation coefficients, which considers the temporal correlation between observation pairs by modelling the residual covariance matrix.
- One-way ANOVA was used to determine how ETIa and GBWP vary between presence and absence sites for *Caesalpinia decapetala*, and the Kruskal-Wallis test was used for *Eucalyptus camaldulensis*.
- To analyse the association between ETIa estimates and GBWP at the catchment level for both AIPs from the spatial WaPOR datasets using Pearson's correlation test (Pearson, 1920).

5.17 Results

5.17.1 Normality tests

To test for conformity to a normal distribution, the two variables from the WaPOR platform data used in this study (ETIa and GBWP) were first plotted using Quantile-Quantile (Q-Q) plots to test for normality of distribution (Fig. 5-12) and then also subjected to the Shapiro-Wilk normality test (Table 5.5) in MINITAB® 21.1.1 (64-BIT).



A Shapiro-Wilk test was used to check if *Caesalpinia decapetala* and *Eucalyptus camaldulensis* occurrence data follow a normal distribution. Since we had a small sample size, determining how the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* affects ETIa and GWBP was important to choose an appropriate statistical method.

Table 5-5: Normality test for ETIa and GBWP data used for analysis

<i>Caesalpinia</i>	<i>decapetala</i>	data	<i>Eucalyptus</i>	<i>camaldulensis</i>	data
Normality Test			Normality Test		

Shapiro-Wilk test (ETIa):		Shapiro-Wilk test (ETIa):	
W	0.972169	W	0.914929
p-value	0.085	p-value	0.000133
alpha	0.05	alpha	0.05
Shapiro-Wilk test (GBWP):		Shapiro-Wilk test (GBWP):	
W	0.9707	W	0.948599
p-value	0.073	p-value	0.0053
alpha	0.05	alpha	0.05

The results from the Shapiro-Wilk normality test show that the data used for the analysis is normally distributed ($p > 0.05$) with test statistics greater than 91 for both variables for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. For this reason, the non-parametric Kruskal-Wallis test was used in place of ANOVA for the RRG samples.

After the normality test, the data was further subjected to a correlation analysis to depict the significance and nature (negative or positive) of the association between the ETIa and GBWP. This was achieved by computing Pearson correlation coefficients for these two variables in the two species in MINITAB® 21.1.1 (64-BIT), as shown in Table 5-6

5.17.2 Correlation of ETIa and GBWP for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*

The correlation analysis of ETIa and GBWP for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* was achieved by computing a correlation matrix in MINITAB® 21.1.1 (64-BIT), as shown in Tables 5-6 and 5-8.

Table 5-6: Pairwise Pearson correlations for *Caesalpinia decapetala*

Sample 1	Sample 2	N	Correlation	95% CI for p	P-Value
AETI19	GBWP19	78	-0.177	(-0.384, 0.047)	0.121

A Pearson's product-moment correlation was run to assess the relationship between ETIa and GBWP for *Caesalpinia decapetala* across 78 sites; there was a negative but non-significant correlation between ETIa and GBWP, $r(78) = -0.177$, $p < 0.121$. Pearson's correlation coefficient is not statistically significant at $p < 0.121$.

Table 5-7: Pairwise Pearson correlations for *Eucalyptus camaldulensis*

Sample 1	Sample 2	N	Correlation	95% CI for p	P-Value
AETI19	GBWP19	72	-0.342	(-0.532, -0.120)	0.003

A Pearson's product-moment correlation was run to assess the relationship between ETIa and GBWP for *Caesalpinia decapetala* Across 72 sites. There was a negative correlation between ETIa and GBWP, $r(72) = -0.342$, $p < 0.003$. Pearson's correlation coefficient is statistically significant at $p < 0.003$.

5.17.3 One-way ANOVA for ETIa and GBWP for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*

A one-way ANOVA was used to determine how ETIa and GBWP vary between presence and absence sites for *Caesalpinia decapetala*, and the Kruskal-Wallis test was used for *Eucalyptus camaldulensis*. This is where we decide whether the ETIa and GBWP bring significant information to the model. The results of the One-way ANOVA analysis are presented in Tables 5-8 to 5-11, and the K-W test in Tables 5-12 to 5-13.

Table 5-8: One-way ANOVA for ETIa versus site of *Caesalpinia decapetala*

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Site	1	1653077	1653077	60.28	0.000
Error	76	2084013	27421		
Total	77	3737089			

Because the p-value is less than the significance level of 0.05, we can reject the null hypothesis and conclude that the presence and absence of data sites have different means. Sites where *Caesalpinia decapetala* species was absent had significantly higher mean values than sites with its presence, as shown in figure 5-13.

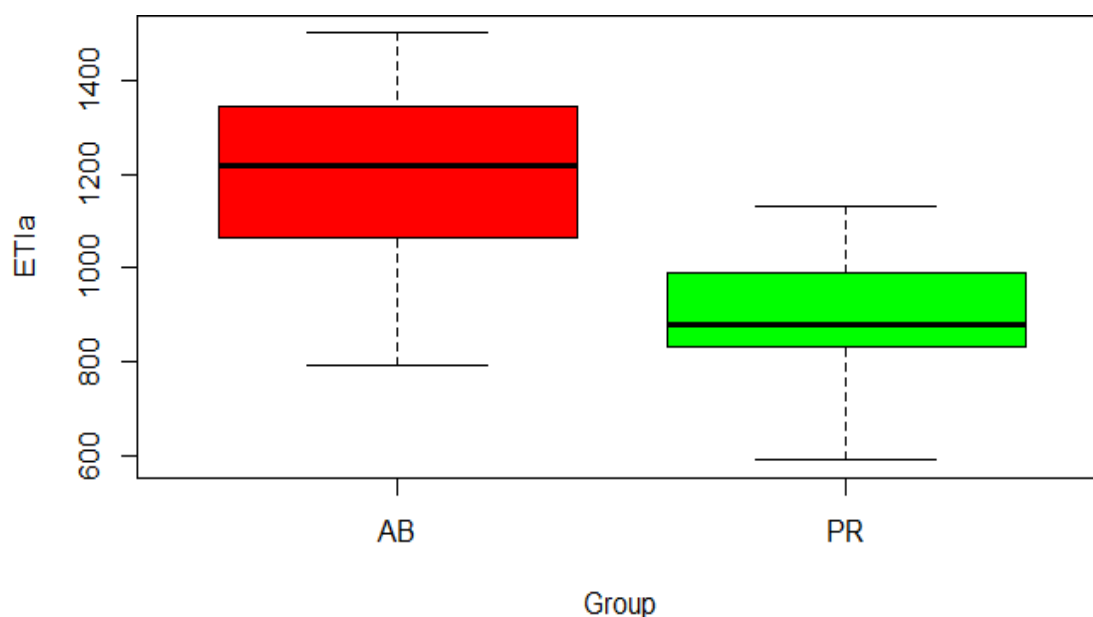


Figure 5-13: Box plot for ETIa presence and absence for *Caesalpinia decapetala*

Table 5-9: Model summary ETIa versus site of *Caesalpinia decapetala*

S	R-sq	R-sq(adj)	R-sq(pred)
165.594	44.23%	43.50%	41.41%

In these results, the ETIa of *Caesalpinia decapetala* at the sites is explained by 44.23% of the species presence and absence variation. S indicates that the standard deviation between the data points and the fitted values is approximately 165.60.

Table 5-10: One-way ANOVA for GBWP versus site of *Caesalpinia decapetala*

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Site	1	83630	83630	0.85	0.359
Error	76	7475175	98358		
Total	77	7558805			

Because the p-value is greater than the significance level of 0.05, we can accept the null hypothesis and conclude that some of the presence and absence of data sites.

Table 5-11: Model summary GBWP versus site of *Caesalpinia decapetala*

S	R-sq	R-sq(adj)	R-sq(pred)
313.620	1.11%	0.00%	0.00%

These results explain the GBWP of *Caesalpinia decapetala* at the sites by 1.11% of the species presence and absence variation.

Table 5-12: Kruskal-Wallis test for GBWP versus site of *Eucalyptus camaldulensis*

Source	DF	χ^2	P-Value
Site	1	19.998	<0.001

Because the p-value is less than the significance level of 0.05, we can reject the null hypothesis and conclude that the presence and absence of data sites have different means in ETIa. Sites, where *Eucalyptus camaldulensis* was absent have significantly higher ETIQ values than sites where the species is present, as illustrated in figure 5-14.

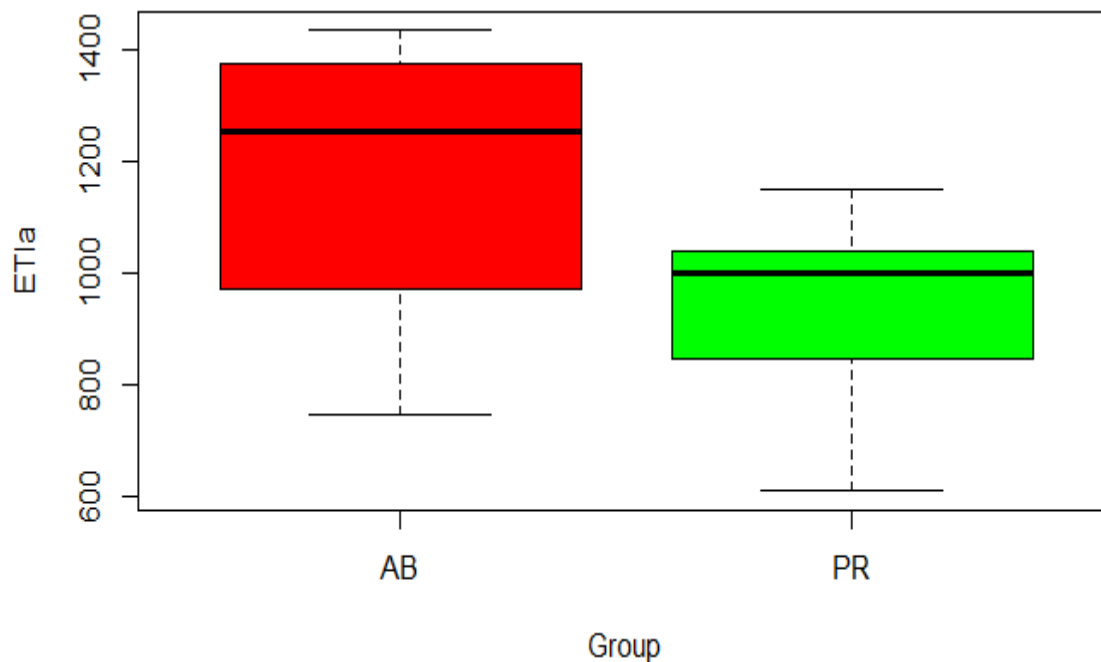


Figure 5-14: Box plot for ETIa presence and absence for *Eucalyptus camaldulensis*

Table 5-13: Kruskal-Wallis test for GBWP versus site of *Eucalyptus camaldulensis*

Source	DF	χ^2	P-Value
Site	1	1.012	0.314

Because the p-value is greater than the significance level of 0.05, we can accept the null hypothesis and conclude that the presence and absence sites do not differ significantly in GBWP in *Eucalyptus camaldulensis*.

5.17.4 Monthly total evaporation estimates

The ETIa and GBWP estimates were derived from the WaPOR repository datasets for the Luvuvhu Catchment from 2017 to 2021 for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* are shown in Figure 5-15.

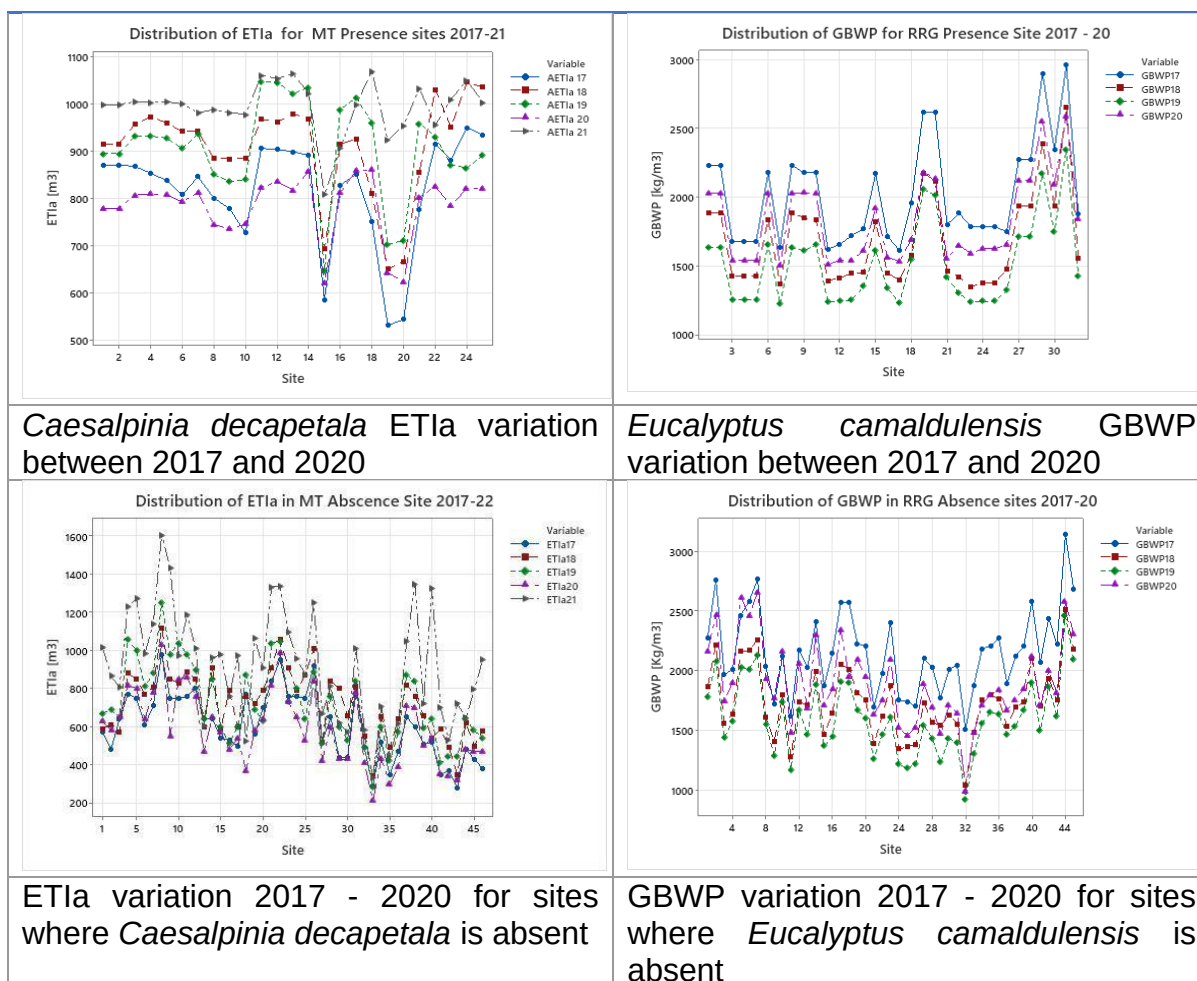


Figure 5-15: ETla and GBWP distribution from MT and RRG presence and absence sites

Data boxplots were plotted using the WaPOR ETla for both *Caesalpinia decapetala* and *Eucalyptus camaldulensis* across land cover types within the Luvuvhu catchment, as illustrated by figure 5-16.

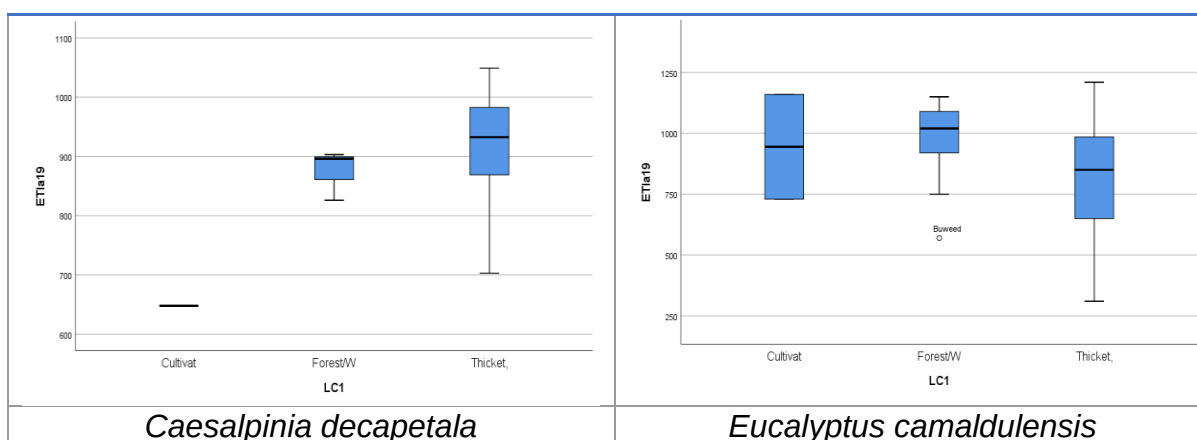


Figure 5-16: Boxplots of ETla across the land covers

The data used for this analysis was quarterly calculated from 2017 to 2020 from the FAO WaPOR repository. The WaPOR dataset showed good variation across the

presence and absence sites. These are well separated, with the median for ETIa for *Caesalpinia decapetala* and *Eucalyptus camaldulensis* highest for sites 505 and 510. The overall spreads (distances between adjacent values) are roughly similar for the data sets. All the batches of data are distributed differently in a way that is not merely the result of differences in location. The main difference between the two species lies in their different concentrations around the median rather than their overall spread of values. The general conclusion is that the ETIa does vary with the site, with IAPS type contributing towards the variable results, as shown by the box plots.

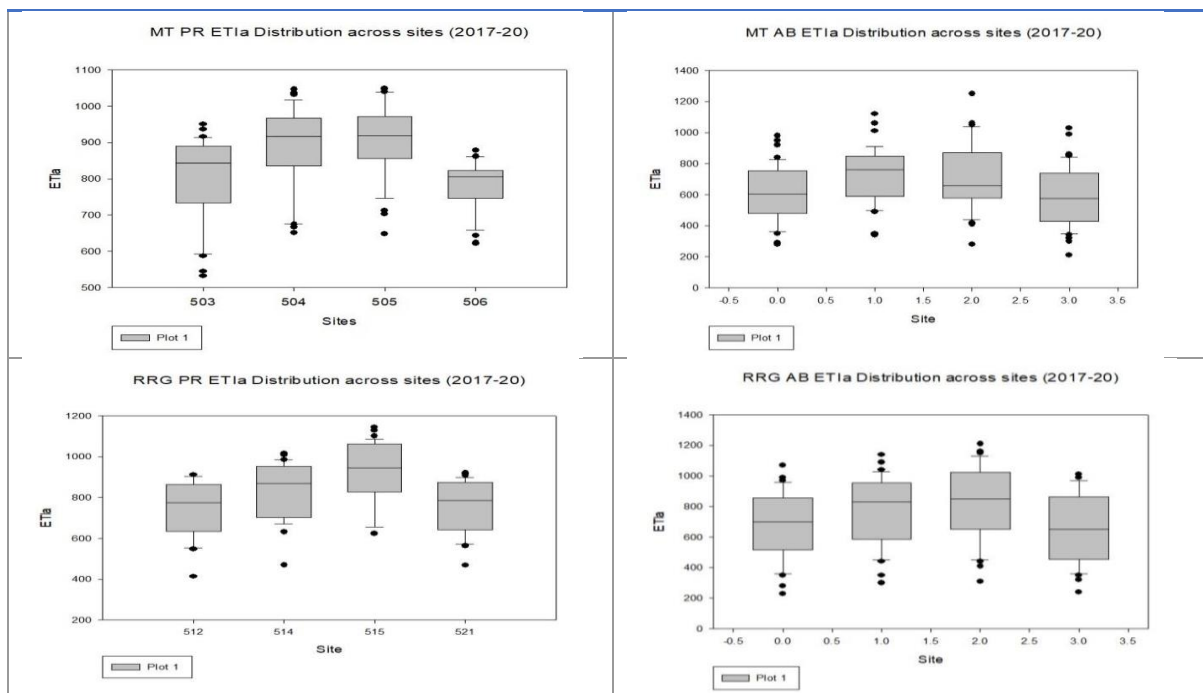


Figure 5-17: Boxplots of ETIa across presence and absence sites for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*.

5.18 Discussion

The Food and Agricultural Organisation of the United Nations (FAO) Water Productivity Open-access portal (WaPOR) datasets show interesting spatial variations in evapotranspiration seasonally and annually coupled with the impacts of land cover on variations of actual Evapotranspiration and Interception (ETIa). A comparison of quarterly mean total evaporation from the WaPOR repository for presence and absence sites for both *Caesalpinia decapetala* and *Eucalyptus camaldulensis* with the analysis done to show how vegetation type and land use affect the ETIa. A statistical comparison of actual Evapotranspiration and Interception (ETIa) and Gross biomass

water productivity (GBWP) shows how evapotranspiration is highly correlated to vegetation productivity within the catchment. The ETIa for presence sites with both *Caesalpinia decapetala* and *Eucalyptus camaldulensis* variables are different (higher) when compared to the ETIa of Absence sites of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*, showing slightly lower medians than presence sites.

It was observed that for both IAPS, the lowest estimates were from built-up areas and the highest for Forestry and woodland land covers for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. The low forecast observed from built-up areas may be due to their hydrological and spatial characteristics across the catchment. Built-up areas with extensive impervious surfaces generally generate more surface runoff, which drains quickly, and, in the long run, less surface water remains for evaporation (Taha, 1997). The two invasive alien plant species behave differently even in the land cover type with the highest ETIa estimates. There was an attractive distribution of the two species across the different land covers, with *Caesalpinia decapetala* dominating in areas classified as Thicket, bushland, bush clumps, and high fynbos. High mean total evaporation estimates from the thicket, bushland, bush clumps and high fynbos may be due to increased water availability for evaporation from rainfall and irrigation combined effects (Uddin et al., 2013).

Forest/Woodland produced the highest mean total evaporation estimates from RRG. Their physiological and spatial characteristics can explain this (large patch size and number, areal coverage, and other catchment factors). The physiological aspects of forests allow them to evapotranspire, even in the dry season, due to their ability to access deeper soil water by their roots (Rwasoka et al., 2011). The contrast in the highest mean total evaporation between *Caesalpinia decapetala* and *Eucalyptus camaldulensis* may be attributed to the physiognomy of the two plant species. *Caesalpinia decapetala* is a thorny, woody, clambering shrub predominantly found in the thicket, bushland, bush clumps and high fynbos land cover class growing as clumps that, in some instances, engulf crowns of endemic vegetation. On the other hand, *Caesalpinia decapetala* and *Eucalyptus camaldulensis* is a tall, evergreen, broad-leaved tree that can be as much as 8m in height that are plantation or plantation remnants dominant in the Forest/Woodland Landcover.

Identifying both *Caesalpinia decapetala* and *Eucalyptus camaldulensis* might be challenging to detect with the 250m spatial resolution of the ETIa WaPOR product. However, both *Caesalpinia decapetala* and *Eucalyptus camaldulensis* can be used to refine the information from the mixed pixel information presented by the ETIa layer. When considering the effect of varying land cover characteristics, it was observed that the spatial factors of the land cover types affect the estimation of total evaporation across the catchment. This was confirmed by the thicket, bushland, bush clumps and high fynbos, which occupy the most elevated land area (approx. 75%) within the Catchment with the highest estimates for *Caesalpinia decapetala*. The predicted occurrence of IAPS in cultivated permanent, commercial, and irrigated areas can be attributed to the spatial and physiological characteristics of these areas. Cultivated, permanent, commercial, and irrigated had the highest patch number and total edge length, reflecting more fragmentation. This may result in patches being incorporated within neighbouring pixels of significant land cover type, among other factors. This was confirmed by Ellis-Cockcroft and Cotter (2014), who reported that fragmentation or isolated patches for a particular land cover type reduce estimates of total evaporation loss within a landscape. The results in Figure 5.10 also show that WaPOR Level 1 ETIa dataset needs more accuracy in capturing pixel-based variations of ETIa across the different land cover types. The WaPOR data only detects total evaporation between 250m for the different land cover types.

This may be attributed to the effect of its 250m resolution on the patch size of varying land cover types, which the ETIa layer failed to discriminate (Roerink et al., 2000). The ETIa layer reflects the pixel's predominant land cover type characteristics, thereby missing its variation. Recent studies (Guerschman et al., 2009; Ha et al., 2011; He et al., 2007) have also highlighted the inability of the WaPOR Level 1 ETIa dataset to differentiate the slight variations in land cover characteristics, mainly when applied on a small scale. Although Landsat 8 can detect more minor spatial variations of total evaporation estimates at the catchment scale, its temporal resolution and the possibility of cloud cover are of significant concern. In contrast, although WaPOR Level 2 ETIa dataset performs poorly in the spatial representation of total evaporation, its daily temporal resolution remains attractive. It provides material estimates for better time series analysis, which is required for well-informed water accounting and subsequent management and allocation.

The calculation of ETIa was done by summing up Evapotranspiration (ET), soil evaporation (E), canopy transpiration (T), and interception. During the year, quarterly ETIa measurements illustrate a variation in seasonal meteorological conditions, with low ETIa in the dry months of May, June, July, August, and September, which constitute the dry period. The ETIa was high from October to January.

The results from a one-way ANOVA for ETIa and GBWP for *Caesalpinia decapetala* were normally distributed. The results indicate ETIa is significantly higher in absence versus presence plots. There was no statistically significant difference between GBWP & ETIa ($F = 60.28$, $p = 0.0001$) for *Caesalpinia decapetala*. Sites where MT species was absent had significantly higher mean values than sites with its presence. A Tukey post hoc test showed that the AETI was statistically significant between Presence and absence. In *Eucalyptus camaldulensis*'s case, ETIa and GBWP were not normally distributed; thus, a Kruskal-Wallis test was done. The results show that the p-value is greater than the significance level of 0.05; we can accept the null hypothesis and conclude that some of the presence and absence of data sites do not differ significantly for ETIa and GBWP in RRG.

The results show that ETIa for *Caesalpinia decapetala* is higher in absence points than in presence points, a result that goes against the expected trend. However, this can be explained by the possibility that *Caesalpinia decapetala* might not be taking as much water from the ecosystem as initially thought. This can be explained by the *Eucalyptus camaldulensis*'s ecophysiology and leaf anatomical traits (Rindyastuti et al., 2021). The inverse is true for *Eucalyptus camaldulensis* as the ETIa and GBWP were higher in presence sites than absence sites. This might be due to the ecophysiology and leaf anatomical traits of *Eucalyptus camaldulensis* that are characterised by a deep-rooted system and broad waxy leaves.

5.20 Conclusion

The focus of this study was to determine spatial variations of actual Evapotranspiration and Interception (ETIa) from the FAO WaPOR platform by comparing it with the biomass productivity within the Luvuvhu catchment, as well as between sites with and without *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. Temporal and spatial variations in climatic conditions, among other factors, considerably affect ETIa estimation at a catchment scale. However, despite these factors, the results show that

evaporative water loss significantly increases in the presence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. Based on this research, the WaPOR platform dataset could be helpful for a better spatial representation of ETIa in accounting for water loss at a catchment scale.

However, despite valuable results on the spatial variations of WaPOR datasets, its low temporal resolution is a cause for concern. Daily total evaporation estimates at a more acceptable resolution are required for better long-term and sustainable management of water resources. There is a need for further research to investigate the possible integration of WaPOR datasets with other RS datasets to estimate ETIa for more comprehensive and well-informed water accounting at a catchment scale.

The Department of Water Affairs has allocated most of the accessible freshwater (DWA, 2010). Increasing plant biomass can directly impact water availability within river catchments (DWA, 1993; Jovanovic et al., 2009). Most IAPS have allelopathic effects, meaning they tend to create monoculture stands of high-water use invaders upon establishment.

However, it is noteworthy that the impacts of IAPS on water quantity need to be considered if the issue of water scarcity must be addressed in South Africa. Prioritising areas for clearing IAPS will be dictated by their impacts on water quantity, streamflow discharge, and groundwater recharge. The adverse effects of IAPS can be addressed by considering the water quantity effects, including areas with high levels of erosion following invasions. After understanding how species distribution affects water use, Chapter 6 provides a synthesis of the results that have been derived from Chapters 3, 4 and 5. It also provides a framework for the management of IAPS in the VBR.

5.21 References

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Chapter 6 : Synthesis of the techniques that were used, their results, and development of prioritisation framework for the monitoring and management of IAPS in the Vhembe Biosphere Reserve

Abstract

The quantity and spread of invasive alien plant species (IAPS) have increased dramatically, with severe consequences for the ecology and economy. Despite this, the limited management resources for invasive alien species control must be prioritised. The framework could be used at different scales and by other authorities. Furthermore, it would make the decision-making process transparent and retraceable for all stakeholders and the public.

6.1. Introduction

This chapter presents a synthesis based on (i) the Selection of best platforms for modelling IAPS, (ii) Modelling IAPS using stepwise logistic regression and maximum entropy model, (ii) using remote sensing derived Water Productivity Open-access Portal (WaPOR) products to estimate water use by IAPS. The chapter will also consider remote sensing and modelling-based prioritisation framework valuable for decision-makers.

6.2. Selection of best platforms for modelling IAPS

To determine the best imagery to use for analysis in this research, a comparison of the performance of three sets of remote sensing imagery was made. Three platforms were selected for this purpose: Colour Digital Aerial Imagery, Digital Globe Worldview 2 Imagery, and SPOT 6 Imagery. All three platforms supervised image classification and estimation of the accuracy of predictive models by measuring the agreement between the predictive model and a set of field-surveyed sample points. The assessments were carried out with the platform providing the highest accuracy and being deemed the most suitable for further identification and analysis of the presence of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* in the Vhembe Biosphere Reserve (VBR).

6.2.1 Comparison of classification results from different platforms

Classification outputs are compared only using the surface reflectance of spectral bands of Colour Digital Aerial Imagery, Worldview 2 imagery, and SPOT 6 imagery datasets and produce average validation overall accuracy of 71%, 81%, and 89%, respectively. Based on the information from the confusion matrix, the overall accuracy of the identification of all classes with Colour Digital Aerial Imagery, Worldview 2 imagery, and SPOT 6 produced Kappa coefficients of 0.76, 0.80, and 0.88, respectively (Table 6.1).

Table 6-1: lists the overall accuracy and kappa statistic for each imagery dataset classification.

	Colour Digital Aerial Imagery	Worldview 2 imagery	SPOT 6 imagery
Overall Accuracy	71%	81%	89%
Kappa Statistic	0.76	0.80	0.88
Rank	3	2	1

Similar studies also showed that Worldview 2 performs better than SPOT 6 and Colour Digital Aerial Imagery (Abutaleb et al., 2021). Odindi et al. (2014) compared the two sensors to estimate the bracken fern. They have concluded that the better performance of Worldview-2 may be related to the red-edge-vegetation bands, as their investigation of the mutual bands of the two sensors did not show any significant difference. On the other hand, in comparing the two sensors for the classification of forests affected by bark beetle outbreaks (Stych et al., 2019), Worldview-2 also showed better results. However, this performance was linked to the better spatial resolution of the sensor.

Interestingly results from the classification using both Worldview 2 and SPOT indicate a higher accuracy and kappa statistic for the SPOT dataset. Table 6.1 thus gives the highest ranking to the SPOT 6 classification compared to Worldview 2 and Colour Digital Aerial Imagery. Given that the results show that the SPOT 6 image with an overall accuracy of 89% is more accurate than the Worldview 2 with an overall accuracy of 81% for classification of the study area.

6.3. Modeling IAPS using stepwise logistic regression maximum entropy model.

Using presence/ absence, environmental, and remote sensing data SDMs were used to model the spatial distribution of river red gum (*Eucalyptus camaldulensis*) and Mauritius thorn (*Caesalpinia decapetala*) at three scales (Global, VBR, and local scale). This was achieved using stepwise logistic regression and the MaxEnt model. The presence/absence data were collected during the fieldwork and downloaded from the Global Biodiversity Information Facility (GBIF). Environmental data was derived from various climatic and environmental grids. On the other hand, the remote sensing data was derived from the SPOT 6 datasets, as indicated in the platform selection chapter.

6.3.1 Stepwise logistic regression modelling

Stepwise linear regression analysis was used to find subsets of the predictor variables that best predict responses to a dependent variable by a regression equation (Wang and Chen, 2006). However, to avoid overfitting a given stepwise regression model, the rule of thumb, as suggested by several authors (Whittingham et al. 2006), is that: (1) the number of predictor variables to enter the model be less than 1/3 of the number of observations and (2) the number of steps in the stepwise linear regression analysis is 10 to 20 times less than the training data set. The number of steps selected for this study was set at six on a training dataset of 75 samples.

After running the stepwise logistic regression (SLR) model for *Caesalpinia decapetala* using environmental variables, the results were done over 8 Fisher Scoring iterations, using a backward logistic regression to produce an AIC of 80.17 and AUC of 0.89. The *Eucalyptus camaldulensis* modelling was done over 7 iterations producing an AIC of 89.64 and AUC of 0.85. The Remote sensing (RS) variable *Caesalpinia decapetala* analysis was done using 7 iterations to produce an AIC of 74.55 and AUC of 0.86. A combination of environmental and RS variables was also used to model the distribution of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*. When run for *Caesalpinia decapetala*, seven (7) iterations were combined with backward logistic regression to produce an AIC of 59.74 and AUC of 0.95. At the same time, *Eucalyptus camaldulensis* analysis involved 10 iterations and backward regression in producing an AIC of 69.45 and AUC of 0.90.

The results from the SLR produce some informative results on the distribution of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* within the VBR. When the environmental and RS variables are modelled independently, the IAC values are high, meaning these models are not suitable to compare to the combined environmental and RS variables model, which produced lower IAC values and indicated better performance of the regression model; this is also supported by the AUC values for both *Eucalyptus camaldulensis* and *Caesalpinia decapetala*.

It is thus essential to note that the variables influencing the distribution of the *Eucalyptus camaldulensis* and *Caesalpinia decapetala* were identified using backward SLR differences across species and geographic locations. The selection of RS and environmental variables that comprise the species 'fundamental niche is essential. Variables from SLR account for a sizable proportion of the driving elements in the current distribution of *Eucalyptus camaldulensis* and *Caesalpinia decapetala*. The SLR shows the IAPS distribution in the Foothills of the Soutpansberg mountains, forests, roads, borders, riparian habitats (South of the Luvuvhu River), and boundaries of plantations (abandoned, unused). The model also shows that IAPS have a high potential to invade disturbed environments influenced by abiotic variables such as past land use and management. On the other hand, mountains, riparian areas, and highways play an essential role in IAPS distribution. Proximity to settlements did not affect IAPS distribution.

As a recommendation based on the results, SLR can be used as a starting point when modelling IAPS as it provides information on distribution, albeit the final product does not present the most accurate mapping products. Thus, it can be suggested that using SLR be preceded by other SDMs.

6.3.2 Maximum entropy modelling (MaxEnt)

In the presence of test data, the MaxEnt program automatically calculates the statistical significance of the prediction using a binomial test of omission (*Eucalyptus camaldulensis* and *Caesalpinia decapetala*). Test data for both species were available, and binomial probabilities were calculated. The Receiver Operating Curve (ROC) has a superior predictive ability with a mean AUC of 0.811. The ROC curve shows a predictive ability with a mean AUC of 0.668 for *Caesalpinia decapetala*. The point-wise

mean maps illustrate that *Caesalpinia decapetala* favours tropical areas, with the highest concentration moving from Southern, central, and east Africa. High mean distribution can be noticed in South and North America, including Indo-Asia-pacific regions. At the same time, *Caesalpinia decapetala* plots show the concentrated distribution in Australia, India, Argentina, Brazil, USA, RSA, and more significant parts of the Sahel region.

MaxEnt Modeling for the VBR shows that the omission on *Eucalyptus camaldulensis* and *Caesalpinia decapetala* matches the predicted omission rate for test data drawn from the MaxEnt distribution, presenting a ROC curve (AUC) of 0.89. The results show that the omission on *Eucalyptus camaldulensis* matches the predicted omission rate for test data drawn from the MaxEnt distribution with the area under the ROC curve (AUC) of 0.956. The point-wise mean maps illustrate that *Eucalyptus camaldulensis* and *Caesalpinia decapetala* favour sites across the VBR. The highest concentration coincides with the peaks of the Soutpansberg mountain ranges, Hangklip summit, and the Lajuma summits. Notable high mean distribution can be noticed southwards in the town of Louis Trichardt. The point-wise mean maps illustrate that *Caesalpinia decapetala* favours areas across the VBR with the highest concentration, following the Soutpansberg mountain ranges. Notable high mean distribution figures can also be noticed in the Luvuvhu valley.

The results show the MaxEnt model run to predict the future global distribution of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* further downscaled to the VBR. This study modelled the distribution areas for *Eucalyptus camaldulensis* and *Caesalpinia decapetala* IAPS in the VBR using MaxEnt. The results confirmed that the highly suitable area for these species is the main areas in the foothills of the Soutpansberg mountains and along rivers and valleys in the Luvuvhu catchment. However, the VBR shows that *Eucalyptus camaldulensis* and *Caesalpinia decapetala* will increase their distribution. Bioclimatic variables predicting species distribution areas do not necessarily indicate the importance of topography. Topography is critical in species dispersion regarding its influence on the microclimate. Topology concerns are essential since the VBR's terrain varies significantly from west to east, causing minor microclimatic impacts.

6.4. Using remote sensing derived WaPOR products to estimate water use by IAPS.

The Food and Agricultural Organisation of the United Nations (FAO) Water Productivity Open-access Portal (WaPOR) datasets show interesting spatial variations in evapotranspiration seasonally and annually coupled with the impacts of land cover on variations of actual Evapotranspiration and Interception (ETIa). A comparison of quarterly mean total evaporation from the WaPOR portal for presence/absence sites for both *Eucalyptus camaldulensis* and *Caesalpinia decapetala* shows how vegetation type and land use affect the ETIa. Statistical comparison of ETIa and Gross biomass water productivity (GBWP) shows how evapotranspiration (ET) correlates highly to vegetation productivity within the catchment. ETIa for presence sites with both *Eucalyptus camaldulensis* and *Caesalpinia decapetala* variables are higher when compared to the ETIa of absence sites of *Eucalyptus camaldulensis* and *Caesalpinia decapetala*, as illustrated by slightly lower medians than presence sites.

For both IAPS, the lowest estimates were from built-up areas and the highest for forestry and woodland land covers for the two IAPS of interest. The low forecast observed from built-up areas may be due to their hydrological and spatial characteristics across the catchment. Built-up areas with extensive impervious surfaces generally generate more surface runoff, which drains quickly, and, in the long run, less surface water remains for evaporation (Taha, 1997). The two invasive alien plant species behave differently even in the land cover type with the highest ETIa estimates. There was an attractive distribution of the two species across the different land covers, with *Caesalpinia decapetala* dominating in areas classified as Thicket, bushland, bush clumps, and high fynbos. High mean total evaporation estimates from the thicket, bushland, bush clumps, and high fynbos may be due to increased water availability for evaporation from rainfall and irrigation combined effects (Uddin et al., 2013).

There was a statistically significant difference between GBWP and ETIa across presence and absence sites for *Eucalyptus camaldulensis* and *Caesalpinia decapetala*. A one-way ANOVA of ETIa across presence and absence sites for *Caesalpinia decapetala* show p-values which are less than the significance level of 0.05, leading to the conclusion that some of the presence and absence data sites have

different means. There were no statistically significant differences between presence and absence means for GBWP as determined by one-way ANOVA ($F(1,70) = 0.85$, $p = 0.359$) for *Eucalyptus camaldulensis* and *Caesalpinia decapetala* ($F(1,70) = 1.59$, $p = 0.212$). The data on *Eucalyptus camaldulensis* was not normally distributed; thus, a Kruskal-Wallis test for ETIa versus the site of *Eucalyptus camaldulensis* was run, and the p-value is less than the significance level of 0.05, we can reject the null hypothesis and conclude that the presence and absence of data sites have different means in ETIa. On the other hand, the p-value is greater than the significance level of 0.05, and we can accept the null hypothesis and conclude that the presence and absence sites do not differ significantly in GBWP in *Eucalyptus camaldulensis*.

6.5. Development of a Remote sensing and modelling-based prioritisation framework for decision-makers.

This section focuses on developing a framework that can evaluate remote sensing and modelling applications in monitoring IAPS and the need for management to thoroughly assess IAPS' impact within the VBR. IAPS have various environmental effects, frequently classified as either socioeconomic or ecological. These effects can have significant monetary consequences and changes to ecosystems and social systems (Vilà et al., 2010).

A framework offers a foundation for constructing additional ideas or applications in this context. Frameworks are frequently utilised flexibly, with specifics altered to match certain settings (Wilson et al. 2020). However, for a framework to be a commonly used and shared tool, definitions and terms must be defined, and ideally, instructions for usage must be codified. A framework becomes a standard in such instances. Adopting a standard has various advantages, including facilitating data sharing within research, representing an agreed-upon foundation for communicating the problem to a larger audience, and providing a fundamental basis for policy. Data standards allow us to gather, compare, share, validate, and exchange data. Both frameworks and standards are real-world abstractions.

6.5.1 Background

Invasive alien plants have a significant detrimental impact on rangeland productivity and influence habitat integrity and biodiversity by replacing species and causing habitat degradation, which includes a decrease in mean annual runoff and streamflows

(Le Maitre et al., 2016). When endemic plant species are replaced by IAPS, food chains, ecological routes, and habitat niches offered by indigenous fauna and flora populations are disturbed or destroyed. Sustainable IAPS control mechanisms entail the systematic removal of IAPS from disturbed areas within a specific time frame and the prevention of the spread of existing and new IAPS in adjacent regions. Every landowner and management organisation, including all governmental organisations, must develop a strategy for managing incursions on their territory.

This chapter concludes the thesis by providing a framework for formulating, composing, and applying IAPS control plans. It is thus critical that these plans are based on the following:

- An adequate assessment of the extent and density of invasions in the area covered by the plan.
- Agreement on a goal for the plan, which should include the desired state and a time frame for the achievement of the goal.
- A list of clearing priorities will direct clearing investment toward those regions that will deliver the most rewards. Long-term and yearly planning tools are being created to assist people engaged in understanding the resources needed to achieve their goals and carry out their plans.

Table 6.1 provides management guidelines for the critical impacts of IAPS and the legal framework for implementing these management actions.

Table 6-2: Key management guidelines for the forestry sector

Key Impact resulting from land-use practice or activity	Key Management Guidelines	Legal framework and existing guidelines
Invasion by plantation species of areas adjacent to the plantations	• Ensure that the management of alien invasive plant species complies with Act 10 of 2004 and Working for Water requirements • Disposal of (seed-bearing) invasive alien plant material must be done sustainably to prevent further spread	• Invasive Alien Species Regulations under the National Environmental Management Biodiversity Act (Act 10 of 2004) • Working for Water Operation Standards³ and species-specific treatment recommendations, the Forestry Stewardship Council standards are currently being updated and will become much stricter about the cultivation of invasive plant species
The colonisation of riparian areas and land areas by invasive alien plants	Clear and prevent reestablishment and further spread of alien invasive plants within the riparian and land areas	Conservation of Agricultural Resources Act [Act No. 43 of 1983]

Key Impact resulting from land-use practice or activity	Key Management Guidelines	Legal framework and existing guidelines
Streamflow reduction and lowering of water tables	- Implement alien invasive plants eradication and management program in compliance with the Alien and Invasive Species Regulations. - Prevent new alien invasive plant species from spreading on disturbed and rehabilitated sites.	- National Environmental Management Biodiversity Act (Act 10 of 2004). - Working for Water Operational Standards and species-specific treatment recommendations
Pollution of water bodies and groundwater and adjacent lands due to herbicide treatments	All herbicide treatments applied to Invasive alien plants must comply with the South African National Standards for handling, storage, and disposal of Pesticides (SANS 10206:2010, Edition 2.2). - Only herbicides registered for a particular plant species are to be used. - Where no herbicide has been registered, use the least hazardous herbicide registered for a similar plant species. - A suitably qualified expert must apply all herbicide treatments. - See also details on herbicides under the Forestry sector	All herbicide treatments applied to Invasive alien plants must comply with the South African National Standards for handling, storage, and disposal of Pesticides (SANS 10206:2010, Edition 2.2).

6.6. The Biotic, Abiotic, and Movement (BAM) framework

When a framework or standard is confronted with real-world facts, it may become clear that it must be altered, only applied in select scenarios, or fundamentally unfit for purpose. While a framework may be updated or changed informally to specific settings, every modification to a standard must be appropriately recorded and, preferably, evaluated and debated by other users, i.e., there must be a straightforward procedure for consulting on and enacting changes.

There is an understanding that communities must develop acceptable ways to control IAPS so that their effects are eliminated, lowered below a certain level, or contained. However, because of rising globalisation and the introduction of potentially harmful species, IAPS management are becoming complex (Essl et al., 2011). The control of IAPS can be approached in two ways. Firstly, by improving border control risk assessments (Hulme 2012 and Leung et al. 2012). Secondly, IAPS that manage to evade border controls but with the potential to invade must be controlled (Bacon et al.,

2012). As a result, a system that allows for the best deployment of limited resources to handle detrimental IAPS in a specific region is required. These methods enable decision-makers to prioritise high-impact IAPS for management based on the severity of their impacts on the environment, economy, and society. However, any management intervention must be cost-effective to be considered.

Invasive alien plant species have far-reaching consequences, with most being purposely introduced as ornamental, horticultural, restorative, agricultural, or forestry plants, with social, economic, and environmental advantages (Pyšek et al., 2012). Management of destructive IAPS needs to consider their dual impact, which can be damaging to biodiversity but helpful in others, such as forestry, which can lead to disputes among concerned parties. This was the case with *Eucalyptus camaldulensis* and *Caesalpinia decapetala*, which were introduced to South Africa for forestry and ornamental purposes, respectively, and quickly became invasive, causing various problems for communities. On the one hand, the two IAPS lead to water shortages due to increased evapotranspiration, while the communities profit from fuelwood, construction lumber, and hedgerows (De Wit et al. 2001). These conditions demonstrate the importance of developing a framework IAPS for multiple stakeholders (Binimelis et al., 2007, Kapler et al., 2012, De Lange et al., 2012, Forsyth et al., 2012).

Soberón and Peterson (2005) advocate for a framework to assess the ecological effect of IAPS, arguing that the total impact of an invader includes three fundamental dimensions: biotic (B), environmental or abiotic (A), and movement-related or dispersal (M). Since then, significant progress has been made in quantifying the overall detrimental consequences of IAPS. (Pluess 2011). Prioritisation is used in decision-making at practically every stage of the invasion process to promote cost-effective resource allocation (Figure 6.1).

IAPS prioritisation occurs throughout and after the invasion process, pre-border and post-border. It is thus essential to develop various analytical decision-support tools that may aid IAPS management. Each emphasis on species, routes, and places has unique data needs. Once an IAPS has arrived and established itself post-invasion or post-border, the emphasis shifts to stopping its spread and protecting high-priority habitats. When species like *Eucalyptus camaldulensis* and *Caesalpinia decapetala* with a known effects threaten to spread, the possibility of elimination or containment

is given top priority. Figure 6.1 shows that the prioritisation techniques based on species, mainly for plants, have grown; however, few have emerged from source literature (Heikkilä 2011). Several standardised, evidence-based methodologies for choosing routes and places that include a diverse range of alien species have recently been presented (McGeoch and Latombe, 2015).

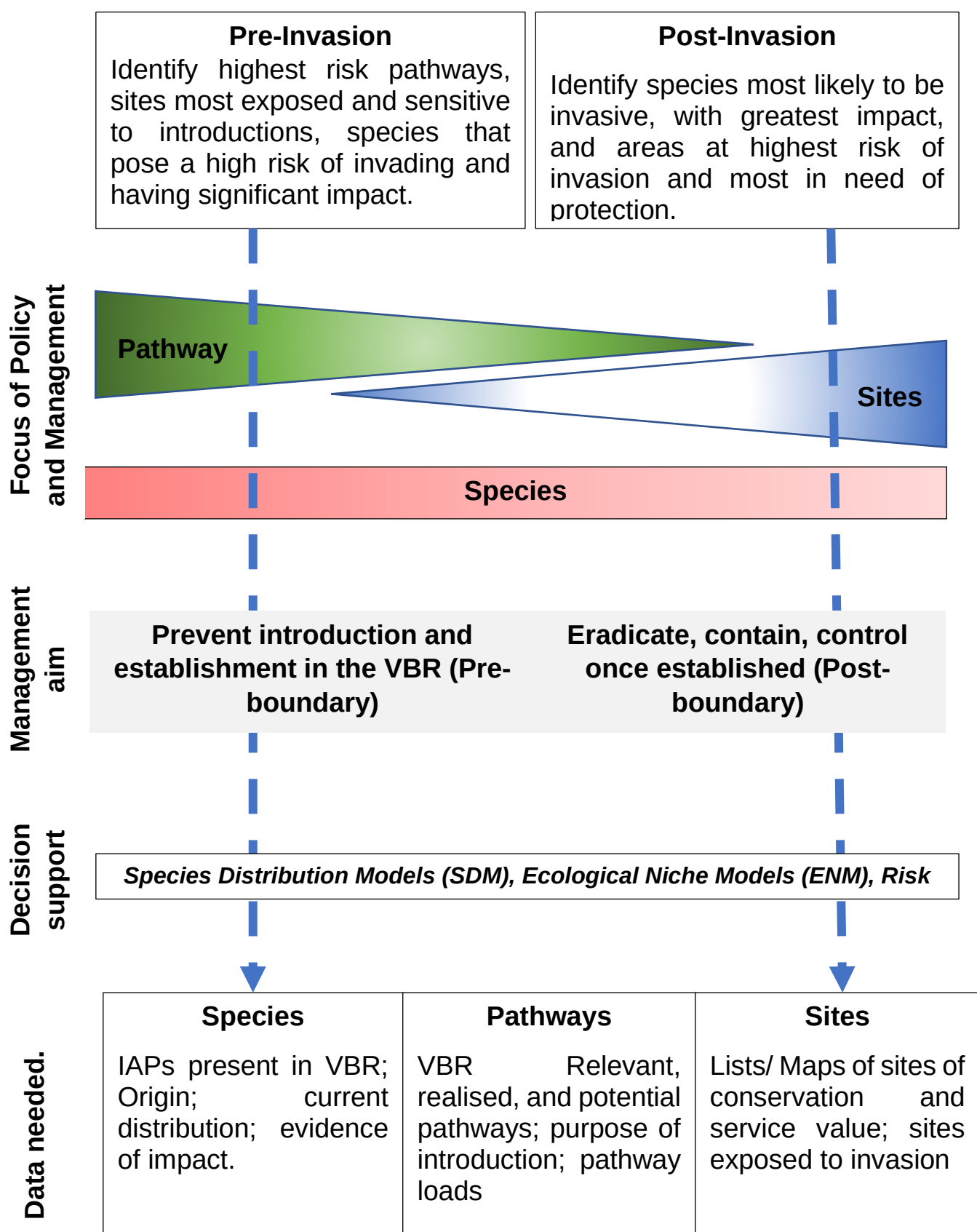


Figure 6-1: Proposed prioritisation methods for the management of IAPS (McGeoch et al., 2016)

The BAM framework allows for investigating the pervasive link between abiotic and biotic variables' spatial and temporal dynamics concerning IAPS. It describes the individual and combined effects of biotic factors, abiotic factors, and movement (Soberón 2007). The BAM framework places biotic, abiotic, and movement aspects within a spatial context. Three overlapping circles (Figure 6.2) are depicted inside the geographical space (G), each symbolising favourable circumstances for a particular species. The intersection between all three factors, as represented by the equation " $B \cap A \cap M$ ", describes the occupied distributional area (G_0) or the "realised" or occupied niche. The intersection between biotic and abiotic factors " $B \cap A$ " means the invadable distributional area (G_1) or areas that can be colonised because of suitable biotic and abiotic conditions. The intersection between abiotic and movement factors " $A \cap M$ " represents the area where the species cannot be found. Finally, the union between the occupied and the invadable regions " $G_0 \cup G_1$ " represents the geographic potential distribution area (GP) or biotically reduced niche (Peterson et al. 2011).

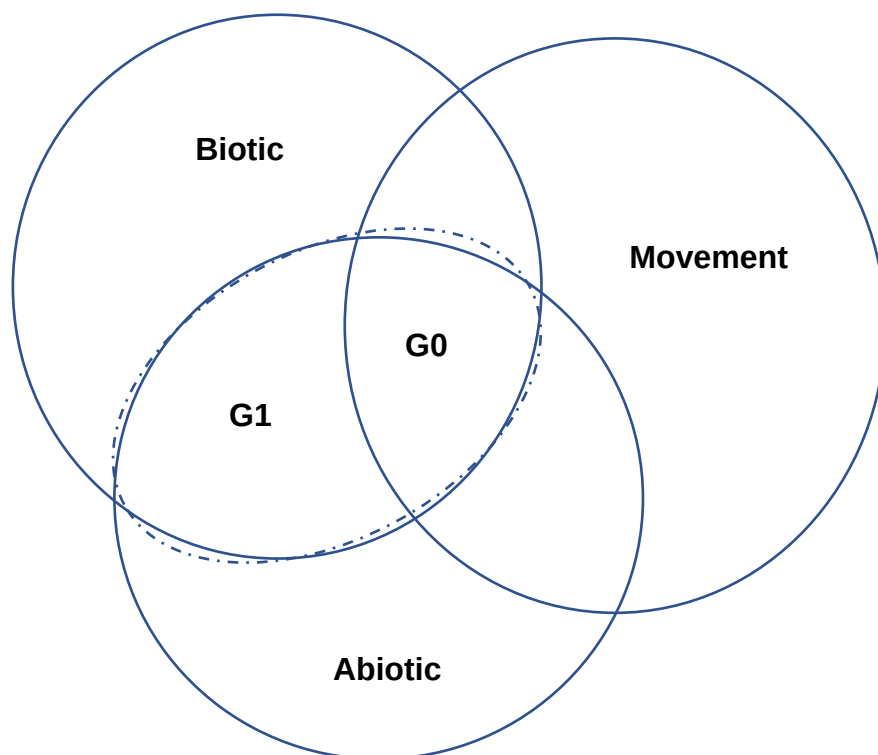


Figure 6-2: The BAM diagram, where B represents Biotic, A Abiotically suitable and M Movement or migration, illustrates the relationship among the three major determinants of species distributions. G_1 is the available distributional area, and G_0 is the occupied distributional area, representing the outcomes from the intersection between the major determinants.

6.7. Remote sensing for detection of plant invasions

Due to its capacity to give synoptic views across broad geographical extents, remote sensing (RS) has long been used as a technique for IAS mapping, particularly for vegetation. This gives it an edge over field surveys, sometimes confined to small regions and maybe in difficult-to-reach locales. RS has always been important in detecting IAPS. Science has advanced significantly throughout time. Current technologies, such as hyperspectral imaging spectroscopy and light detection and ranging (lidar), enable the identification and differentiation of plant species belonging to the same functional groupings. Combined with developments in image processing techniques, these technologies have enabled precise, repeatable RS measurements throughout time, resulting in consistent monitoring records to help control efforts. Three variables contribute to the viability of mapping IAPS using RS (He et al., 2015).

- i. It is simpler to train a classifier to detect IAPS when it is the prevalent growth type or contains vast homogenous regions; this is evident in cases where *Eucalyptus* plantations stand out from the surrounding natural vegetation (Venugopal 2002) making it much easier for simple Colour IR aerial photography (Rouse et al. 1975) or multispectral satellite data such as that from Satellite Pour l'Observation de la Terre (SPOT) or Landsat to be able to discriminate *Eucalyptus camaldulensis* from endemic vegetation.
- ii. The fact that *Caesalpinia decapetala* and *Eucalyptus camaldulensis* have unique phenology makes it easier to distinguish the two species from native plants during the winter seasons in sub-Saharan Africa. This was the case with the *Caesalpinia decapetala* during its blossoming phase when its bright yellow blossoms made it spectrally distinguishable from the surrounding foliage. Temporally rich imaging, together with high spectral resolution, can be utilised to detect the optimal period for differentiation and differentiate phenological variations (Andrew and Ustin, 2008)
- iii. *Eucalyptus camaldulensis* and *Caesalpinia decapetala* have unique chemistry or physiology. It is possible to differentiate the two species from other co-occurring plant species using differences in canopy water content since most IAPS have higher plant-water content than co-occurring species. This necessitates the collection of spectrally rich data that can characterise canopy biochemistry.

These three criteria correspond to the three RS data domains: spatial, temporal, and spectral (Khanna et al., 2011). Invasion detection frequently entails species mapping, requiring much more data than functional-type or general biodiversity mapping. Hyperspectral imaging often uses phenology to time picture collection, and extra auxiliary variables, such as height, are required. Sensors capture data in three fundamental domains, as previously stated: spectral, spatial, and temporal, with a fourth domain, radiometric resolution, being crucial for aquatic applications. Generally, hyperspectral imaging contains a wealth of data in the spectral domain, aerial images from piloted and unpiloted aircraft in the spatial domain, and time-domain satellite imagery. Each platform and sensor type makes trade-offs between the three parts and is often weak in one. The best classification maps are produced by selecting the optimal platform/sensor and integrating the obtained imagery with relevant supplemental data. Each species and ecosystem provide its own set of obstacles for detecting and mapping IAPS using RS. The overall procedure of detecting and mapping IAPS stays the same regardless of the environment and comprises the following phases (Figure 6.3).

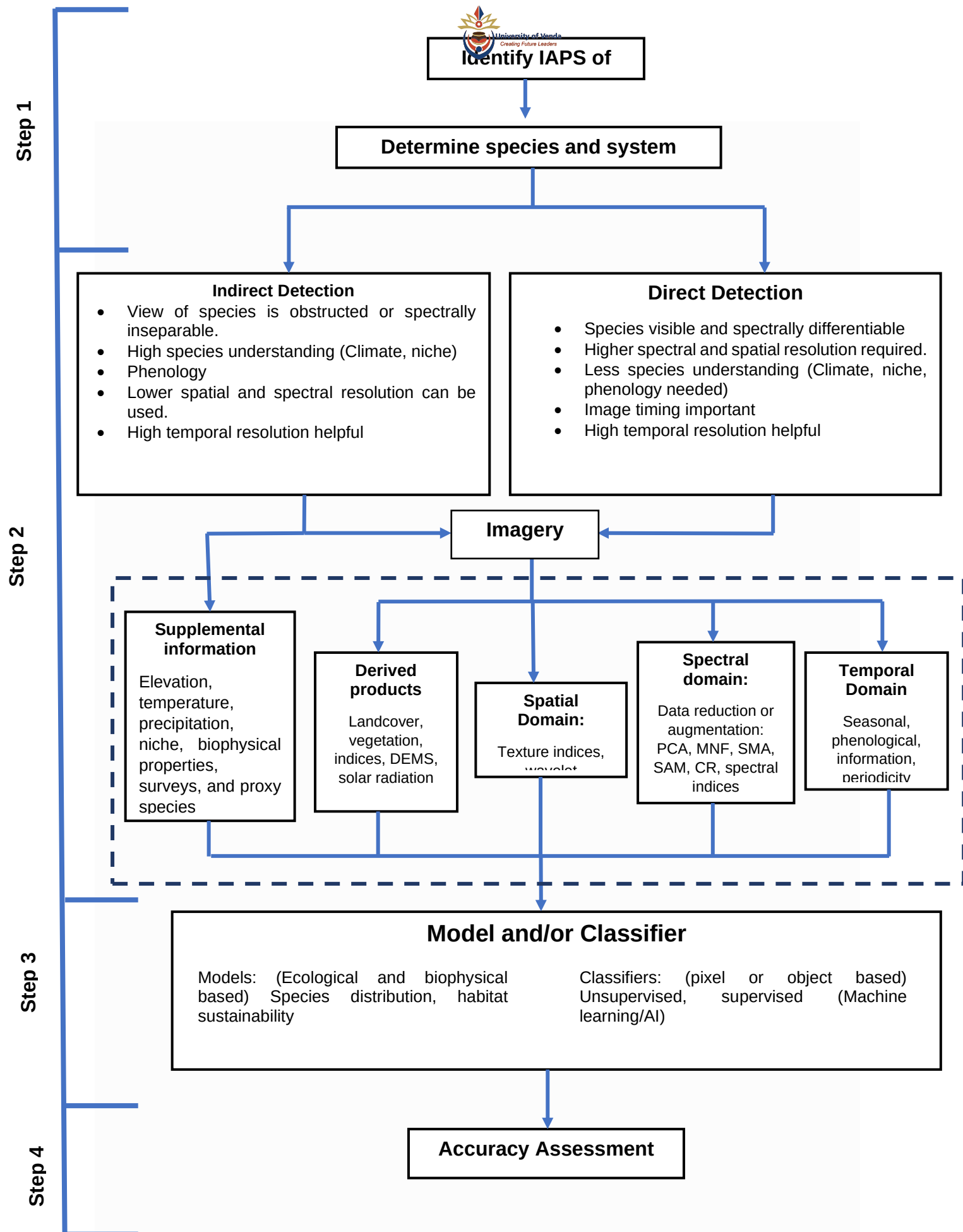


Figure 6-3: Method for identifying IAS using RS. MNF, SMA, SMA; PCA, SAM, is a technique for mapping the angles of a spectrum. (CR) (Bloch et al., 2020).

- i. *Identify the target species and area:* This process identifies what IAPS in the VBR are harming biodiversity, ecological services, or other economic functions—presenting what is known about the target IAPS (spectral characteristics, phenology, ecosystem function, habitat requirements). Consider knowledge or possible hypothesis about the IAPS extent and community composition of other species in the
- ii. *Determine the appropriate platform/sensor and identify/collect supplementary data based on species and habitat knowledge:* Direct or indirect approaches might be used to detect the target species. Direct detection makes use of spectral data as well as imagery-derived products. Indirect detection uses the ecological interactions between species and their habitat to anticipate distribution.

It is essential to acknowledge that each species and habitat has specific characteristics that can be exploited to detect IAPS. Differences in the temporal, spatial, and spectral domains can be used. The temporal part comprises the timing of data collecting and revisiting. For example, if an IAPS blooms earlier or later than other species in its surroundings, this information may be utilised to plan picture capture for when the target species looks most spectrally distinct. The spatial domain comprises pixel size and total geographic coverage. In contrast, the spectral domain consists of the number of wavelengths recorded, their location and bandwidth, and the sensor's spectral range to measure radiance safely.

Sensors often make trade-offs between domains based on sensor design, size, and data volume constraints. For example, there is a trade-off between total coverage area or swath width and pixel size; both may be driven to increase but at the price of sensor size, which restricts the platform on which it can be mounted. There are other trade-offs across domains, most connected to platforms. Most satellite platforms have bigger pixel sizes (20–100s of meters) than other platforms, although they have a shorter return period (days to weeks) and broader geographic coverage.

Due to costs and logistics, airborne platforms have a longer revisit time and lesser geographical coverage. Still, they provide smaller pixel sizes (centimetres) and frequently accommodate hyperspectral sensors. Unmanned Aerial Systems (UAS) feature a short return time, on-demand deployment, and small pixel size; however,

they have relatively limited geographic coverage and spectral resolution due to size constraints.

Indirect approaches can forecast species placements when direct detection is impossible due to canopy cover or other causes. Other data products can be utilised to regulate a model using species information about habitat limits or coexisting species. These data include digital elevation models (DEMs), climatic layers, soil wetness, and other elements limiting a species distribution. These data can be coupled with direct detection methods in some cases to improve outcomes.

- iii. *Enhance data and model/classify.* A classifier model is a collection of rules or a mathematical function that assigns or predicts class membership based on pixel data. This can be supervised (already defined pixels or spectra are used to create classes) or unsupervised (pixel spectral/statistical similarity is utilised to construct classes). Surface reflectance data that has been atmospherically adjusted is often sent into the classifier. Image enhancement is frequently used to boost the information richness of input data.

The classifier may be fed improved products in addition to reflectance data. Spectral indices, principal component analysis (PCA), and minimal noise percentage improve spectral data (MNF). Spectral indices are combinations of spectral reflectance from two or more wavelengths that highlight a specific reflectance or absorption feature and frequently indicate the relative abundance of features of interest; for example, the Normalized Difference Vegetation Index (NDVI) is a normalised difference ratio of red and near-infrared (NIR) bands that are commonly used as an indicator of vegetation vigour.

Many narrowband indices are available with hyperspectral data to offer extra information on plant features, such as light usage efficiency from the photochemical reflectance index (PRI) (Gamon et al., 1997), canopy nitrogen from the normalised difference nitrogen index (NDNI) (Serrano et al. 2002), canopy water content from the normalised difference water index (NDWI; Gao 1995), and a large number of leaf pigment indices (Sims & Gamon, 2002). Another method for focusing on absorption properties is continuum removal. A convex hull is fitted across the top of the spectrum for each pixel reflectance, absorption features are normalised to that hull, and the depth of a single absorption feature, such as leaf water content, may be assessed.

The principal component analysis (PCA) is a linear transformation approach that optimises data variance. When PCA is applied to a hyperspectral picture, it generates a sequence of components corresponding to linear combinations of the original bands aligned to reflect variation within the original data set. The first component is the plane responsible for the highest variation. This enables the identification of the essential class-related properties inside an image. MNF rescales the noise in the data (a technique known as noise whitening), allowing the analyst to remove bands with excessive sensor noise and leave only coherent picture data.

Assess accuracy. Following mapping accuracy assessment is one of the most critical aspects. Some sorts of inaccuracy may be acceptable depending on the study's aims, while others may not. Typical accuracy metrics for image classification include overall accuracy, user's accuracy, producer's accuracy, and Kappa coefficient. The likelihood that an image classifier properly categorises a pixel is considered overall accuracy. This measure does not consider the number of validation pixels per class and may be deceptive if a similar quantity is not utilised for each category. The user's and producer's accuracy may be preferable for evaluating the classification. The user's accuracy (error of commission) is the proportion of correctly classified pixels divided by the total number of classified pixels is the user accuracy (error of commission).

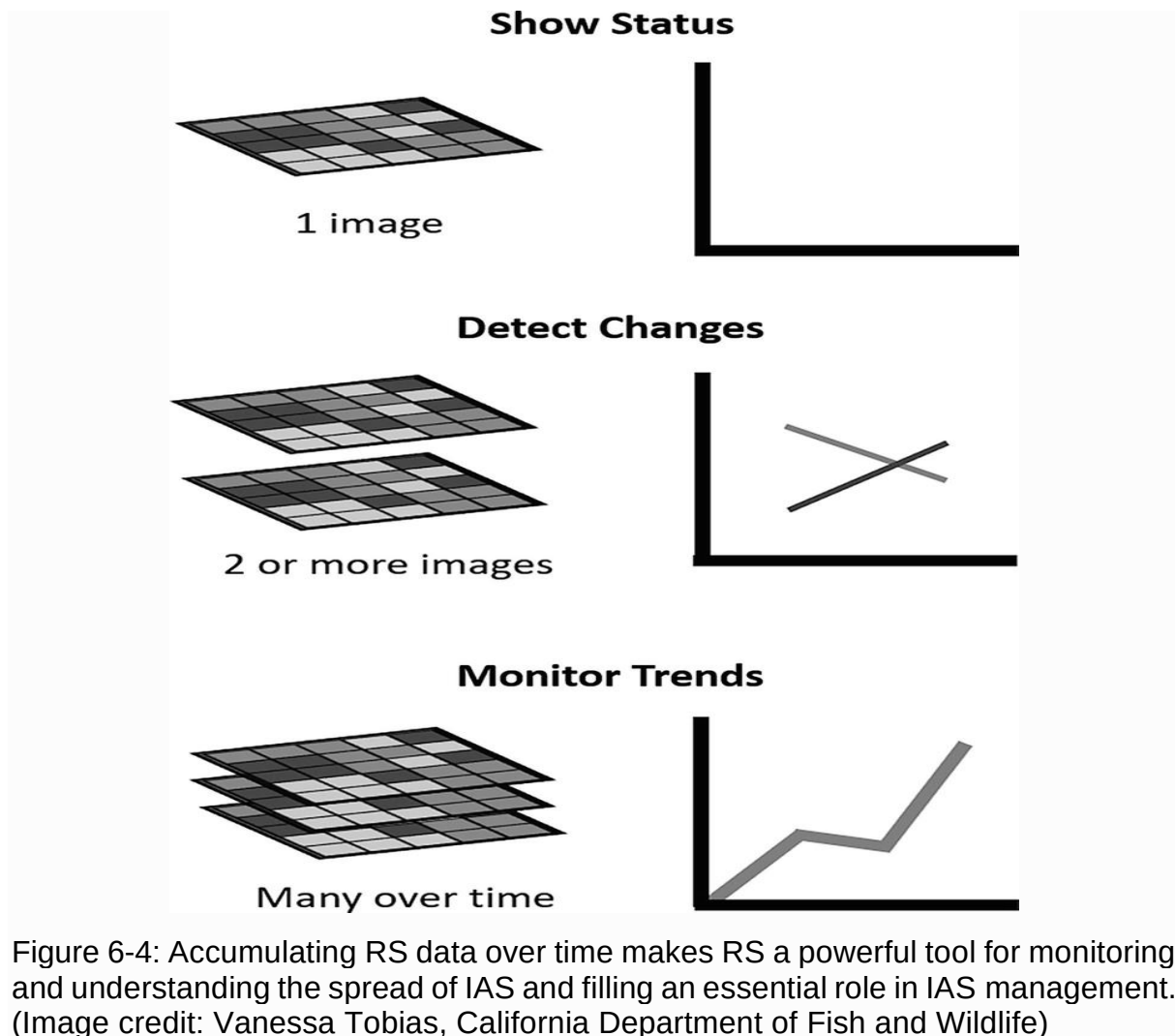
The proportion of correctly identified pixels regarding all ground reference validation pixels is the producer's accuracy (errors of omission). Overall accuracy and producer accuracy may not be as crucial as user accuracy in some cases, such as automated IAPS administration. Mapping IAPS to understand species spread and the invasion process is one example when maximising producer accuracy may be more critical; any missed species data as changes are tracked over time may impair process comprehension and spread projections.

The Kappa coefficient, the final statistic, might help compare several categorisation algorithms within the same data set. The Kappa coefficient measures how closely a classifier's overall accuracy compares to predicted accuracy, determined by the random categorisation of pixels from the data set. The last factor for accuracy evaluation is the relevance of obtaining independent validation data not included in

the mapping operation. When accuracy is measured using training data, it only indicates how effective the classifier is for the specific data it was trained on; nevertheless, the classifier may not be as accurate with other non-training pixels in the image.

Based on the ecosystem type and image analysis technique, data collection in the three RS domains (spectral, spatial, and temporal) may be optimised for a species. For species below the forest canopy, indirect approaches such as models based on the species' ecological knowledge may be required, or photography may be acquired during a leaf-off time. However, regular evaluation is necessary for a fast reaction to reduce crop loss. Because of the excellent potential for introductions and atypical landscape characteristics, such as impervious surfaces, RS detection of IAPS in urban environments necessitates various approaches and modifications.

These considerations highlight the significance of mission design for two critical data-gathering platforms. First, aerial platforms (both piloted and unpiloted), essential for quick, local-scale evaluations, must collect data at critical periods significant to IAPS phenology. Second, satellite platforms are crucial for delivering global-scale systematic IAPS monitoring. Current and future missions must contain high-resolution sensors capable of creating climate-relevant time series (length of a decade) to define phenology for broad IAPS detection, particularly in grasslands and forests (Figure 6.4).



6.8. Conclusion

Most IAPS management frameworks have been reactive, making preventive treatment an integral part of IAPS control in the future. Remote sensing (RS) and species distribution modelling (SDM) can assist land managers in identifying IAPS, targeting removal, monitoring growth and expansion rates, and evaluating treatment efficacy. The new studies focus on invasion mechanisms, effects, and management evaluations (Santos et al., 2009; Hestir et al., 2016; Santos et al., 2016). However, more studies are needed to determine how RS and SDM may be incorporated into understanding the invasion process, from arrival to establishment and dissemination. Achieving such a goal may be possible because of freely available time-series data and increasing volumes of field data related to the early diagnosis of IAPS.

As a result, it is critical to developing a multidisciplinary knowledge of the invasion process and the consequences of IAPS on ecosystems and biodiversity. Two

promising developments that have the potential to increase support for IAPS mapping and monitoring are the upcoming Surface Biology and Geology (SBG) global mapping hyperspectral satellite (Schimel et al., 2020) and the use of UAS imaging spectroscopy. The new satellite can increase the worldwide mapping of IAPS; despite its poor spatial resolution, it will still be capable of species-level identification in many instances. UAS provides on-demand high spatial resolution mapping, allowing for greater flexibility and simplicity of RS operations while lowering costs compared to human flights and enhancing safety. These breakthroughs can significantly increase the data gathered and, in conjunction with other scientific innovations, will aid in reducing the economic and environmental costs of IAPS.

The SDM results suggest that, for the time being, work in the VBR should be concentrated on the collecting and modelling of presence-absence data rather than abundance data. This is reinforced by the fact that presence/absence data are typically less expensive and faster to acquire. When modelled on relevant environmental factors, provide models capable of distinguishing between occupied and unoccupied evaluation sites with reasonable accuracy (Pearce et al., 2006). This technique will allow limited resources to expand the management area's geographical and environmental scope. The current work reveals that for *Eucalyptus camaldulensis* and *Caesalpinia decapetala*, the anticipated likelihood of occurrence obtained by SLR models might potentially serve as a fair relative measure of abundance; however, the MaxEnt model outperforms these.

The findings also point to the need for more study into the assumptions inherent in abundance modelling and the validity of these assumptions for the two IAPS of interest in the VBR. A notable example is an implicit assumption in species abundance models that more individuals correspond to better habitat quality. Van Horne (1983) disputed this assumption on theoretical grounds, arguing that more studies should be focused on improving our knowledge of population dynamics. Additional field research is required to address each of these difficulties.

If species abundance can be a meaningful predictor of habitat quality, then the significant effort should be put into developing appropriate methodologies for monitoring each IAPS of interest. Complexities such as detectability fluctuation in varied habitats, seasons and weather conditions, observer bias, and the geographic

scale at which species abundance should be recorded and simulated must all be handled by the SLR and MaxEnt models. This scale must be fine enough to be physiologically relevant and coarse enough to identify enough people to develop regional regression models.

It is also necessary to emphasise the improvement of habitat predictors. This study used abiotic, RS, and broad vegetation data to estimate species abundance over the VBR. Other research employing presence/absence data has discovered that more detailed explanatory factors, such as finer-scaled vegetation and growth stage features, and expert knowledge of species distribution modelling can boost prediction power (Valavi et al., 2021). This data may also be anticipated to enhance species abundance models.

A broader relevance of this study is that for many applications of species distribution and habitat modelling, careful consideration of the idea of optimum scales is required. What defines an ideal scale is determined by the study's aims and the purpose of model construction. Our findings show that how we define optimal cannot be independent of the model selection procedures used to pick the scales of environmental variables. It is common practice to choose geographical extents for predictor variables, which is essentially equivalent to defining the size of each ecological neighbourhood for each environmental variable (McGarigal et al. 2016) and hence the area affected by each variable in terms of occupancy (Jackson and Fahrig 2015) considering the findings of this research, an equally foresighted question such as “how should we choose which property defines best for selecting optimum scales for applied SDM and habitat modelling”? It can be asked.

Finally, our analyses and findings are based on a focal-patch-landscape research design (Brennan et al. 2002). However, the primary concepts here should also apply to more recently established methodologies that estimate effect sizes in continuous space when environmental variables are collected at numerous discrete spatial scales (Miguet et al., 2017). Predictive model selection procedures are equally relevant when analysing covariate scales in continuous space. However, minimal research explicitly chooses continuous distance-decay functions for predictive purposes with SDMs. This research shows that models based on known high abundance point locations might

perform better than merely modelling impact/non-impact by forecasting levels of potential abundance.

Understanding how present and future land use choices may impact seed distribution and colonisation of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* in high-risk locations is critical. According to this study, human land usage increases danger, and high-risk regions are found near currently invaded areas. As a result, intensive management to cure and reseed *Eucalyptus camaldulensis* and *Caesalpinia decapetala* monoculture is required (Ponzetti., 1997) to minimise further seed dispersal and colonisation, should consider closeness to uninvaded, high-risk locations. The current presence of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* can also be utilised to detect localised incursions, or foci, that require immediate management attention (Hobbs and Humphries 1995).

We are aware of the limits of our model forecasts for two IAPS, which were used to determine climatic appropriateness for multiple IAPS formations. Because SDMs are based on various assumptions, ecological ideas, and theories, ambiguity is a typical concern connected with modelling methodologies. When conducting distribution studies, estimates of species distributions under climate change can produce varying findings depending on how the environmental factors are simulated (Wiens et al., 2010). However, because it consistently outperforms alternative presence-only modelling techniques, we employed the well-established and highly acknowledged MaxEnt modelling methodology (Merow et al., 2013; Elith et al., 2011). Further, this modelling study was undertaken entirely on bioclimatic variables since climate controls the geographical distribution of plants predominantly over the other non-climatic factors, and we did not use non-climatic variables (Woodward et al., 1987).

As a result, we recognise the potential limits of removing non-climatic variables. Imperfect detection is another prevalent problem in MaxEnt models that is difficult to solve in modelling experiments and often goes unnoticed (Lahoz-Monfort et al., 2014). As a result, it contradicts one of the basic assumptions of distribution modelling, which states that species are identified evenly over the research site (Monk, 2014). However, presence-only data are routinely employed when absence data are unavailable, especially in less frequently sampled tropical nations (Phillips et al., 2006). The spatial predictions from modelling in this study show how a species or habitat distribution

occurs throughout geographical space rather than the ecological niche of a species in environmental space (Franklin, 2009). Though known by several titles, such as habitat modelling and ecological niche modelling, all SDMs identify adequate habitat for a species to live and reproduce; nevertheless, this is not the same as ecological niche modelling (Soberón, and Nakamura, 2009). Chapter 7 provides a conclusion and recommendations based on the study and its finding.

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Chapter 7 : Recommendations and Conclusions

7.1 Remote sensing and GIS

Remote sensing (RS) and geographic information systems (GIS) have been utilised to depict IAPS distribution and predict future dispersion by applying modelling approaches to predict suitable or unsuitable bioclimatic conditions in invaded regions (Cowling and Richardson, 1992; Bradley, 2009). This study has shown that it is possible to identify areas susceptible to invasion using simple and ecologically sound RS and GIS techniques. Mapping the potential spread of IAPS using RS and GIS offers a foundation for risk assessment, which VBR managers may use to better understand the needs for appropriately preventing and mitigating invasions while minimising economic damage.

Using remotely sensed data with spectral, spatial, and temporal resolutions can reveal environmental sensitivity to invasion, and these circumstances can be employed for early detection. The remote sensing results can be validated by comparing them to conditions produced from modelling methodologies and long-term field monitoring data. Remote sensing can also aid in the management of IAPS.

It appears that variations in the optical features of endemic and IAPS may be determined based on the studies covered in this research. Information derived from RS and GIS analyses might be used in assessing the efficacy of IAPS management approaches in the VBR and the broader region. We suggest the concepts above in the hopes that additional studies might be performed in these areas.

A closer look at the results of the RS and GIS monitoring approaches used in this study to determine the distribution of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* reveals how RS and GIS are sufficient, comprehensive, cost-effective, and flexible enough to model IAPS distribution from local to global scales over time, as well as monitor changes in IAPS. The optimal method for mapping and modelling IAPS distribution is determined by the scope of the inquiry, the amount of information required, the available resources, and the period.

We advocate including a wide variety of stakeholders throughout the process to optimise the effect of the produced models. All stakeholders must buy-in from the proposal stage through the experimental design stage. Developing a sense of

ownership or investment in a project increases the likelihood that the finished items will be used. As RS and GIS products are being produced, visit with potential consumers to see whether the format (metric scale/range, spatial resolution, file format, etc.) is advantageous and, if not, how items may be modified to meet their needs. We also believe that data products should be easily accessible and discoverable. Posting finished items in online databases, or web portals is one example of ensuring that the data format does not limit the use of the generated RS and GIS data.

Involving stakeholders in this manner increases the value and effect of your activities and helps to develop bridges between the scientific and managerial communities. Proper and timely communication is critical to reducing distrust when items are promised but delivered on a scientific timetable rather than an administrative timeline. Such actions can help to foster partnerships that will benefit all communities interested in preserving wooded environments.

Future research must investigate the capabilities of publicly available and upgraded spatial and spectral resolution multispectral datasets such as SPOT 6 and 7, as well as Sentinel-2 and 3, in conjunction with robust and sophisticated machine learning techniques to maximise IAPS identification and mapping in the VBR. Sentinel 3, just launched, provides daily coverage with enhanced spatial resolution, which is helpful for multi-temporal vegetation monitoring. Sentinel-3 provides extensive area coverage and spatial resolution, which are required for a more effective operational strategy in IAPS monitoring. The findings of this study may be utilised to propose future research efforts that focus on validating the capabilities of these classifiers using a recently published multispectral dataset with improved spatial and spectral information for operational scale mapping of AIPs.

7.2 Modeling Invasion

Methods like MaxEnt have been specially designed for IAPS modelling and include some safety precautions. These strategies will not work for all species or conditions; hence, developing new ways and instruments that can better map present and future distributions is essential. I hope our work will serve as a foundation for understanding and managing IAPS. That future advancement may enhance it to provide models more

suited to the job and tools helpful to practitioners to understand forecasts and their uncertainties better.

7.3 Strategising for combating invasions.

The study's findings indicate that the predictability of the possible geography of species invasions allows for the formulation of different scenarios of successful versus failed invasions. These scenarios may then be utilised to predict important invasion routes, arrival places, and starting points for the two IAPS within the VBR (NAS, 2002). Such knowledge would be critical in developing a successful plan to combat a specific invasion. Projections of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* using SDMs show higher certainty in predicting presence. Combining SDM findings with Stepwise logistic regression models of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* can demonstrate expansion and dispersion inside the VBR while considering climate suitability variables (Hargrove et al., 2000).

According to the data, most successful invasions started around the Soutpansberg mountain, regardless of where invasions have expanded. Hence these remnants should be prioritised for the management of IAPS in the VBR. Although the models indicated adequately appropriate habitat across the agricultural, riverine portions of the VBR's Luvuvhu valley, the area around the Soutpansberg mountains looks to be essential to the two IAPS successful invasion. As a result, SDM techniques may be used to assess the invasive potential of a *Eucalyptus camaldulensis* and *Caesalpinia decapetala* significantly over geographic locations, corridors, or places of widespread spread. This feature, which has received substantial empirical backing from both the climate and SDM experiences, may considerably influence fighting and control efforts for a specific species after it has been discovered as existing in an IAPS distribution inside the VBR.

7.4 Anticipating invasions before they occur

When it comes to projected geographic distributions of *Eucalyptus camaldulensis* and *Caesalpinia decapetala*, the predictive feature of SDMs may be expanded beyond the simple premise of retroactively assessing invasive potential but contribute to the management and control of the two IAPS. That is, the invasive potential of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* may be discovered and analysed before

the invasion, as has been widely implemented in South Africa's state and national invasive species monitoring programmes (Van Wilgen et al., 2020). This capability allows for assessing invasion risk even before a species is considered invasive.

7.5 Predicting invasions across scenarios of change

The predictive nature of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* from their biological niches may be extended across invasion scenarios and independently over climate change scenarios (Martnez-Meyer 2002). The results of the SDMs reflect ecosystems, including changing climate as evidenced by biodiversity, implying that future *Eucalyptus camaldulensis* and *Caesalpinia decapetala* invasions will occur in the context of changing climates and therefore shifting possibilities for invasion throughout geography (Walther et al. 2002).

Based on this research, we may conclude that combining predictive analyses for invasions and climate change phenomena is viable, generating projections of potential for invasion from *Eucalyptus camaldulensis* and *Caesalpinia decapetala* throughout the VBR in the face of climate change. It is similarly possible to integrate invasion estimates with other change scenarios, such as anthropogenic changes in land use and land cover. However, one constraint of these investigations is the absence of sufficient baseline data sets to allow quantitative statistical confirmation of predictivity across numerous change scenarios. This study provides a theoretical foundation for IAPS ecological control using risk assessment.

7.6 Biome-wide risk assessments

The data on *Eucalyptus camaldulensis* and *Caesalpinia decapetala* 's broad predictability opens the door to biome-wide risk assessments of invasive potential into the VBR (Honig et al. 1992). Although the availability of occurrence information for the VBR did not cover the whole reserve, it has the potential to significantly influence efforts to avert future *Eucalyptus camaldulensis* and *Caesalpinia decapetala* invasive issues.

7.7 Extrapolating to spatial and Higher temporal scales

This study demonstrated that expanding ET or transpiration estimates to larger geographical and longer temporal scales may be utilised to predict IAPS water usage with remarkable effectiveness. As previously found in similar research, the availability of observable data to test predictions and assumptions is critical to significantly reducing uncertainty (Allen et al. 1998). To properly handle the water resource repercussions of IAPS, an integrated strategy that can cope with many species, which typically occur as combinations of different densities within a temperature range and have access to groundwater and surface water, is required. One strategy for investigating this variability at broad spatial scales is to use remote sensing data to estimate evapotranspiration from IAPS and compare it to estimates of evapotranspiration from native vegetation. This technique has disadvantages, but it also can consistently measure and compare the water resource consequences of various IAPS across the VBR (van Niekerk et al., 2018). The use of remote sensing ET derivatives as proxies for water loss in AIPS becomes increasingly robust and helpful as the geographical and temporal resolution of the dataset increases.

7.8 Policy and governance

Despite developing the Working for Water Programme (WfWP) in response to the expected effects of IAPS on runoff, no regulatory or legislative procedures have been developed to require their management to reduce water impacts. The findings of this study, albeit preliminary, can give guidance on how invaded land in major surface water supply sites can be prioritised for enforcement and investment to maximise water benefits. The Department of Environment, Forestry, and Fisheries (DEFF) is prioritising places with the most significant water benefits (Forsyth et al. 2012), with a new emphasis on significant water source areas (Le Maitre et al. 2018), which corresponds with the VBR's Soutpansberg mountain ranges and Luvuvhu valley. A recent review of the condition of invasions highlighted the significance of prioritising regions to maximise the rewards from clearing, including water. However, there is still a legacy of initiatives that were launched in locations that were not appropriate (van Wilgen and Wilson 2018).

Using biomass for furniture manufacture at the Albasini Dam through a public-private partnership and cost-sharing arrangement might result in a net gain from IAPS in the VBR (Stafford and Blignaut 2017). This enterprise's viability depends on farmers' and communities' willingness to share the cost of IAPS biomass supply with the Albasini furniture manufacturer. In this case, the advantages listed omit further downstream effects such as the contribution to job creation, Gross Domestic Product (GDP), and the benefits of skill development, rural development stimulation, and assisting in steering the VBR towards a more sustainable growth path. Suppose anticipated water flow gains are used to direct the site of these investments, and they are factored in and realised. In that case, such programs might significantly contribute to water security in the VBR.

7.9 Financial and economic impacts of water lost through invasions

The opportunity cost of IAPS in terms of money includes the lost value of output due to a decrease in water supplies, the increased requirement for water supply augmentation projects and the early development of such facilities in the VBR. IAPS have a far more significant economic impact on the VBR since they modify ecosystem functioning, processes, biodiversity, and every aspect of human existence and livelihood that is dependent on or influenced by them.

7.10 Conflicts and controversies relating to IAPS hydrological impacts and the impacts of clearing

The expansion of IAPS in the VBR, including those from plantations, can significantly increase fuel loads, fire intensity, and severity, especially if coarse dead fuels are present on the soil surface, potentially resulting in severe erosion and flooding downstream (Le Maitre et al. 2014). Dense and closed stands of *Eucalyptus camaldulensis* and *Caesalpinia decapetala* thorn restrict ground-layer vegetation, altering infiltration and decreasing soil stability, thus influencing water quality, increasing dam sedimentation (van der Waal et al. 2012), and reducing grazing capacity (Yapi 2013). Several long-term watershed studies have shown that plantations influence surface runoff. The principal invading tree species are the same as those in plantations, achieving equivalent stand densities and heights. However, the Department of Water Affairs and Sanitation (DWS) has refused to admit that the

effects of incursions might be just as severe as those of crops. According to the growing body of research, production reductions should impact future water supply system decisions while promoting successful IAPS management activities as part of VBR maintenance.

7.11 References

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Appendix

Appendix 4.1: Description of Bioclim variables and the contributing variables used in their calculation.

Variable Number	Variable	Minimum temp (°C)	Maximum temp (°C)	Rainfall (mm month ⁻¹)	Radiation (W m ⁻² d ⁻¹)	Pan evaporation (mm d ⁻¹)	Ref.
Bio01	Annual mean temperature (°C)	x	x				1
Bio02	Mean diurnal temperature range (mean (period max-min)) (°C)	x	x				1
Bio03	Isothermality (Bio02 ÷ Bio07)	x	x				1
Bio04	Temperature seasonality (C of V)	x	x				1
Bio05	Max temperature of the warmest week (°C)		x				1
Bio06	Min temperature of the coldest week (°C)	x					1
Bio07	Temperature annual range (Bio05-Bio06) (°C)	x	x				1
Bio08	Mean temperature of the wettest quarter (°C)	x	x	x			1
Bio09	Mean temperature of the driest quarter (°C)	x	x	x			1
Bio10	Mean temperature of warmest quarter (°C)	x	x				1
Bio11	Mean temperature of coldest quarter (°C)	x	x				1
Bio12	Annual precipitation (mm)			x			1
Bio13	Precipitation of wettest week (mm)			x			1
Bio14	Precipitation of driest week (mm)			x			1
Bio15	Precipitation seasonality (C of V)			x			1
Bio16	Precipitation of wettest quarter (mm)			x			1

Variable Number	Variable	Minimum temp (°C)	Maximum temp (°C)	Rainfall (mm month ⁻¹)	Radiation (W m ⁻² d ⁻¹)	Pan evaporation (mm d ⁻¹)	Ref.
Bio17	Precipitation of driest quarter (mm)			x			1
Bio18	Precipitation of warmest quarter (mm)	x	x	x			1
Bio19	Precipitation of coldest quarter (mm)	x	x	x			1
Bio20	Annual mean radiation (W m ⁻²)				x		1
Bio21	Highest weekly radiation (W m ⁻²)				x		1
Bio22	Lowest weekly radiation (W m ⁻²)				x		1
Bio23	Radiation seasonality (C of V)				x		1
Bio24	Radiation of wettest quarter (W m ⁻²)			x	x		1
Bio25	Radiation of driest quarter (W m ⁻²)			x	x		1
Bio26	Radiation of warmest quarter (W m ⁻²)	x	x		x		1
Bio27	Radiation of coldest quarter (W m ⁻²)	x	x		x		1
Bio28	Annual mean moisture index			x		x	1
Bio29	Highest weekly moisture index			x		x	1
Bio30	Lowest weekly moisture index			x		x	1
Bio31	Moisture index seasonality (C of V)			x		x	1
Bio32	Mean moisture index of wettest quarter			x		x	1
Bio33	Mean moisture index of driest quarter			x		x	1
Bio34	Mean moisture index of warmest quarter	x	x	x		x	1
Bio35	Mean moisture index of coldest quarter	x	x	x		x	1
Bio36	The first principal component of the first 35 Bioclim variables	x	x	x	x	x	2
Bio37	The second principal component of the first 35 Bioclim variables	x	x	x	x	x	2

Variable Number	Variable	Minimum temp (°C)	Maximum temp (°C)	Rainfall (mm month ⁻¹)	Radiation (W m ⁻² d ⁻¹)	Pan evaporation (mm d ⁻¹)	Ref.
Bio38	The third principal component of the first 35 Bioclim variables	x	x	x	x	x	2
Bio39	The fourth principal component of the first 35 Bioclim variables	x	x	x	x	x	2
Bio40	The fifth principal component of the first 35 Bioclim variables	x	x	x	x	x	2

Variables without units are dimensionless indices. Source: 1: Hutchinson et al. (2009); 2: Kriticos et al. (2014).

Appendix 4.2: Sampling sites and coordinates for the Presence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*

Site ID	Latitude	Longitude	Species (Cat)
456	-22.981484	29.888762	1
462	-22.981600	29.889286	1
468	-22.981827	29.889790	1
473	-22.985423	29.976981	1
474	-22.979296	29.986612	1
475	-23.018644	30.304874	1
476	-23.008256	30.331941	1
478	-22.983286	30.143457	1
479	-22.983156	30.143403	1
482	-22.995156	30.119696	1
484	-23.006343	30.095050	1
486	-23.010549	30.098089	1
487	-23.016598	30.101667	1
496	-23.010927	29.900354	1
498	-23.021219	29.979758	1
500	-23.017704	29.990130	1
501	-23.011024	30.012821	1
502	-23.011787	30.011574	1
512	-23.081279	30.096378	1

Site ID	Latitude	Longitude	Species (Cat)
514	-23.080879	30.096022	1
515	-23.080583	30.095502	1
521	-23.052559	30.075629	1
Buweed	-23.012193	30.293992	1
Ecalforest	-23.011051	30.328200	1
Ek1	-23.052232	30.074082	1
End of hanklip	-22.992548	29.884908	1
Eu20	-23.003259	30.099039	1
Euc28	-23.061405	30.078634	1
Euc29	-23.061131	30.079045	1
Euc30	-23.009050	29.884018	1
Laj2	-23.031882	29.424426	1
Lajbg2	-23.031090	29.426380	1
Maur27	-23.069443	30.075839	1
Mur17	-23.061615	30.078332	1
T1	-23.054006	30.072362	1
T25	-23.061492	30.078247	1
T26	-23.061469	30.078085	1
T27	-23.061339	30.077646	1
T7	-23.016992	30.220476	1
475	-23.018644	30.304874	2
476	-23.008256	30.331941	2
477	-23.010892	30.328369	2
488	-23.064846	30.083534	2
491	-23.066135	30.082607	2
493	-23.066214	30.081465	2
498	-23.021219	29.979758	2
499	-23.019770	29.981747	2
503	-23.081438	30.094362	2
504	-23.081445	30.094362	2
505	-23.080990	30.093242	2
506	-23.080916	30.092383	2
507	-23.080564	30.092643	2
508	-23.080234	30.092642	2

Site ID	Latitude	Longitude	Species (Cat)
510	-23.082602	30.094908	2
511	-23.081646	30.095810	2
513	-23.081236	30.096274	2
517	-23.079196	30.092880	2
518	-23.055572	30.070696	2
519	-23.055119	30.071755	2
520	-23.055961	30.070520	2
523	-23.058061	30.072611	2
524	-23.074260	30.194350	2
525	-23.074109	30.183205	2
526	-23.087029	30.116891	2
528	-23.031824	29.424640	2
La3	-23.040503	29.450393	2
Laj1	-23.039088	29.446576	2
Lajbg1	-23.033766	29.423576	2
Maur100m	-23.019101	29.976661	2
Maur30	-23.018490	29.976095	2
Maut	-22.989863	29.925585	2

Appendix 4.3: Sampling sites and coordinates for the Absence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis*

Site ID	Latitude	Longitude	Species (Cat)
0	-23.096466	29.981042	2
1	-23.094087	30.084310	2
2	-23.093331	29.465224	2
3	-23.075501	29.494503	2
4	-23.075467	30.014492	2
5	-23.070015	30.053560	2
6	-23.068556	29.472356	2
7	-23.055951	29.963830	2
8	-23.049225	29.787479	2
9	-23.048662	29.428626	2
10	-23.043233	30.115004	2
11	-23.042059	30.059305	2

Site ID	Latitude	Longitude	Species (Cat)
12	-23.041586	29.591543	2
13	-23.040591	29.690634	2
14	-23.038527	29.515336	2
15	-23.038339	29.543489	2
16	-23.038151	29.774341	2
17	-23.036838	29.455840	2
18	-23.034683	29.918298	2
19	-23.034022	29.653660	2
20	-23.032896	29.599606	2
21	-23.030832	29.417365	2
22	-23.030644	29.676557	2
23	-23.028549	29.805560	2
24	-23.027912	29.934574	2
25	-23.024345	30.009581	2
26	-23.018257	29.542963	2
27	-23.017694	29.426749	2
28	-23.016624	29.895798	2
29	-23.014292	29.906648	2
30	-23.012063	29.512108	2
31	-23.006710	29.889543	2
32	-23.003331	29.903165	2
33	-22.998007	30.003730	2
34	-22.997379	29.964584	2
35	-22.990533	29.885852	2
36	-22.989344	29.895560	2
37	-22.984989	29.886256	2
38	-22.983752	29.894775	2
39	-22.983728	29.881355	2
40	-22.979397	29.893966	2
41	-22.978993	29.879665	2
42	-22.977020	29.981316	2
43	-22.962751	29.935577	2
44	-22.945954	29.925779	2
45	-22.929904	29.906803	2

Site ID	Latitude	Longitude	Species (Cat)
0	-23.070015	30.053560	1
1	-23.063110	30.067476	1
2	-23.053329	30.090929	1
3	-23.050973	30.084327	1
4	-23.048662	29.428626	1
5	-23.045833	30.101664	1
6	-23.043450	29.990139	1
7	-23.042059	30.059305	1
8	-23.040591	29.417928	1
9	-23.036838	29.455840	1
10	-23.033022	30.033937	1
11	-23.030832	29.403851	1
12	-23.030832	29.417365	1
13	-23.025952	29.451335	1
14	-23.024345	30.009581	1
15	-23.022470	29.954671	1
16	-23.017723	29.969227	1
17	-23.017694	29.426749	1
18	-23.016624	29.895798	1
19	-23.016386	29.902127	1
20	-23.015246	29.899112	1
21	-23.014879	29.414174	1
22	-23.014292	29.906648	1
23	-23.014255	29.897127	1
24	-23.011688	29.450772	1
25	-23.010342	29.895703	1
26	-23.008878	29.901562	1
27	-23.005431	29.975320	1
28	-22.998007	30.003730	1
29	-22.997379	29.964584	1
30	-22.995866	29.989454	1
31	-22.992296	29.992166	1
32	-22.990912	30.021120	1

Appendix 4.4: Presence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* from sampling sites within the VBR

SiteID	Latitude	Longitude	Altitude (MASL)	Species	Aspect	Soil	Soil depth (mm)	LandType	Landform	Geology	SoilStb (%)	GBWP	Anl P(p(mm)	AETI	Pot Evap	Rel hum(%RH)	Intercept(I)	Soil Rdn	Bioclim 1	Bioclim 4	Cover	Addnl	Bioclim 15
456	-22.981484	29.888762	1377	<i>Eucalyptus camaldulensis</i>	S	ACH	>750mm	Ab151	SH	Mwy	81 - 100%	1544	912	1020	1684	62	355	17.10	16.49	295.34	Closed		82.27
462	-22.981600	29.889286	1411	<i>Eucalyptus camaldulensis</i>	S	ACH	>750mm	Ab151	SH	Mwy	81 - 100%	1544	912	1020	1684	62	355	17.10	16.49	295.34	Canopy		82.27
468	-22.981827	29.889790	1417	<i>Eucalyptus camaldulensis</i>	SW	ACH	>750mm	Ab151	SH	Mwy	81 - 100%	1544	912	1020	1684	62	355	17.10	16.49	295.34	Closed		82.27
473	-22.985423	29.976981	1259	<i>Eucalyptus camaldulensis</i>	S	ACH	>750mm	Ab109	SH	Mt	81 - 100%	1818	980	610	1702	64	305	16.50	17.07	291.42	Open	Gravel	81.51
474	-22.979296	29.986612	1278	<i>Eucalyptus camaldulensis</i>	SE	ACH	>750mm	Ab109	SH	Mf	81 - 100%	1864	980	610	1708	64	263	16.50	17.07	291.42	Open	Tar	81.51
475	-23.018644	30.304874	1102	<i>Eucalyptus camaldulensis</i>	SW	ACH	450mm - 750mm	Ab111	SH	Mt	81 - 100%	2351	2248	880	1740	67	698	16.00	18.99	273.60	Closed		81.11
476	-23.008256	30.331941	1085	<i>Eucalyptus camaldulensis</i>	N W	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1748	1757	840	1752	69	633	16.40	18.99	273.60	Closed		81.11
478	-22.983286	30.143457	981	<i>Eucalyptus camaldulensis</i>	N	ACH	>750mm	Ab109	SH	Mf	81 - 100%	1770	1175	640	1785	61	166	17.30	17.99	282.07	Canopy		82.09
479	-22.983156	30.143403	983	<i>Eucalyptus camaldulensis</i>	N	ACH	>750mm	Ab109	SH	Mf	81 - 100%	1770	1175	640	1785	61	166	17.30	17.99	282.07	Canopy		82.09
482	-22.995156	30.119696	1090	<i>Eucalyptus camaldulensis</i>	N	ACH	>750mm	Ab109	SH	Mt	81 - 100%	1540	1131	1140	1724	61	603	17.40	17.17	284.19	Closed		81.74
484	-23.006343	30.095050	1227	<i>Eucalyptus camaldulensis</i>	SE	ACH	>750mm	Ab109	SH	Mt	81 - 100%	1965	1253	750	1693	63	305	16.90	17.98	283.42	Closed		80.53
486	-23.010549	30.098089	1213	<i>Eucalyptus camaldulensis</i>	SE	ACH	>750mm	Ab109	SH	Mt	81 - 100%	1998	1478	890	1693	64	483	16.50	17.98	283.42	Closed		80.53
487	-23.016598	30.101667	1177	<i>Eucalyptus camaldulensis</i>	NE	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1989	1478	1040	1688	64	595	16.50	17.98	299.21	Open	Gravel	80.53
496	-23.010927	29.900354	1099	<i>Eucalyptus camaldulensis</i>	SE	LPe	450mm - 750mm	Ae291	SH	Mt	81 - 100%	1266	996	1150	1733	63	526	16.90	18.08	292.08	Open	Gravel	80.27
498	-23.021219	29.979758	1039	<i>Eucalyptus camaldulensis</i>	W	ACH	>750mm	Ab107	SH	Mt	81 - 100%	1238	920	880	1791	60	353	17.60	18.41	292.08	Open	Gravel	80.83
500	-23.017704	29.990130	1161	<i>Eucalyptus camaldulensis</i>	S	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1351	920	850	1767	60	414	17.60	18.41	289.26	Canopy		80.83
501	-23.011024	30.012821	1222	<i>Eucalyptus camaldulensis</i>	N	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1993	976	1010	1761	62	475	17.20	18.51	289.26	Canopy		80.70
502	-23.011787	30.011574	1231	<i>Eucalyptus camaldulensis</i>	N	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1513	976	880	1749	62	435	17.20	18.51	285.51	Closed	Gravel	80.70
512	-23.081279	30.096378	809	<i>Eucalyptus camaldulensis</i>	SE	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1612	910	820	1835	59	344	17.80	18.74	285.51	Canopy		80.27
514	-23.080879	30.096022	807	<i>Eucalyptus camaldulensis</i>	SE	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1612	910	820	1835	59	344	17.80	18.74	285.51	Closed	Gravel	80.27
515	-23.080583	30.095502	815	<i>Eucalyptus camaldulensis</i>	SE	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1634	910	870	1835	59	402	17.80	18.74	293.28	Open	Gravel	80.27
521	-23.052559	30.075629	848	<i>Eucalyptus camaldulensis</i>	SE	ACH	>750mm	Ab107	SH	Mt	81 - 100%	1237	1064	1090	1785	59	542	17.80	19.62	273.60	Open	Gravel	81.72
Buwee d	-23.012193	30.293992	1196	<i>Eucalyptus camaldulensis</i>	S	ACH	450mm - 750mm	Ab107	SH	Mt	81 - 100%	2277	2248	800	1712	67	444	16.00	18.99	273.60	Closed		81.11
Ecalfor est	-23.011051	30.328200	1017	<i>Eucalyptus camaldulensis</i>	N	ACH	>750mm	Ab108	SH	Mt	81 - 100%	2173	1757	1090	1752	65	465	16.40	18.99	293.28	Canopy	Gravel	81.11
Ek1	-23.052232	30.074082	854	<i>Eucalyptus camaldulensis</i>	SW	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1237	1004	990	1785	60	542	17.70	19.62	295.34	Canopy	Gravel	81.72
End of hanklip	-22.992548	29.884908	1524	<i>Eucalyptus camaldulensis</i>	N	ACH	450mm - 750mm	lb349	SH	Mwy	81 - 100%	2105	1178	1040	1686	69	495	15.30	16.49	283.42	Closed		82.27

SiteID	Latitude	Longitude	Altitude (MASL)	Species	Aspect	Soil	Soil depth (mm)	LandType	Landform	Geology	SoilStb (%)	GBWP	Anl Prcp(mm)	AETI	Pot Evap	Rel hum(%RH)	Intercept(I)	Soil Rdn	BioClim 1	BioClim 4	Cover	Addnl	BioClim 15
Eu20	-23.003259	30.099039	1200	Eucalyptus camaldensis	N	ACH	>750mm	Ab109	SH	Mt	81 - 100%	2061	1253	1140	1693	63	535	16.90	17.98	293.28	Closed		80.53
Euc28	-23.061405	30.078634	917	Eucalyptus camaldensis	SW	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1384	1137	1140	1817	62	491	17.10	19.62	293.28	Closed		81.72
Euc29	-23.061131	30.079045	927	Eucalyptus camaldensis	W	ACH	>750mm	Ab108	SH	Mt	61 - 80%	1384	1137	980	1817	62	491	17.10	19.62	299.21	Closed		81.72
Euc30	-23.009050	29.884018	1364	Eucalyptus camaldensis	W	LPe	450mm - 750mm	Fa535	SH	Mt	81 - 100%	1448	1055	630	1713	66	646	16.10	18.08	332.15	Open	Gravel	80.27
Laj2	-23.031882	29.424426	1371	Eucalyptus camaldensis	S	LPe	>750mm	Ab147	SH	Mwy	81 - 100%	2015	723	920	1787	62	408	16.90	16.70	332.15	Closed		84.41
Lajbg2	-23.031090	29.426380	1375	Eucalyptus camaldensis	S	LPe	>750mm	Ab147	SH	Mwy	81 - 100%	1577	782	1040	1775	66	548	16.00	16.70	293.28	Closed		84.41
Maur27	-23.069443	30.075839	827	Eucalyptus camaldensis	W	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1287	1137	1140	1820	62	464	17.10	19.62	293.28	Canopy		81.72
Mur17	-23.061615	30.078332	909	Eucalyptus camaldensis	SW	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1384	1137	1040	1820	62	491	17.10	19.62	293.28	Closed		81.72
T1	-23.054006	30.072362	836	Eucalyptus camaldensis	SW	ACH	>750mm	Ab107	LP	Mt	81 - 100%	1245	1004	1140	1825	60	552	17.70	19.62	293.28	Open		81.72
T25	-23.061492	30.078247	884	Eucalyptus camaldensis	SW	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1384	1137	1000	1817	62	491	17.10	19.62	293.28	Closed		81.72
T26	-23.061469	30.078085	907	Eucalyptus camaldensis	S	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1294	1137	1000	1820	62	441	17.10	19.62	293.28	Closed		81.72
T27	-23.061339	30.077646	924	Eucalyptus camaldensis	S	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1294	1137	1020	1817	62	441	17.10	19.62	293.28	Closed		81.72
T7	-23.016992	30.220476	1056	Eucalyptus camaldensis	SW	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1545	1776	1020	1728	65	657	16.50	18.62	274.81	Closed		81.30
475	-23.018644	30.304874	1102	Caesalpinia decapetala	SW	ACH	450mm - 750mm	Ab111	SH	Mt	81 - 100%	2351	2248	880	1740	67	698	16.00	18.99	273.60	Canopy	Gravel	81.11
476	-23.008256	30.331941	1085	Caesalpinia decapetala	N W	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1748	1829	840	1752	69	633	15.50	18.99	273.60	Canopy	Gravel	81.11
477	-23.010892	30.328369	1017	Caesalpinia decapetala	N	ACH	>750mm	Ab108	SH	Mt	81 - 100%	2173	1757	800	1752	65	463	16.40	18.99	273.60	Canopy	Gravel	81.11
488	-23.064846	30.083534	932	Caesalpinia decapetala	SE	ACH	>750mm	Ab108	SH	Zgo	81 - 100%	1717	1137	860	1820	62	442	17.10	19.62	285.51	Closed		80.27
491	-23.066135	30.082607	913	Caesalpinia decapetala	W	ACH	>750mm	Ab108	SH	Zgo	81 - 100%	1717	1137	860	1820	62	513	17.10	19.62	293.28	Closed		81.72
493	-23.066214	30.081465	894	Caesalpinia decapetala	N W	ACH	>750mm	Ab108	SH	Zgo	81 - 100%	1322	1137	1020	1820	62	513	17.10	19.62	293.28	Closed		81.72
498	-23.021219	29.979758	1039	Caesalpinia decapetala	W	ACH	>750mm	Ab107	SH	Mt	81 - 100%	1238	920	880	1791	60	353	17.60	18.41	292.08	Canopy	Gravel	80.83
499	-23.019770	29.981747	1057	Caesalpinia decapetala	N W	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1302	920	1000	1791	60	296	17.60	18.41	292.08	Canopy	Gravel	80.83
503	-23.081438	30.094362	795	Caesalpinia decapetala	S	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1634	910	870	1835	59	296	17.80	18.74	285.51	Closed		80.27
504	-23.081445	30.094362	803	Caesalpinia decapetala	S	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1634	910	870	1835	59	402	17.80	18.74	285.51	Closed		80.27
505	-23.080990	30.093242	799	Caesalpinia decapetala	SW	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1255	910	990	1835	59	402	17.80	18.74	285.51	Closed		80.27
506	-23.080916	30.092383	795	Caesalpinia decapetala	SW	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1255	910	990	1835	59	404	17.80	18.74	285.51	Closed		80.27
507	-23.080564	30.092643	799	Caesalpinia decapetala	SW	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1255	910	990	1835	59	404	17.80	18.74	285.51	Closed		80.27
508	-23.080234	30.092642	805	Caesalpinia decapetala	SW	ACH	>750mm	Ab107	LP	Zgo	81 - 100%	1656	910	840	1835	59	404	17.80	18.74	285.51	Canopy	Gravel	80.27

SiteID	Latitude	Longitude	Altitude (MASL)	Species	Aspect	Soil	Soil depth (mm)	LandType	Landform	Geology	SoilStb (%)	GBWP	Anl Pyp(mm)	AETI	Pot Evap	Rel hum(%RH)	Intercept(I)	Soil Rdn	BioClim 1	BioClim 4	Cover	Addnl	BioClim 15
510	-23.082602	30.094908	792	Caesalpinia decapetala	S	ACh	>750mm	Ab107	LP	Zgo	81 - 100%	1634	910	1010	1835	59	374	17.80	18.74	285.51	Canopy	Gravel	80.27
511	-23.081646	30.095810	801	Caesalpinia decapetala	SW	ACh	>750mm	Ab107	LP	Zgo	81 - 100%	1634	910	870	1835	59	402	17.80	18.74	285.51	Canopy	Gravel	80.27
513	-23.081236	30.096274	807	Caesalpinia decapetala	SW	ACh	>750mm	Ab107	LP	Zgo	81 - 100%	1612	910	820	1835	59	402	17.80	18.74	285.51	Canopy	Gravel	80.27
517	-23.079196	30.092880	812	Caesalpinia decapetala	SW	ACh	>750mm	Ab107	LP	Zgo	81 - 100%	1656	910	820	1835	59	344	17.80	18.74	285.51	Open	Gravel	80.27
518	-23.055572	30.070696	821	Caesalpinia decapetala	SW	ACh	>750mm	Ab107	LP	Mt	81 - 100%	1239	1004	1130	1825	60	374	17.70	19.62	293.28	Open	Gravel	81.72
519	-23.055119	30.071755	826	Caesalpinia decapetala	SW	ACh	>750mm	Ab107	LP	Mt	81 - 100%	1239	1004	1040	1825	60	532	17.70	19.62	293.28	Canopy		81.72
520	-23.055961	30.070520	823	Caesalpinia decapetala	N	ACh	>750mm	Ab107	LP	Mt	81 - 100%	1255	1004	950	1825	60	552	17.70	19.62	293.28	Canopy	Gravel	81.72
523	-23.058061	30.072611	855	Caesalpinia decapetala	N	ACh	>750mm	Ab107	LP	Mt	81 - 100%	1351	1004	1120	1825	60	441	17.90	19.62	293.28	Canopy		81.72
524	-23.074260	30.194350	763	Caesalpinia decapetala	SE	RGe	450mm - 750mm	Fa331	LP	Zgo	61 - 80%	1615	1303	590	1826	59	197	17.70	19.97	282.16	Open	Tar	80.94
525	-23.074109	30.183205	778	Caesalpinia decapetala	NE	ACh	450mm - 750mm	Fa331	LP	Zgo	61 - 80%	1337	1341	1080	1821	60	554	17.40	19.97	282.16	Canopy	Gravel	80.94
526	-23.087029	30.116891	795	Caesalpinia decapetala	SE	ACh	>750mm	Ab107	LP	Zgo	81 - 100%	1231	1102	970	1831	61	408	16.90	20.07	294.46	Open	Tar	81.55
528	-23.031824	29.424640	1372	Caesalpinia decapetala	S	LPe	>750mm	Ab147	SH	Mwy	81 - 100%	2015	723	630	1787	62	554	16.60	16.70	332.15	Closed		84.41
La3	-23.040503	29.450393	1215	Caesalpinia decapetala	SE	LPe	>750mm	Ab147	SH	Mwy	81 - 100%	1417	851	990	1812	64	508	16.60	16.70	332.15	Canopy	Gravel	84.41
Laj1	-23.039088	29.446576	1284	Caesalpinia decapetala	S	LPe	>750mm	Ab147	SH	Mwy	81 - 100%	1551	851	950	1812	64	660	16.90	16.70	332.15	Closed		84.41
Lajbg1	-23.033766	29.423576	1344	Caesalpinia decapetala	NE	ACh	>750mm	Ab147	SH	Mwy	81 - 100%	2062	723	690	1787	62	320	16.60	16.70	332.15	Canopy	Gravel	84.41
Maur10m	-23.019101	29.976661	1015	Caesalpinia decapetala	N W	ACh	>750mm	Ab107	SH	Mt	81 - 100%	1244	920	690	1768	60	363	17.60	18.41	292.08	Canopy	Gravel	80.83
Maur30	-23.018490	29.976095	1013	Caesalpinia decapetala	SW	ACh	>750mm	Ab107	SH	Mt	81 - 100%	1244	920	690	1768	60	363	17.60	18.41	292.08	Canopy	Gravel	80.83
Maut	-22.989863	29.925585	1331	Caesalpinia decapetala	SW	ACh	450mm - 750mm	Fa535	SH	Mt	61 - 80%	1426	1128	980	1720	68	363	15.40	17.15	293.33	Canopy	Gravel	82.14

Appendix 4.5: Absence of *Caesalpinia decapetala* and *Eucalyptus camaldulensis* from sampling sites within the VBR

Site ID	Latitude	Longitude	Species	Species (Cat)	Altitude (MASL)	Aspect	Soil	Soil depth (mm)	LandType	Landform	Geology	SoilStb (%)	Anl P(p)(mm)	GBWP	AETI	Pot Evap	Intercept(I)	Rel hum(%RH)	Soil Rdn	BioClim 1	BioClim 4	BioClim 15	Cover
0	-23.096466	29.981042	Caesalpinia decapetala Abscent	2	1388	N W	ACh	>750mm	Ab151	SH	Mwy	81 - 100%	912	1781	1299	1691	255	75	23.40	16.49	295.34	82.27	Closed
1	-23.094087	30.084310	Caesalpinia decapetala Abscent	2	1496	N	ACh	>750mm	Ab151	SH	Mwy	81 - 100%	912	2078	1065	1686	305	75	23.40	16.49	295.34	82.27	Canopy
2	-23.093331	29.465224	Caesalpinia decapetala Abscent	2	1418	W	ACh	>750mm	Ab151	SH	Mwy	81 - 100%	912	1439	1087	1691	216	75	23.40	16.49	295.34	82.27	Closed
3	-23.075501	29.494503	Caesalpinia decapetala Abscent	2	1433	N W	ACh	>750mm	Ab151	SH	Mwy	81 - 100%	912	1579	1169	1684	603	75	23.40	16.49	295.34	82.27	Open
4	-23.075467	30.014492	Caesalpinia decapetala Abscent	2	1455	NE	ACh	>750mm	Ab151	SH	Mwy	81 - 100%	1071	2032	1264	1684	414	75	23.40	16.49	295.34	82.27	Open
5	-23.070015	30.053560	Caesalpinia decapetala Abscent	2	1459	N W	ACh	>750mm	Ab151	SH	Mwy	81 - 100%	1071	2013	1029	1684	287	75	23.40	16.49	295.34	82.27	Closed
6	-23.068556	29.472356	Caesalpinia decapetala Abscent	2	1520	SE	ACh	450mm - 750mm	Ib349	SH	Mwy	61 - 80%	1071	2132	1034	1685	574	75	23.40	16.49	295.34	82.27	Closed
7	-23.055951	29.963830	Caesalpinia decapetala Abscent	2	1306	S	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	1178	1891	1318	1711	656	75	23.30	18.08	299.21	80.27	Canopy
8	-23.049225	29.787479	Caesalpinia decapetala Abscent	2	1270	N	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	1080	1290	1338	1750	666	75	23.50	18.08	299.21	80.27	Canopy
9	-23.048662	29.428626	Caesalpinia decapetala Abscent	2	1139	SE	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	996	1737	1208	1769	363	74	24.10	18.08	299.21	80.27	Closed
10	-23.043233	30.115004	Caesalpinia decapetala Abscent	2	1047	NE	LXh	450mm - 750mm	Ae291	LP	Mt	81 - 100%	996	1171	1394	1783	305	74	24.10	18.08	299.21	80.27	Closed
11	-23.042059	30.059305	Caesalpinia decapetala Abscent	2	1138	NE	ACh	< 450mm	Ag174	SH	Mwy	61 - 80%	829	1668	1366	1820	363	75	23.70	17.15	293.33	82.14	Closed
12	-23.041586	29.591543	Caesalpinia decapetala Abscent	2	991	N W	LPq	450mm - 750mm	Ae310	SH	Mnz	61 - 80%	671	1469	1256	1869	216	73	24.80	18.70	299.28	85.17	Open
13	-23.040591	29.690634	Caesalpinia decapetala Abscent	2	1210	SE	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	1080	1886	1251	1749	403	75	23.70	17.07	291.42	81.51	Open
14	-23.038527	29.515336	Caesalpinia decapetala Abscent	2	970	SE	LXh	450mm - 750mm	Ae291	LP	Mt	61 - 80%	680	1369	1046	1833	138	71	26.10	18.53	296.72	80.26	Open
15	-23.038339	29.543489	Caesalpinia decapetala Abscent	2	1009	SE	LPe	450mm - 750mm	Fa535	SH	Mt	81 - 100%	906	1446	961	1809	168	73	25.00	18.53	296.72	80.26	Canopy
16	-23.038151	29.774341	Caesalpinia decapetala Abscent	2	1318	SW	ACh	>750mm	Ab109	SH	Mf	81 - 100%	980	1906	1136	1683	267	75	23.50	17.07	291.42	81.51	Canopy

Site ID	Latitude	Longitude	Species	Species (Cat)	Altitude (MASL)	Aspect	Soil	Soil depth (mm)	LandType	Landform	Geology	SoilStb (%)	Anl Ptp(mm)	GBWP	AETI	Pot Evap	Intercept(I)	Rel hum(%RH)	Soil Rdn	BioClim 1	BioClim 4	BioClim 15	Cover
17	-23.036838	29.455840	Caesalpinia decapetala Abscent	2	1192	E	ACH	>750mm	Ab108	SH	Mt	81 - 100%	825	1902	925	1740	346	75	23.80	17.27	290.13	81.63	Closed
18	-23.034683	29.918298	Caesalpinia decapetala Abscent	2	1028	S	ACH	>750mm	Ab108	SH	Mt	81 - 100%	976	1671	1163	1770	384	74	24.50	18.51	289.26	80.70	Canopy
19	-23.034022	29.653660	Caesalpinia decapetala Abscent	2	917	S	RGe	450mm - 750mm	Fa308	LP	Zgo	81 - 100%	838	1605	1289	1840	343	73	25.20	19.46	299.63	80.63	Closed
20	-23.032896	29.599606	Caesalpinia decapetala Abscent	2	918	S	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1004	1265	1318	1785	471	72	25.70	19.62	293.28	81.72	Open
21	-23.030832	29.417365	Caesalpinia decapetala Abscent	2	1074	N W	ACH	>750mm	Ab108	SH	Mt	81 - 100%	1714	1469	1116	1727	423	75	23.60	18.74	285.51	80.27	Open
22	-23.030644	29.676557	Caesalpinia decapetala Abscent	2	834	SW	ACH	>750mm	Fa308	LP	Zgo	81 - 100%	855	1613	1357	1845	400	72	26.00	19.62	293.28	81.72	Closed
23	-23.028549	29.805560	Caesalpinia decapetala Abscent	2	848	N W	RGe	450mm - 750mm	Fa308	LP	Zgo	81 - 100%	654	1218	1405	1851	224	72	26.00	19.59	296.60	81.23	Canopy
24	-23.027912	29.934574	Caesalpinia decapetala Abscent	2	896	SE	RGe	450mm - 750mm	Fa308	LP	Zgo	81 - 100%	641	1183	1434	1839	333	71	26.00	19.48	301.10	79.70	Canopy
25	-23.024345	30.009581	Caesalpinia decapetala Abscent	2	786	NE	RGe	>750mm	Fa396	LP	Zgo	61 - 80%	776	1222	1434	1843	462	71	26.30	20.07	294.46	81.55	Closed
26	-23.018257	29.542963	Caesalpinia decapetala Abscent	2	1104	S	LPq	< 450mm	Ag174	SH	Mwy	81 - 100%	781	1542	1143	1839	207	74	24.50	18.43	301.23	81.55	Closed
27	-23.017694	29.426749	Caesalpinia decapetala Abscent	2	944	SE	LXh	450mm - 750mm	Ae291	LP	Mt	61 - 80%	748	1434	1463	1865	347	72	25.40	18.21	308.51	81.51	Closed
28	-23.016624	29.895798	Caesalpinia decapetala Abscent	2	885	W	LXh	450mm - 750mm	Ae291	LP	Mt	61 - 80%	673	1234	1356	1895	189	71	26.20	19.66	327.57	81.71	Closed
29	-23.014292	29.906648	Caesalpinia decapetala Abscent	2	916	S	LXh	450mm - 750mm	Ae291	LP	Mt	61 - 80%	836	1434	1365	1878	277	72	25.40	18.02	313.42	82.46	Open
30	-23.012063	29.512108	Caesalpinia decapetala Abscent	2	842	SW	LXh	>750mm	Dc58	LP	Mt	41 - 60%	450	1015	880	1914	50	71	26.40	18.52	325.70	83.76	Closed
31	-23.006710	29.889543	Caesalpinia decapetala Abscent	2	841	S	CMe	>750mm	Ia135	LP	Mt	21 - 40%	450	1396	1024	1902	118	71	26.40	18.52	325.70	83.76	Closed
32	-23.003331	29.903165	Caesalpinia decapetala Abscent	2	835	S	LXh	450mm - 750mm	Ae333	LP	Mt	81 - 100%	557	918	794	1934	78	71	26.50	19.67	333.74	83.76	Canopy
33	-22.998007	30.003730	Caesalpinia decapetala Abscent	2	837	NE	CMe	>750mm	Ia135	LP	Mt	21 - 40%	545	1302	1297	1925	138	71	26.50	19.53	333.59	83.67	Closed
34	-22.997379	29.964584	Caesalpinia decapetala Abscent	2	847	SW	CMe	>750mm	Ia135	LP	Mt	21 - 40%	712	1563	1064	1914	148	72	25.70	19.93	333.59	83.98	Open

Site ID	Latitude	Longitude	Species	Species (Cat)	Altitude (MASL)	Aspect	Soil	Soil depth (mm)	LandType	Landform	Geology	SoilStb (%)	Anl Prip(mm)	GBWP	AETI	Pot Evap	Intercept(I)	Rel hum(%RH)	Soi Rdn	Bioclim 1	Bioclim 4	Bioclim 15	Cover
35	-22.990533	29.885852	Caesalpinia decapetala Abscent	2	964	S	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	465	1652	1226	1888	367	72	25.40	18.31	329.47	82.03	Closed
36	-22.989344	29.895560	Caesalpinia decapetala Abscent	2	944	S	LPe	450mm - 750mm	Ae291	LP	Mt	61 - 80%	851	1637	1500	1883	377	72	25.70	17.63	330.39	82.41	Closed
37	-22.984989	29.886256	Caesalpinia decapetala Abscent	2	1305	S	LPe	>750mm	Ab147	SH	Mwy	81 - 100%	736	1470	1434	1820	539	73	24.40	16.70	332.15	84.41	Closed
38	-22.983752	29.894775	Caesalpinia decapetala Abscent	2	927	S	LVf	450mm - 750mm	Ae291	LP	Mt	61 - 80%	723	1538	1344	1889	295	72	25.80	19.05	342.73	81.62	Closed
39	-22.983728	29.881355	Caesalpinia decapetala Abscent	2	1456	NE	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	759	1663	1115	1787	179	73	24.40	16.70	332.15	84.41	Canopy
40	-22.979397	29.893966	Caesalpinia decapetala Abscent	2	1399	S	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	605	1905	862	1807	140	73	24.60	17.87	339.91	82.73	Canopy
41	-22.978993	29.879665	Caesalpinia decapetala Abscent	2	899	E	LPe	450mm - 750mm	Ae291	SH	Rho	61 - 80%	735	1503	1160	1924	168	70	26.60	19.56	353.77	82.22	Canopy
42	-22.977020	29.981316	Caesalpinia decapetala Abscent	2	1627	S	LPe	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	557	1865	902	1788	138	73	24.20	16.70	332.15	84.41	Closed
43	-22.962751	29.935577	Caesalpinia decapetala Abscent	2	902	E	LPe	< 450mm	Ag153	SH	Mt	81 - 100%	923	1865	1188	1913	335	71	26.50	19.05	342.73	81.62	Closed
44	-22.945954	29.925779	Caesalpinia decapetala Abscent	2	1521	N	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	880	2462	873	1746	238	74	23.90	19.05	330.39	82.41	Closed
45	-22.929904	29.906803	Caesalpinia decapetala Abscent	2	1487	N W	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	880	2094	1233	1808	318	74	24.00	18.31	329.47	82.03	Canopy
0	-23.070015	30.053560	Eucal Cam Abscent	1	1114	S	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	996	1266	1396	1750	656	74	24.00	18.08	299.21	80.27	Canopy
1	-23.063110	30.067476	Eucal Cam Abscent	1	1188	SE	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	996	1288	1415	1733	564	74	24.10	18.08	299.21	80.27	Closed
2	-23.053329	30.090929	Eucal Cam Abscent	1	1108	NE	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	996	1298	1405	1769	394	74	24.10	18.08	299.21	80.27	Closed
3	-23.050973	30.084327	Eucal Cam Abscent	1	1092	NE	LXh	450mm - 750mm	Fa535	LP	Mt	61 - 80%	996	1709	1347	1769	354	74	24.10	18.08	299.21	80.27	Closed
4	-23.048662	29.428626	Eucal Cam Abscent	1	1085	NE	LXh	450mm - 750mm	Fa535	LP	Mt	61 - 80%	996	1515	1268	1783	273	74	24.10	18.08	299.21	80.27	Closed
5	-23.045833	30.101664	Eucal Cam Abscent	1	1153	N	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	996	1737	1208	1769	363	74	24.10	18.08	299.21	80.27	Closed
6	-23.043450	29.990139	Eucal Cam Abscent	1	1046	SE	LXh	450mm - 750mm	Ae291	LP	Mt	61 - 80%	996	1171	1394	1783	305	74	24.10	18.08	299.21	80.27	Canopy
7	-23.042059	30.059305	Eucal Cam Abscent	1	1210	N W	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	1080	1886	1251	1749	403	75	23.70	17.07	291.42	81.51	Canopy
8	-23.040591	29.417928	Eucal Cam Abscent	1	974	S	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	1026	1133	1424	1815	423	73	24.80	18.53	296.72	80.26	Canopy
9	-23.036838	29.455840	Eucal Cam Abscent	1	1013	S	ACH	>750mm	Ab107	SH	Mt	81 - 100%	923	1205	747	1771	373	73	24.80	18.41	292.08	80.83	Canopy
10	-23.033022	30.033937	Eucal Cam Abscent	1	1211	NE	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	1001	1249	843	1738	128	75	23.70	17.07	291.42	81.51	Open

Site ID	Latitude	Longitude	Species	Species (Cat)	Altitude (MASL)	Aspect	Soil	Soil depth (mm)	LandType	Landform	Geology	SoilStb (%)	Anl Ptp(mm)	GBWP	AETI	Pot Evap	Intercept(I)	Rel hum(%RH)	Soi Rdn	BioClim 1	BioClim 4	BioClim 15	Cover
11	-23.030832	29.403851	Eucal Cam Abscent	1	1204	S	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	825	1449	925	1724	293	75	23.80	17.07	291.42	81.51	Open
12	-23.030832	29.417365	Eucal Cam Abscent	1	1195	E	ACh	>750mm	Ab108	SH	Mt	81 - 100%	825	1902	1123	1740	346	75	23.80	17.07	290.13	81.51	Canopy
13	-23.025952	29.451335	Eucal Cam Abscent	1	1229	SW	LPe	450mm - 750mm	Fa535	SH	Mt	61 - 80%	1001	1861	1163	1740	403	75	23.70	18.41	292.08	80.83	Canopy
14	-23.024345	30.009581	Eucal Cam Abscent	1	1028	S	ACh	>750mm	Ab108	SH	Mt	81 - 100%	976	1671	1347	1770	384	74	24.50	18.51	289.26	80.70	Canopy
15	-23.022470	29.954671	Eucal Cam Abscent	1	915	SE	ACh	>750mm	Ab107	LP	Zgo	81 - 100%	872	1534	1115	1819	383	73	25.20	19.46	299.63	80.63	Closed
16	-23.017723	29.969227	Eucal Cam Abscent	1	1322	SW	ACh	>750mm	Ab109	SH	Mt	81 - 100%	986	1493	1255	1712	413	75	23.20	17.27	290.13	81.63	Closed
17	-23.017694	29.426749	Eucal Cam Abscent	1	959	N	ACh	>750mm	Ab108	SH	Mt	81 - 100%	1014	1289	1318	1806	393	73	24.70	18.51	289.26	80.70	Closed
18	-23.016624	29.895798	Eucal Cam Abscent	1	918	S	ACh	>750mm	Ab108	SH	Mt	81 - 100%	1004	1265	1396	1785	471	72	25.70	19.62	293.28	81.72	Closed
19	-23.016386	29.902127	Eucal Cam Abscent	1	860	S	ACh	>750mm	Ab107	SH	Mt	81 - 100%	1064	1647	1208	1784	665	72	25.70	18.74	285.51	80.27	Closed
20	-23.015246	29.899112	Eucal Cam Abscent	1	937	N W	ACh	>750mm	Ab108	LP	Mt	81 - 100%	1195	1398	1376	1773	704	73	24.80	18.74	285.51	80.27	Closed
21	-23.014879	29.414174	Eucal Cam Abscent	1	913	W	ACh	>750mm	Ab107	LP	Mt	81 - 100%	1064	1299	1347	1807	482	72	25.70	18.74	285.51	80.27	Canopy
22	-23.014292	29.906648	Eucal Cam Abscent	1	821	SW	ACh	>750mm	Ab107	LP	Zgo	81 - 100%	869	1597	1366	1829	284	71	26.20	19.62	293.28	81.72	Canopy
23	-23.014255	29.897127	Eucal Cam Abscent	1	834	SW	ACh	>750mm	Ab107	LP	Zgo	81 - 100%	855	1595	1434	1845	400	72	26.00	19.62	293.28	81.72	Canopy
24	-23.011688	29.450772	Eucal Cam Abscent	1	1305	S	LPe	>750mm	Ab147	SH	Mwy	81 - 100%	851	1470	1434	1820	539	73	26.00	16.70	332.15	84.41	Canopy
25	-23.010342	29.895703	Eucal Cam Abscent	1	1423	S	LPe	450mm - 750mm	Ab147	SH	Mwy	81 - 100%	851	1600	1279	1763	228	73	24.40	16.70	332.15	84.41	Closed
26	-23.008878	29.901562	Eucal Cam Abscent	1	1456	NE	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	723	1663	1115	1787	179	73	24.40	16.70	332.15	84.41	Closed
27	-23.005431	29.975320	Eucal Cam Abscent	1	1507	SW	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	723	1537	863	1794	98	73	24.40	16.70	332.15	84.41	Closed
28	-22.998007	30.003730	Eucal Cam Abscent	1	1406	S	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	759	1905	862	1807	140	73	24.60	17.87	339.91	82.73	Closed
29	-22.997379	29.964584	Eucal Cam Abscent	1	1602	SE	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	776	1949	940	1775	184	73	24.40	16.56	334.66	85.79	Closed
30	-22.995866	29.989454	Eucal Cam Abscent	1	1627	S	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	735	1865	902	1788	138	73	24.20	16.70	332.15	84.41	Closed
31	-22.992296	29.992166	Eucal Cam Abscent	1	1642	NE	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	784	1852	971	1781	128	73	23.90	16.56	334.66	85.79	Canopy
32	-22.990912	30.021120	Eucal Cam Abscent	1	1479	E	LPq	450mm - 750mm	Ib362	SH	Mwy	81 - 100%	785	1967	970	1791	148	73	24.20	16.70	332.15	84.41	Canopy

Appendix 4.6: *Caesalpinia decapetala* environmental variable Stepwise logistic regression code for R

```
library(tidyselect)
attach(Data)
names(Data)

fullmod = glm(PA~ Alt+Aspect+Soil+Soildh+LandTy+Landform+Geology+SoilStb+GBWP+AnlPrp+PotEvp+Intercept+BioCliM1+BioCliM4+BioCliM15,family = binomial)

summary (fullmod)

cor(Data, method = c("pearson", "kendall", "spearman"))

fullmod = glm(PA~ Alt+Aspect+Soil+Soildh+LandTy+Landform+Geology+SoilStb+GBWP+AnlPrp+PotEvp+Intercept+BioCliM1+BioCliM4+BioCliM15,family = binomial)

summary (fullmod)

backwards = step(fullmod)

formula(backwards)

summary(backwards)

back2 = glm(PA~ Alt+Aspect+Soil+Soildh+LandTy+Landform+Geology+SoilStb+GBWP+AnlPrp+PotEvp+Intercept+BioCliM1+BioCliM4+BioCliM15,family = binomial)

summary(back2)

finalmod = glm(PA~ Alt+Geology+SoilStb+PotEvp+BioCliM4,family = binomial)

summary(finalmod)

library(ROCR)

p <- predict(finalmod, newdata=subset(Data), type="response")

pr <- prediction(p, Data$PA)

prf <- performance(pr, measure = "tpr", x.measure = "fpr")

plot(prf)

auc <- performance(pr, measure = "auc")

auc <- auc@y.values[[1]]

auc
```

Appendix 4.7: *Eucalyptus camaldulensis* environmental variable Stepwise logistic regression code for R

```
library(tidyselect)
attach(Data)
names(Data)

fullmod = glm(PA~ Alt+Aspect+Soil+Soildh+LandTy+Landform+Geology+SoilStb+GBWP+AnlPrp+PotEvp+Intercept+BioCliM1+BioCliM4+BioCliM15,family = binomial)

summary (fullmod)
```

```
cor(Data, method = c("pearson", "kendall", "spearman"))

fullmod = glm(PA~ Alt+Aspect+Soil+Soildh+LandTy+Landform+Geology+SoilStb+GB
WP+AnlPrp+PotEvp+Intercept+BioClim1+BioClim4+BioClim15,family = binomial)

summary (fullmod)

backwards = step(fullmod)

formula(backwards)

summary(backwards)

back2 = glm(PA~Geology,family = binomial)

summary(back2)

finalmod = glm(PA ~ Geology, family = binomial)

summary(finalmod)

library(ROCR)

p <- predict(finalmod, newdata=subset(Data), type="response")

pr <- prediction(p, Data$PA)

prf <- performance(pr, measure = "tpr", x.measure = "fpr")

plot(prf)

auc <- performance(pr, measure = "auc")

auc <- auc@y.values[[1]]

auc
```

Appendix 4.8: *Caesalpinia decapetala* GIS/Remote sensing variable Stepwise logistic regression code for R

```
library(tidyselect)

attach(Data)

names(Data)

fullmod = glm(PA~B1R+B2G+B3B+B4NIR+NDVI+SRI+ARI2+TDVI+RDVI,family = binomial)

summary (fullmod)

cor(Data, method = c("pearson", "kendall", "spearman"))

fullmod = glm(PA~B1R+B2G+B3B+B4NIR+NDVI+SRI+ARI2+TDVI+RDVI,family = binomial)

summary (fullmod)

backwards = step(fullmod)

formula(backwards)

summary(backwards)

back2 = glm(PA~NDVI+RDVI,family = binomial)

summary(back2)
```



```
finalmod = glm(PA~NDVI+RDVI,family = binomial)
summary(finalmod)
library(ROCR)
p <- predict(finalmod, newdata=subset(Data), type="response")
pr <- prediction(p, Data$PA)
prf <- performance(pr, measure = "tpr", x.measure = "fpr")
plot(prf)
auc <- performance(pr, measure = "auc")
auc <- auc@y.values[[1]]
auc
```

Appendix 4.9: *Eucalyptus camaldulensis* GIS/Remote sensing variable Stepwise logistic regression code for R

```
library(tidyselect)
attach(Data)
names(Data)
fullmod = glm(PA~B1R+B2G+B3B+B4NIR+NDVI+SRI+ARI2+TDVI+SAVI+RDVI+OSAVI,famil
y = binomial)
summary (fullmod)
cor(Data, method = c("pearson", "kendall", "spearman"))
fullmod = glm(PA~B1R+B2G+B3B+B4NIR+NDVI+SRI+ARI2+TDVI+SAVI+RDVI+OSAVI,famil
y = binomial)
summary (fullmod)
backwards = step(fullmod)
formula(backwards)
summary(backwards)
back2 = glm(PA~NDVI,family = binomial)
summary(back2)
finalmod = glm(PA~NDVI,family = binomial)
summary(finalmod)
library(ROCR)
p <- predict(finalmod, newdata=subset(Data), type="response")
pr <- prediction(p, Data$PA)
prf <- performance(pr, measure = "tpr", x.measure = "fpr")
plot(prf)
auc <- performance(pr, measure = "auc")
auc <- auc@y.values[[1]]
```

```
auc
```

Appendix 4.10: *Caesalpinia decapetala* Environmental & Remote sensing Variables Stepwise logistic regression code for R

```
library(tidyselect)
attach(Data)
names(Data)

fullmod = glm(PA~Alt+Aspect+Soil+Soildh+LandTy+Landform+Geology+SoilStb+GBW
P+AnlPrp+PotEvp+Intercept+BioClim1+BioClim4+BioClim15+B1R+B2G+B3B+NDVI+SRI+
ARI2+TDVI+SAVI+RDVI,family = binomial)

summary (fullmod)

cor(Data, method = c("pearson", "kendall", "spearman"))

fullmod = glm(PA~Alt+Aspect+Soil+Soildh+LandTy+Landform+Geology+SoilStb+GBW
P+AnlPrp+PotEvp+Intercept+BioClim1+BioClim4+BioClim15+B1R+B2G+B3B+NDVI+SRI+
TDVI+RDVI,family = binomial)

summary (fullmod)

backwards = step(fullmod)
formula(backwards)
summary(backwards)

back2 = glm(PA~ Intercept+LandTy+Geology+Landform+Geology+SoilStb+PotEvp+Bi
oClim4+BioClim15,family = binomial)

summary(back2)

finalmod = glm(PA~ Intercept+LandTy+Geology+Landform+Geology+SoilStb+PotEvp
+BioClim4+BioClim15,family = binomial)

summary(finalmod)

library(ROCR)
p <- predict(finalmod, newdata=subset(Data), type="response")
pr <- prediction(p, Data$PA)
prf <- performance(pr, measure = "tpr", x.measure = "fpr")
plot(prf)
auc <- performance(pr, measure = "auc")
auc <- auc@y.values[[1]]
auc
```

Appendix 4.11: *Eucalyptus camaldulensis* Environmental & Remote sensing Variables Stepwise logistic regression code for R

```
library(tidyselect)
attach(Data)
```

```
names(Data)

fullmod = glm(PA~Alt+Aspect+Soil+Soildh+LandTy+Landform+Geology+SoilStb+GBW
P+AnlPrp+Intercept+BioClim1+BioClim4+BioClim15+B1R+B2G+B3B+B4NIR+NDVI+SRI+A
RI2+SAVI,family = binomial)

summary (fullmod)

cor(Data, method = c("pearson", "kendall", "spearman"))

fullmod = glm(PA~Alt+Aspect+Soil+Soildh+LandTy+Landform+Geology+SoilStb+GBW
P+AnlPrp+Intercept+BioClim1+BioClim4+BioClim15+B1R+B2G+B3B+B4NIR+NDVI+SRI+A
RI2,family = binomial)

summary (fullmod)

backwards = step(fullmod)

formula(backwards)

summary(backwards)

back2 = glm(PA~ Alt+BioClim15+B1R+B2G+SRI,family = binomial)

summary(back2)

finalmod = glm(PA~ Alt+BioClim15+B1R+B2G+SRI,family = binomial)

summary(finalmod)

library(ROCR)

p <- predict(finalmod, newdata=subset(Data), type="response")

pr <- prediction(p, Data$PA)

prf <- performance(pr, measure = "tpr", x.measure = "fpr")

plot(prf)

auc <- performance(pr, measure = "auc")

auc <- auc@y.values[[1]]

auc
```

Appendix 4.12: *Caesalpinia decapetala* environmental variable Stepwise logistic regression code for R

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5823  -0.5315  -0.2656   0.7298   2.3031

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -17.640759   30.260354  -0.583   0.55992
Alt          -0.001223    0.004898  -0.250   0.80282
Geology      -0.424957    0.239516  -1.774   0.07602.
SoilStb       3.067529    1.084126   2.829   0.00466 **
PotEvp        0.017013    0.020353   0.836   0.40322
BioClim4     -0.075513    0.049295  -1.532   0.12556
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 105.604  on 77  degrees of freedom
Residual deviance:  68.168  on 72  degrees of freedom
AIC: 80.168

Number of Fisher Scoring iterations: 6

> library(ROCR)
> p <- predict(finalmod, newdata=subset(Data), type="response")
> pr <- prediction(p, Data$PA)
> prf <- performance(pr, measure = "tpr", x.measure = "fpr")
> plot(prf)
> auc <- performance(pr, measure = "auc")
> auc <- auc@y.values[[1]]
> auc
[1] 0.8851902
```

Appendix 4.13: *Eucalyptus camaldulensis* environmental variable stepwise logistic regression code for R

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.2305  -1.2305   0.7839   0.7839   2.3003

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   1.9213     0.6053   3.174  0.00150 **
Geology       -0.8987     0.2965  -3.031  0.00244 **

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 99.313  on 71  degrees of freedom
Residual deviance: 85.641  on 70  degrees of freedom
AIC: 89.641

Number of Fisher Scoring iterations: 4

> library(ROCR)
> p <- predict(finalmod, newdata=subset(Data), type="response")
> pr <- prediction(p, Data$PA)
> prf <- performance(pr, measure = "tpr", x.measure = "fpr")
> plot(prf)
```

```
> auc <- performance(pr, measure = "auc")
> auc <- auc@y.values[[1]]
> auc
[1] 0.8531469
```

Appendix 4.14: *Caesalpinia decapetala* GIS/Remote sensing variable Stepwise logistic regression code for R

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9086  -0.6280  -0.3595   0.6171   2.3144

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -3.4315     0.8545  -4.016 5.93e-05 ***
NDVI          -13.1806     7.5890  -1.737 0.08242 .
RDVI           0.5699     0.2108   2.704 0.00685 **
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 105.604  on 77  degrees of freedom
Residual deviance:  68.549  on 75  degrees of freedom
AIC: 74.549

Number of Fisher Scoring iterations: 5

> library(ROCR)
> p <- predict(finalmod, newdata=subset(Data), type="response")
> pr <- prediction(p, Data$PA)
> prf <- performance(pr, measure = "tpr", x.measure = "fpr")
> plot(prf)
> auc <- performance(pr, measure = "auc")
> auc <- auc@y.values[[1]]
> auc
[1] 0.857337
```

Appendix 4.15: *Eucalyptus camaldulensis*, GIS/Remote sensing variable Stepwise logistic regression code for R

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8666 -0.8520  0.5237  0.7581  1.8618

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.7788      0.7889  -3.522 0.000428 ***
NDVI         6.7793      1.7421   3.892 9.96e-05 ***
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 99.313  on 71  degrees of freedom
Residual deviance: 80.279  on 70  degrees of freedom
AIC: 84.279
Number of Fisher Scoring iterations: 4

> library(ROCR)
> p <- predict(finalmod, newdata=subset(Data), type="response")
> pr <- prediction(p, Data$PA)
> prf <- performance(pr, measure = "tpr", x.measure = "fpr")
> plot(prf)
> auc <- performance(pr, measure = "auc")
> auc <- auc@y.values[[1]]
> auc
[1] 0.7878788
```

Appendix 4.16: *Caesalpinia decapetala* Environmental & Remote sensing Variables Stepwise logistic regression code for R

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.29581 -0.25232 -0.02018  0.39140  2.25161

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -111.61267    44.51367  -2.507  0.0122 *
Intercept     0.01054     0.00439   2.402  0.0163 *
LandTy       -0.33341     0.13407  -2.487  0.0129 *
```



```

Geology      -0.88024    0.44045   -1.998    0.0457 *
Landform      2.10564    1.49056    1.413    0.1578
SoilStb       3.59872    1.68532    2.135    0.0327 *
PotEvp        0.02767    0.01282    2.158    0.0310 *
BioClim4      -0.12518    0.05409   -2.314    0.0207 *
BioClim15     1.00912    0.56857    1.775    0.0759 .
Signif. codes:  0 '***' 0.001 '**' 0.01 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 105.604  on 77  degrees of freedom
Residual deviance:  41.735  on 69  degrees of freedom
AIC: 59.735
Number of Fisher Scoring iterations: 7

> library(ROCR)
> p <- predict(finalmod, newdata=subset(Data), type="response")
> pr <- prediction(p, Data$PA)
> prf <- performance(pr, measure = "tpr", x.measure = "fpr")
> plot(prf)
> auc <- performance(pr, measure = "auc")
> auc <- auc@y.values[[1]]
> auc
[1] 0.951087

```

Appendix 4.17: *Eucalyptus camaldulensis* Environmental & Remote sensing Variables Stepwise logistic regression code for R

```

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.5107  -0.5534   0.1166   0.7274   2.0595

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.225e+02  4.585e+01  -2.672  0.00755 **
Alt          1.720e-03  2.158e-03   0.797  0.42544
BioClim15    1.692e+00  6.260e-01   2.703  0.00687 **
B1R          3.275e-02  1.405e-02   2.332  0.01972 *
B2G         -8.816e-02  2.834e-02  -3.110  0.00187 **
SRI          7.494e-01  3.250e-01   2.306  0.02113 *
Signif. codes:  0 '***' 0.001 '**' 0.01 '.' 0.1 ' ' 1

```

```
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 99.313 on 71 degrees of freedom
Residual deviance: 57.445 on 66 degrees of freedom
AIC: 69.445
Number of Fisher Scoring iterations: 6
> library(ROCR)
> p <- predict(finalmod, newdata=subset(Data), type="response")
> pr <- prediction(p, Data$PA)
> prf <- performance(pr, measure = "tpr", x.measure = "fpr")
> plot(prf)
> auc <- performance(pr, measure = "auc")
> auc <- auc@y.values[[1]]
> auc
[1] 0.9036519
```

Appendix 4.18: Shows the script for the model created in R for MaxEnt following the above-mentioned step for *Caesalpinia decapetala* and *Eucalyptus camaldulensis*

```
require (raster)
require (rgdal)
require (rgeos)
require (dismo)
require (rJava)
library(maptools)
library(sp)
library(spatstat)

#To project ASCII raster files (VBR scale)
r=raster("C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/VBR Analysis/bioclim4.asc")

proj4string(r) <- CRS("+proj=longlat +datum=WGS84 +no_defs")## set projects
as default WP84: EPSG: 4326

writeRaster (r, format="ascii", file="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/All ASCII/BioClim4_final.asc")

r2=raster("C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/All ASCII/alt.asc")

proj4string(r2) <- CRS("+proj=longlat +datum=WGS84 +no_defs")## set projects
as default WP84: EPSG: 4326

writeRaster (r2, format="ascii", file="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/All ASCII/alt_final.asc")
```

```

dim(r)

dim(r2)

resample(r2,r, method="bilinear", filename="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/All ASCII/alt_final.asc")

proj4string(r3) <- CRS("+proj=longlat +datum=WGS84 +no_defs")## set project
s as default WP84: EPSG: 4326

r3=raster("C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data
Analysis/All ASCII/geology.asc")

dim(r3)

resample(r3,r, method="bilinear", filename="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/All ASCII/geology_final.asc")

r4=raster("C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data
Analysis/All ASCII/rdvi.asc")

proj4string(r4) <- CRS("+proj=longlat +datum=WGS84 +no_defs")## set project
s as default WP84: EPSG: 4326

dim(r4)

resample(r4,r, method="bilinear", filename="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/All ASCII/RDVI_final.asc")

r5=raster("C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data
Analysis/All ASCII/soilstb.asc")

proj4string(r5) <- CRS("+proj=longlat +datum=WGS84 +no_defs")## set project
s as default WP84: EPSG: 4326

dim(r5)

resample(r5,r, method="bilinear", filename="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/All ASCII/soilstb_final.asc")

r6=raster("C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data
Analysis/All ASCII/potevp.asc")

proj4string(r6) <- CRS("+proj=longlat +datum=WGS84 +no_defs")## set project
s as default WP84: EPSG: 4326

dim(r6)

resample(r6,r, method="bilinear", filename="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/All ASCII/potevp_final.asc")

r6=raster("C:/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis
/All ASCII/potevp.asc")

proj4string(r6) <- CRS("+proj=longlat +datum=WGS84 +no_defs")## set project
s as default WP84: EPSG: 4326

dim(r7)

# ANALYSIS OF MAURITIAN THORN

MT <-read.csv("C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/
Data Analysis/VBR Analysis/Ocurrences/Mauritian_thorn_gbif_eaw.csv")

MT2 <- MT[,22:23]

attach (MT2)

head (MT2)

```

```

tail (MT2)

coordinates(MT2) <- c("x", "y")

proj4string(MT2) <- CRS("+proj=longlat +datum=WGS84 +no_defs")## set projec
ts as default WP84: EPSG: 4326

res <- spTransform(MT2, CRS("+proj=cea +lon_0=0 +lat_ts=0 +x_0=0 +y_0=0 +da
tum=WGS84 +units=m +no_defs")) ## project to USER100000

res

plot (res)

as(res, "SpatialPoints")

write.csv (res, file="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/
Maxent/Data Analysis/VBR Analysis/Ocurrences/MT_prj.csv")

data ("wrld_simpl")

world_prj <- spTransform(wrld_simpl, CRS("+proj=cea +lon_0=0 +lat_ts=0 +x_0
=0 +y_0=0 +datum=WGS84 +units=m +no_defs"))

plot(world_prj)

# restore the box around the map

box()

points(res)

files <- list.files ("C:/Personal/PhD/Write up/Complete Section Drafts/GIS/
Maxent/Data Analysis/Worldclim/bio_2-5m_esri/Projected_ASCII",pattern='asc'
, full.names=TRUE )

files

predictors <- stack(files)

predictors

names (predictors)

plot(predictors)

# Create 200 km buffer around points

b <- buffer(res, width=200000, dissolve=TRUE)

plot (b)

mask <- raster (files[1])

plot(mask)

pol <- polygons (b)

# sample randomly from all circles

samp1 <- spsample(pol, 10000, type='random', iter=25)

points(samp1)

# get unique cells

cells <- cellFromXY(mask, samp1)

length(cells)

cells <- unique(cells)

```

```
length(cells)

xy <- xyFromCell(mask, cells)# this is our background for pseudoabsences for Maxent

plot(pol, axes=TRUE)

plot (world_prj)

points(xy, cex=0.75, pch=20, col='blue')

files[1]

r <- raster (files[1])

MT_sub <- gridSample(res, mask, n=1)

points(res)

# selected points in red

points(MT_sub, cex=1, col='red', pch='x')

write.csv (MT_sub, "C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/MT_prj_sub.csv")

set.seed(0)

plot (predictors, 1)

# run maxent with 1 replicate.

# run Maxent with background as 200 km buffers around presence-points

xm <- maxent (predictors, MT_sub, xy, args=c('responsecurves=TRUE','outputgrids=FALSE', 'projectionlayers=C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/Worldclim/bio_2-5m_esri/Projected_ASCII'), filename= "C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/R_out2_MT/maxent_pres_MT_prj.asc", path="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/R_out2_MT")

par(mfrow=c(1,1))

plot(xm)

e <- evaluate(MT_sub, xy, xm, predictors)

e

px <- predict(predictors, xm, progress='text')

par(mfrow=c(1,1))

px

writeRaster (px, format="ascii", file="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/R_out2_MT/maxent_pres_MT_prj.asc")

plot(px, main='Maxent_MT_200km',cex.axis=0.6, legend.shrink=0.75)

plot(world_prj, add=TRUE, border='dark grey')

tr <- threshold(e, 'equal_sens_spec')

tr

plot(px > tr, main='Maxent_MT_200km',cex.axis=0.6, legend.shrink=0.75)

plot(world_prj, add=TRUE, border='dark grey')

points(MT_sub, pch='+')
```

```
# Maxent with 5 replicates

xm2 <- maxent (predictors, MT_sub, xy, args=c('replicates=5','responsecurve
s=TRUE','outputgrids=FALSE', 'projectionlayers=C:/Personal/PhD/Write up/Com
plete Section Drafts/GIS/Maxent/Data Analysis/Worldclim/bio_2-5m_esri/Proje
cted_ASCII'),filename= "C:/Personal/PhD/Write up/Complete Section Drafts/GI
S/Maxent/Data Analysis/R_out3_5reps_MT/maxent_pres_MT_prj.asc", path="C:/Pe
rsonal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/R_out3
_5reps_MT")

# ANALYSIS OF River Red GumRRG <-read.csv("C:/Personal/PhD/Write up/Comple
e Section Drafts/GIS/Maxent/Data Analysis/VBR Analysis/Ocurrences/Red_river
_gum_gbif.csv")

RRG2 <- RRG[,22:23]

attach (RRG2)

head (RRG2)

tail (RRG2)

coordinates(RRG2) <- c("x", "y")

proj4string(RRG2) <- CRS("+proj=longlat +datum=WGS84 +no_defs")## set proje
cts as default WP84: EPSG: 4326

res2 <- spTransform(RRG2, CRS("+proj=cea +lon_0=0 +lat_ts=0 +x_0=0 +y_0=0 +
datum=WGS84 +units=m +no_defs")) ## project to USET100000

res2

plot (res2)

write.csv (res2, file="C:/Personal/PhD/Write up/Complete Section Drafts/GIS
/Maxent/Data Analysis/VBR Analysis/Ocurrences/RRG_prj.csv")

files <- list.files ("C:/Personal/PhD/Write up/Complete Section Drafts/GIS/
Maxent/Data Analysis/Worldclim/bio_2-5m_esri/Projected_ASCII",pattern='asc'
, full.names=TRUE)

files

predictors <- stack(files)

predictors

names (predictors)

plot(predictors)

# Create 200 km buffer around points

b2 <- buffer(res2, width=200000, dissolve=TRUE)

plot (b2)

mask <- raster (files[1])

plot(mask)

pol2 <- polygons (b2)

# sample randomly from all circles

samp2 <- spsample(pol2, 10000, type='random', iter=25)

points(samp2)

# get unique cells
```



```

cells2 <- cellFromXY(mask, samp2)
length(cells2)
## [1] 250
cells2 <- unique(cells2)
length(cells2)
## [1] 161
xy2 <- xyFromCell(mask, cells2) # this is our background for pseudoabsances
for Maxent

plot(pol2, axes=TRUE)
points(xy2, cex=0.75, pch=20, col='blue')
files[1]
RRG_sub <- gridSample(res2, mask, n=1)
points(res2)
# selected points in red
points(RRG_sub, cex=1, col='red', pch='x')
write.csv (RRG_sub, "C:/Personal/PhD/Write up/Complete Section Drafts/GIS/M
axent/Data Analysis/Ocurrences/RRG_prj_sub.csv")
# setting random seed to always create the same
# random set of 500 points for this example, using altensteinii mask
set.seed(0)
plot (predictors, 1)
# run maxent with 1 replicate
#maxent with 200km buffers
xm3 <- maxent (predictors, RRG_sub, xy2, args=c('responsecurves=TRUE','outp
utgrids=FALSE', 'projectionlayers=C:/Personal/PhD/Write up/Complete Section
Drafts/GIS/Maxent/Data Analysis/Worldclim/bio_2-5m_esri/Projected_ASCII'),f
ilename= "C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data
Analysis/R_out2_RRG/maxent_pres_RRG.asc", path="C:/Personal/PhD/Write up/Co
mplete Section Drafts/GIS/Maxent/Data Analysis/R_out2_RRG")
plot(xm1)
e1 <- evaluate(RRG_sub, xy2, xm3, predictors)
e1
px1 <- predict(predictors, xm3, progress='text')
par(mfrow=c(1,1))
px1
writeRaster (px1, format="ascii", file="C:/Personal/PhD/Write up/Complete S
ection Drafts/GIS/Maxent/Data Analysis/R_out2_RRG/maxent_present_RRG_200k_2
.asc")
plot(px1, main='Maxent_200km buffer',cex.axis=0.6, legend.shrink=0.75)
plot(world_prj, add=TRUE, border='dark grey')
tr1 <- threshold(e1, 'equal_sens_spec')

```

```
tr1

plot(px1 > tr1, main='Maxent_RRG_200km',cex.axis=0.6, legend.shrink=0.75)
plot(world_prj, add=TRUE, border='dark grey')
points(RRG_sub, pch='+')

#maxent without buffers

xm4 <- maxent (predictors, RRG_sub, args=c('responsecurves=TRUE','outputgrids=FALSE', 'projectionlayers=C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/Worldclim/bio_2-5m_esri/Projected_ASCII'),filename= "C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/R_out3_RRG/maxent_pres_RRG.asc", path="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/R_out3_RRG")

par(mfrow=c(1,1))

plot(xm4)

e2 <- evaluate(RRG_sub, mask, xm4, predictors)
e2

px2 <- predict(predictors, xm4, progress='text')
par(mfrow=c(1,1))

px2

writeRaster (px2, format="ascii", file="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/R_out1_RRG/maxent_present_RRG.asc")

plot(px2, main='Maxent_global background',cex.axis=0.6, legend.shrink=0.75)
plot(world_prj, add=TRUE, border='dark grey')

tr2 <- threshold(e2, 'equal_sens_spec')

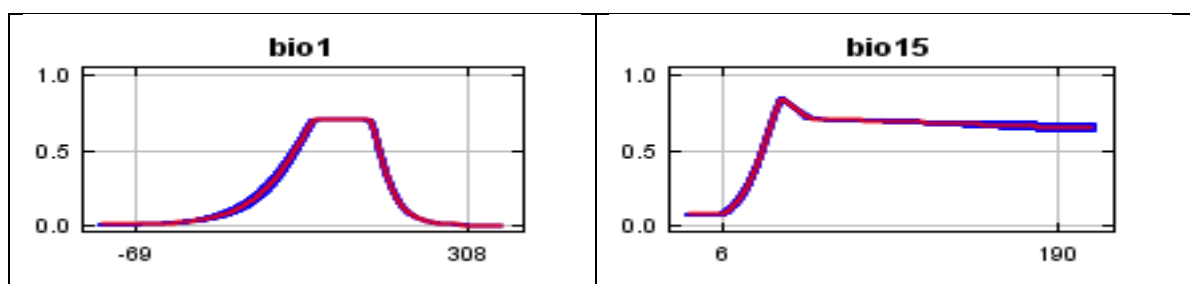
tr2

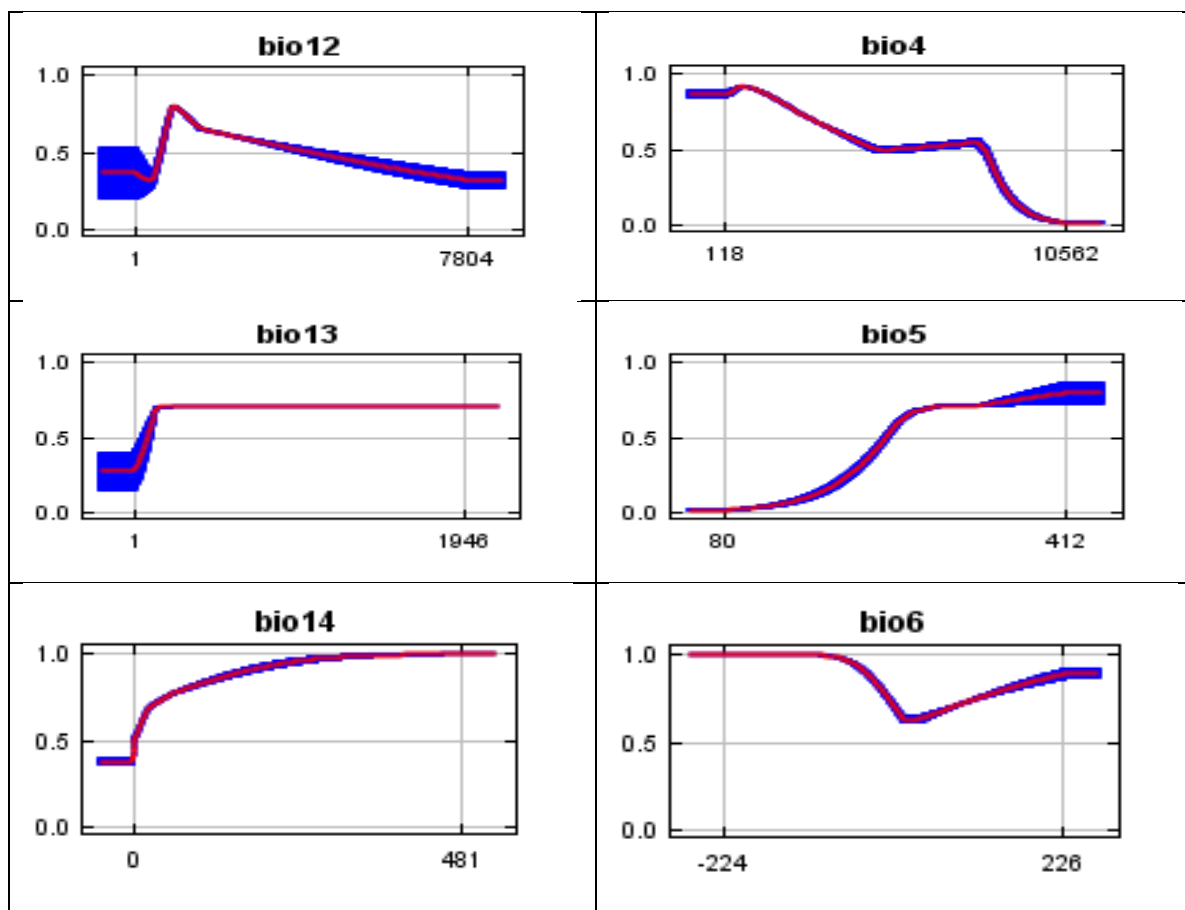
plot(px2 > tr2, main='Maxent_RRG_200km',cex.axis=0.6, legend.shrink=0.75)
plot(world_prj, add=TRUE, border='dark grey')
points(RRG_sub, pch='+')

# Maxent with 5 replicates

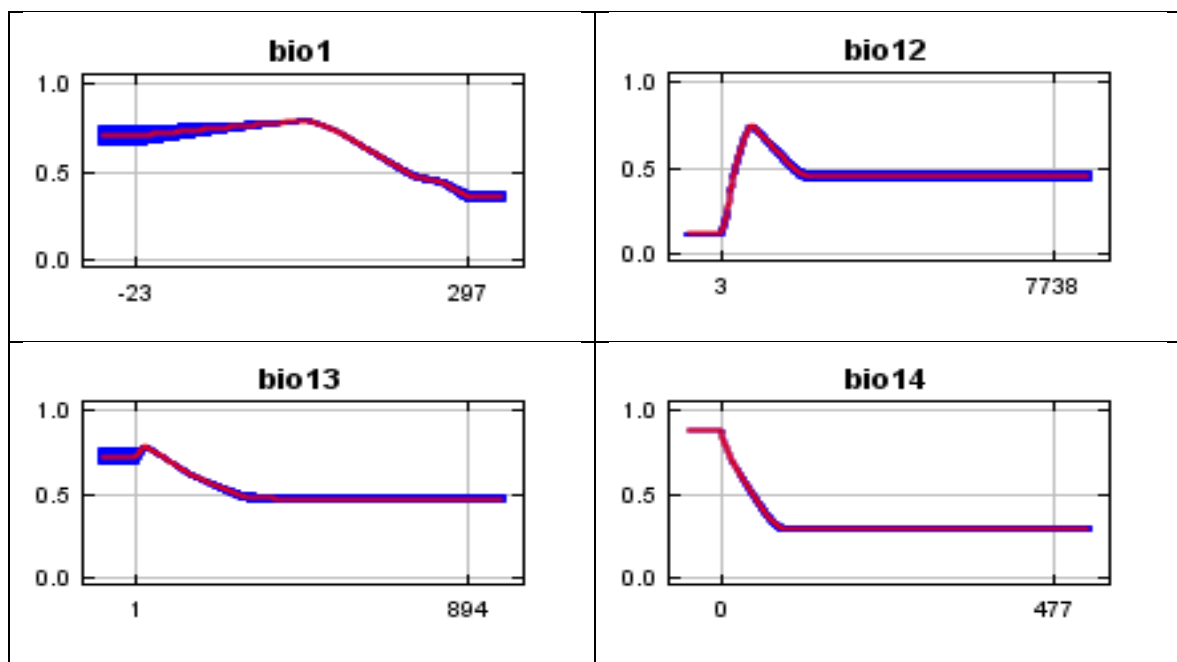
xm5 <- maxent(predictors, RRG_sub, xy2, args=c('replicates=5', 'responsecurves=TRUE','outputgrids=FALSE', 'projectionlayers=C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/Worldclim/bio_2-5m_esri/Projected_ASCII'),filename= "C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/R_out4_RRG/maxent_pres.asc", path="C:/Personal/PhD/Write up/Complete Section Drafts/GIS/Maxent/Data Analysis/R_out4_RRG")
```

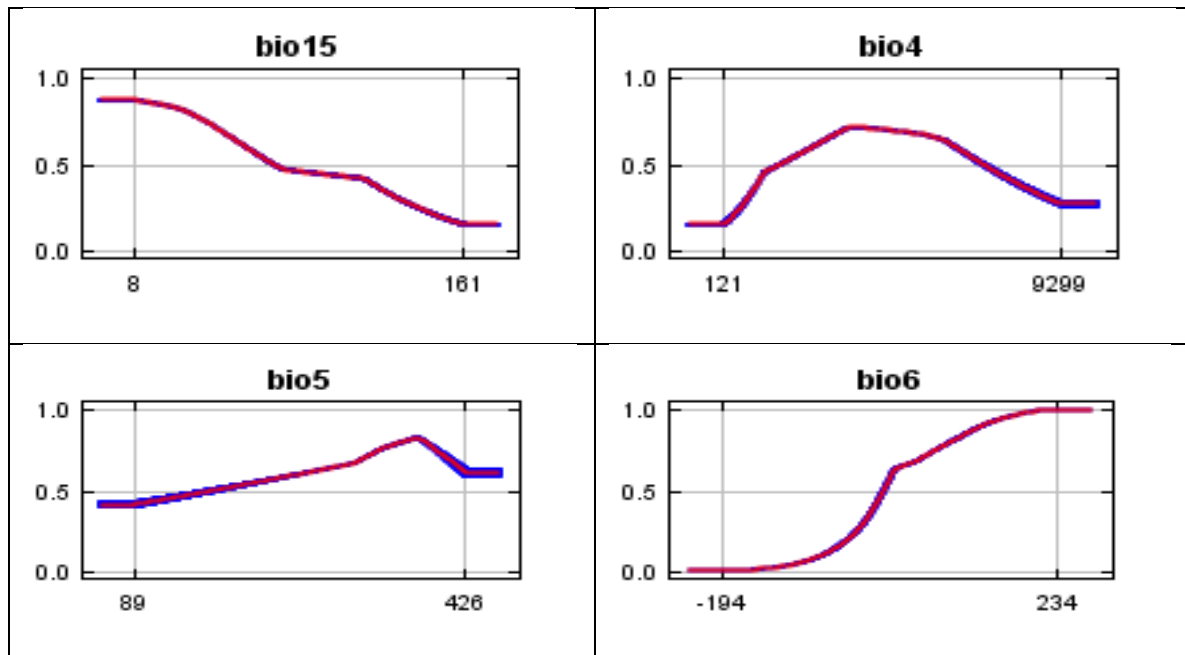
Appendix 4.19: Response Curve for *Caesalpinia decapetala*



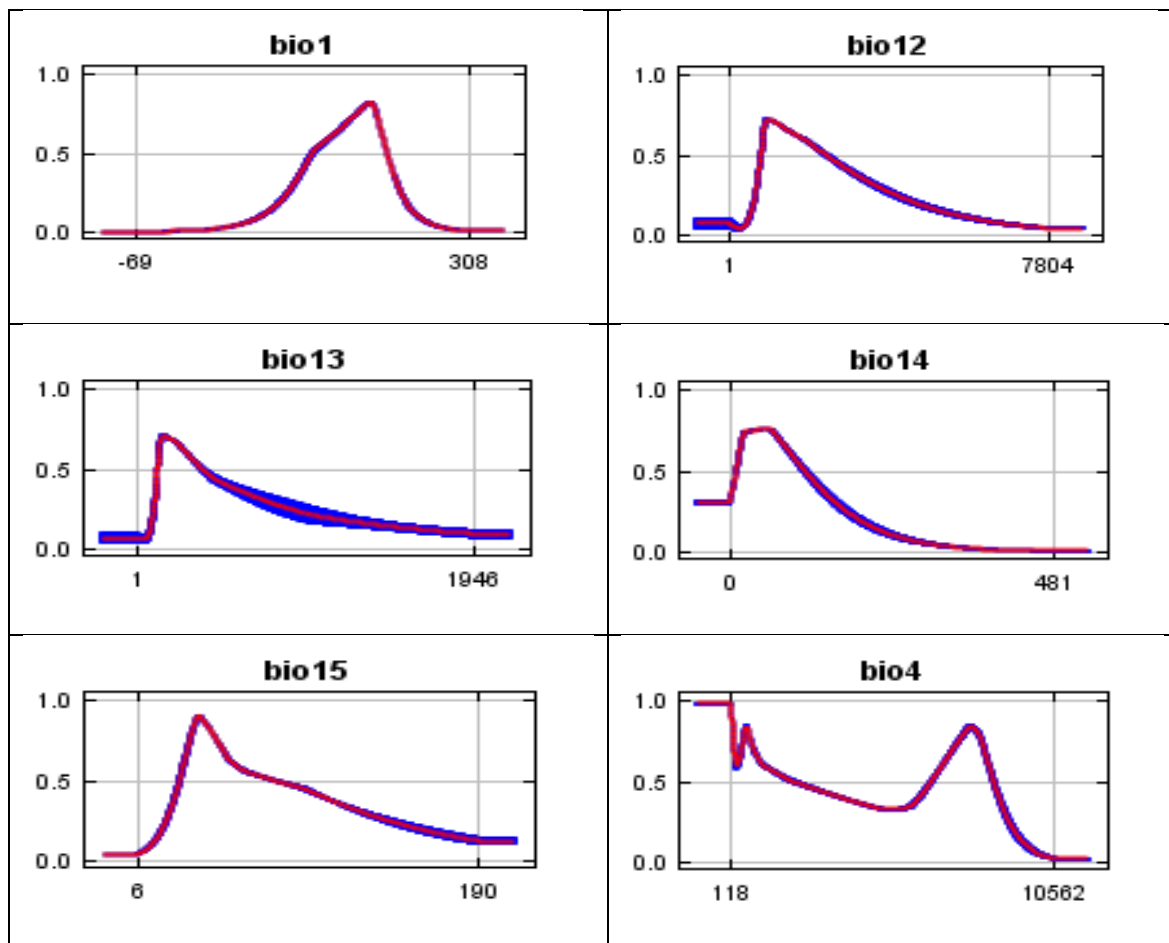


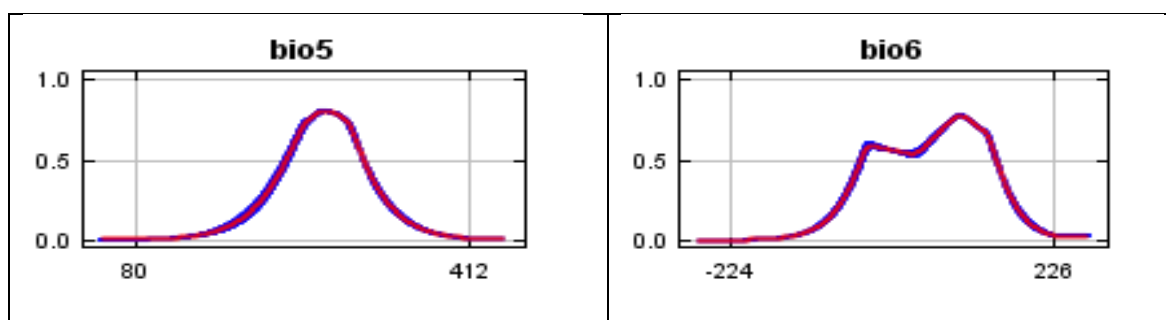
Appendix 4.20: Response Curve for *Eucalyptus camaldulensis*



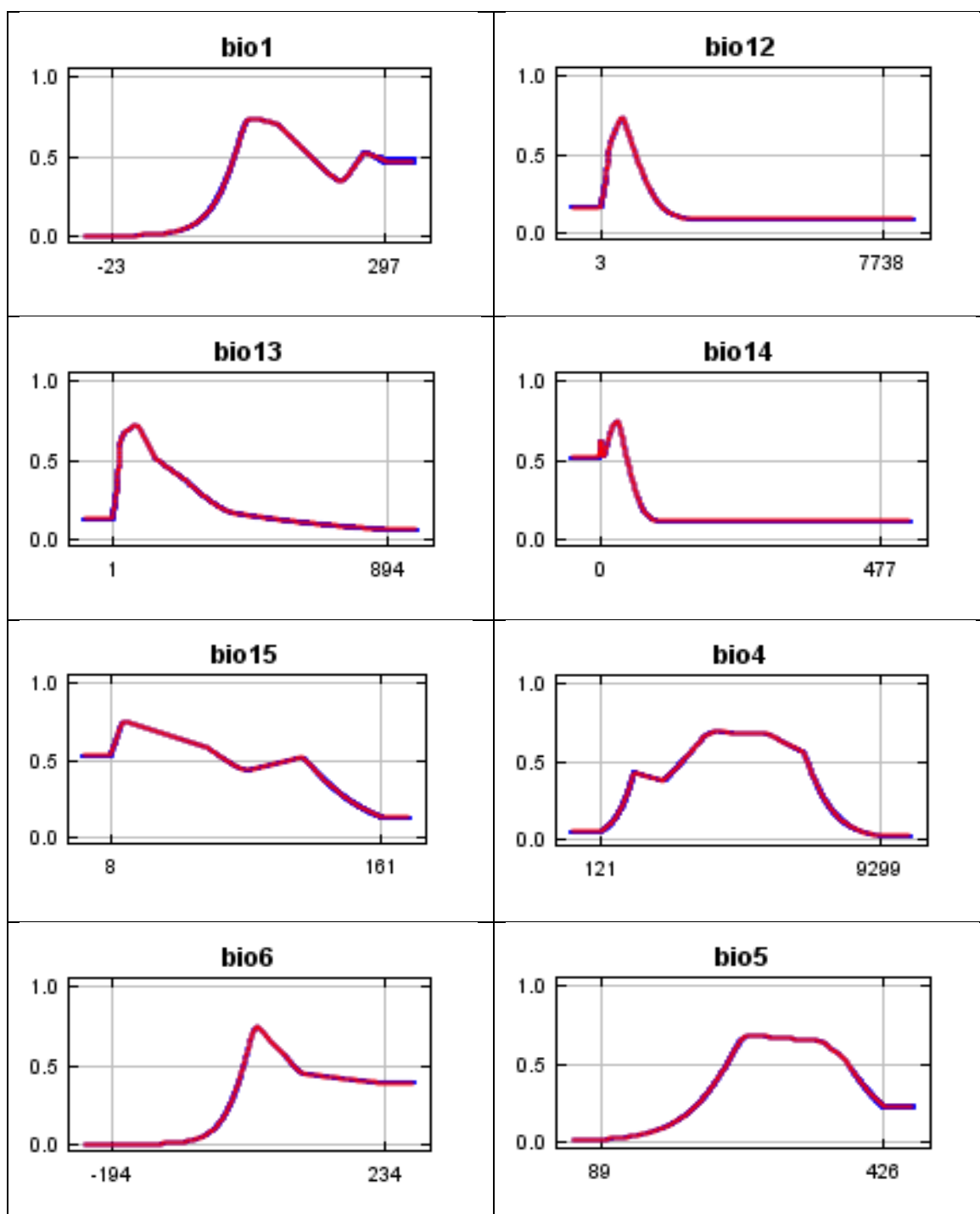


Appendix 4.21: Marginal response curves for *Caesalpinia decapetala*

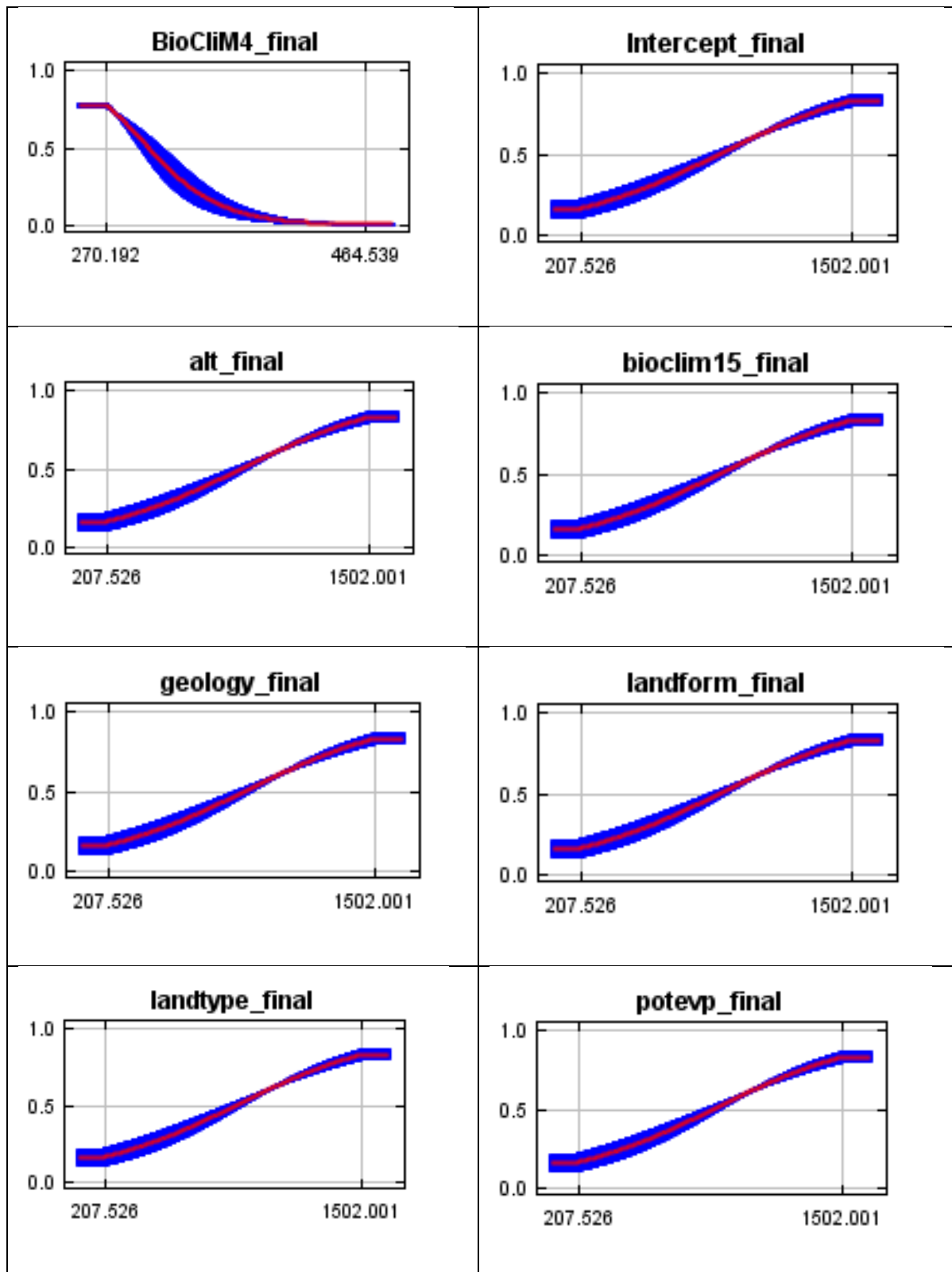


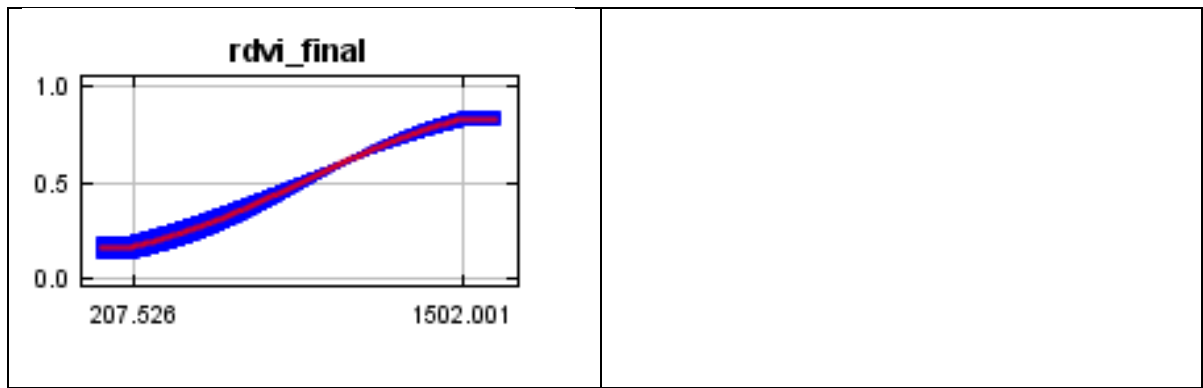


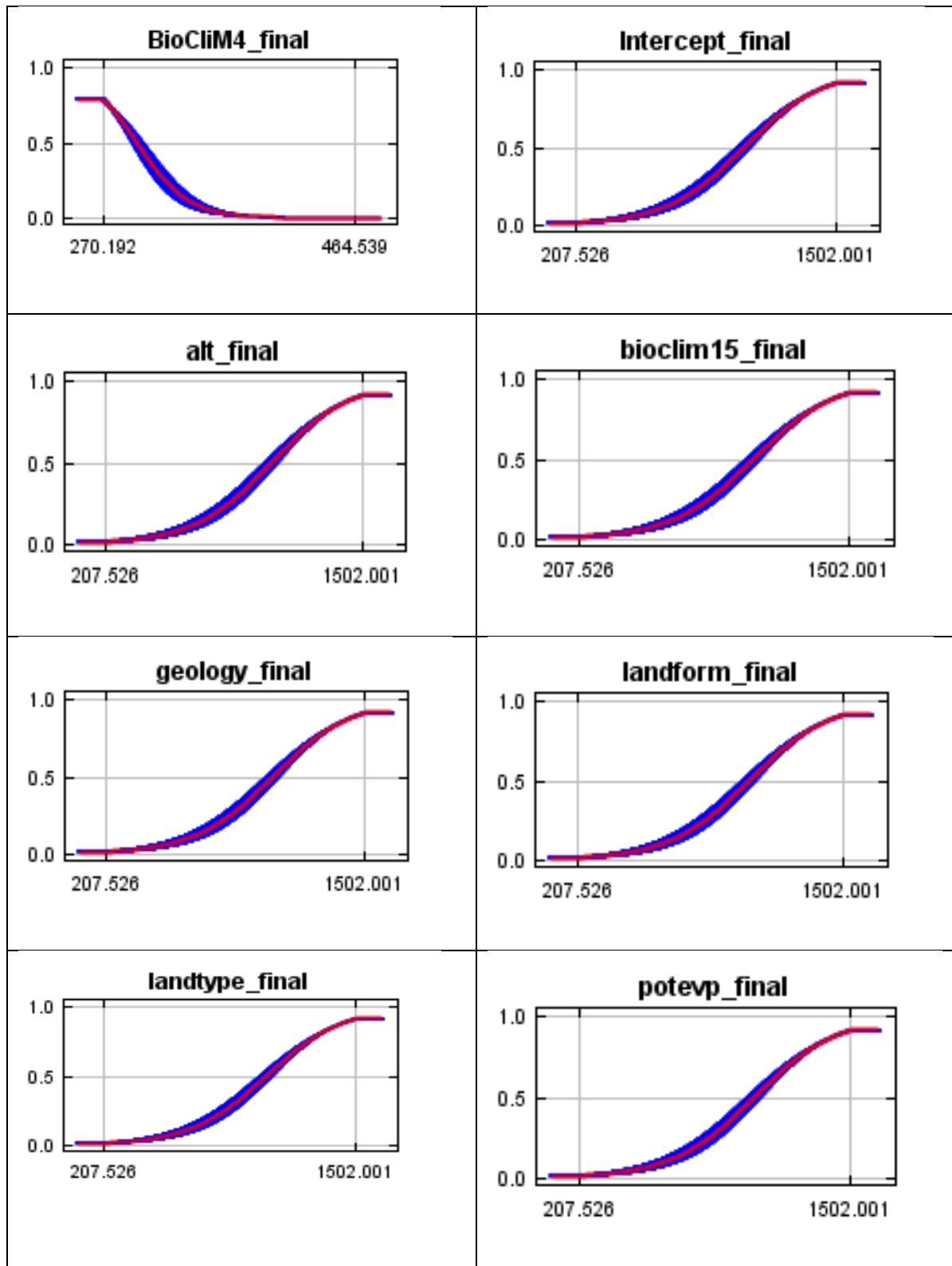
Appendix 0.22: Marginal response curves for *Eucalyptus camaldulensis*

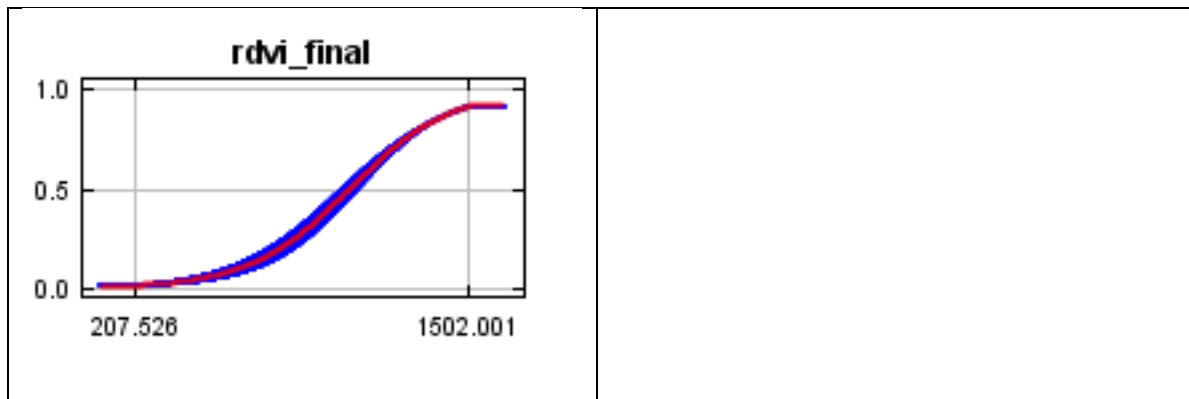


Appendix 4.23: Marginal response curves for *Caesalpinia decapetala*









Appendix 0-24: Marginal response curves for *Eucalyptus camaldulensis*

Variable	Spatial resolution	Data Source
DEM	30m	SANSA
Aspect	30m	Created in ArcGIS from DEM
Soil	250m	ARC-ISCW
Soil depth (mm)	250m	ARC-ISCW
LandType	250m	ARC-ISCW
Landform	250m	ARC-ISCW
Geology	250m	Council for Geoscience (CGS)
SoilStb (%)	250m	ARC-ISCW
GBWP	250m	WaPOR 2.1
Anl Prp(mm)	250m	SAWS
AETI	250m	WaPOR 2.1
Pot Evap	250m	WaPOR 2.1
Rel hum(%RH)	250m	SAWS
Intercept(l)	250m	WaPOR 2.1
Sol Rdn	30m	Created in ArcGIS from DEM
BioClim 1	900 m	WorldClim version 2.1
BioClim 4	900 m	WorldClim version 2.1
BioClim 15	900 m	WorldClim version 2.1
Cover	250m	DEA
B1R	1.5m	SPOT 6/7
B2G	1.5m	SPOT 6/7
B3B	1.5m	SPOT 6/7
B4NIR	1.5m	SPOT 6/7
NDVI	1.5m	Created in ENVI from SPOT 6/7
SRI	1.5m	Created in ENVI from SPOT 6/7
ARI2	1.5m	Created in ENVI from SPOT 6/7
TDVI	1.5m	Created in ENVI from SPOT 6/7
SAVI	1.5m	Created in ENVI from SPOT 6/7
RDVI	1.5m	Created in ENVI from SPOT 6/7
OSAVI	1.5m	Created in ENVI from SPOT 6/7

Appendix 0-25: Environmental variable GIS layers included in the analysis