

Scale Effects of Climatic Predictors in Species Distribution Models of the Okavango River Basin:

Implications for Conservation and Management Planning

Under Climate Change

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Abstract

Climate change is an unrelenting issue for Southern Africa and one that will become even more important for biodiversity conservation than at present. The distributions of plant species are strongly determined by climatic conditions. Species Distribution Models (SDMs) are at present the most extensively used tools in the assessment of the potential impacts of climate-change on biodiversity, and their results are used to inform conservation planning. Modelling of contemporary and future species distributions demands spatially explicit climatic predictor data. However, generating high resolution datasets using regional climate models and/or statistical downscaling techniques produces projected data for which there is no matching observed data sets for comparison, especially over Africa. The untested assumption is that the high-resolution climate models and statistical downscaling techniques generate more realistic historical climate and climate change projections, than do the low-resolution models that are evaluated by observational data. The influence of the resolution of climatic predictors on predicting species distributions and how the predictions might change, therefore remains inadequately addressed in species distribution modelling.

To address the deficiency, this thesis aims to advance knowledge of the sensitivity of predictions of species distribution to different spatial resolutions of climatic predictor data using the high-value biodiversity area of Okavango River Basin (ORB) in Southern Africa as a study system. The steps involved are:

Step 1: Comparing climate datasets across different spatial resolution to establish the degree of difference in spatial distribution of climate features. I did the comparisons between, Global Climate Model (GCM) climatologies and climate projections of rainfall and 2-meter air temperature and AFRICLIM historical baseline (WorldClim interpolated observations) and AFRICLIM future projection (statistically downscaled and bias corrected CORDEX projections), over the Southern Africa domain which includes the ORB. I then proceeded the work to the analysis of the variability in changes in future climate simulations from the GCM and AFRICLIM climate datasets for the period 2071-2100.

From this first analytical step I found that the fine resolution dataset benefits from the addition of spatial detail such as more structure reflecting the topography of the region which is not clear in the coarse resolution dataset. Climatologies obtained showed that the rainfall gradient depicted in

the course spatial resolution models is smoother along the south east of Southern Africa where steep topography leads to a sharp gradient in the observed field. In contrast the fine spatial resolution observational product displayed a clear zonal rainfall gradient from the southern Namibia area to central Botswana, this in agreement with the observed climatology. I therefore decided it was worth proceeding to test whether this seemingly added value presents any benefit in modelling species distribution under contemporary climate envelopes obtained from both fine and coarse models.

Step 2: Creating species distribution models to explore the sensitivity of SDM predictions to different spatial resolutions of climatic data. I used field sampled vegetation plots data on species occurrences and current climate conditions to model one hundred and fifty terrestrial plant species in the ORB, to map their contemporary projected distributions at 2km×2km, 5km×5km, 10km×10km, 20km×20km and 50km×50km spatial resolution. I investigated relationships between the climatic variable importance scores and climatic variable identity and their interaction with climatic predictor spatial resolutions using Generalised Linear Models and Multiple Comparison Analysis (Post-hoc analysis). I found that the relative influence of temperature and precipitation variables varied with spatial resolution. The importance of the determinants of species distribution change between species but such changes are less determined by the predictor's spatial resolution. Potential evapotranspiration consistently showed the greatest influence in determining species and richness distributions, across the fine to coarse spatial resolutions. Through the thesis I found that the spatial resolution of predictors had no effect on the model predictive power and that differing predictor spatial resolutions had only negligible effects on the model performance measured by Area Under the curve (AUC) of the Receiver Operator Characteristic Curve statistics. The spatial resolution of the used climatic predictors exhibited no effect on species richness pattern either.

Through the sensitivity analysis, I conclude that the use of climatic predictors at different spatial resolutions will not intrinsically bias future species distribution models in certain landscapes. As a result, I believe that modelling at coarser spatial resolutions for conservation purposes in areas with relatively homogenous topographic and climatic conditions can be acceptable. This result will help conservation planning in situations where no high-resolution climatology exists.

Step 3: Projecting future suitable climate space for a subset of the contemporary ORB conservation relevant plants, to assess the potential implications of climate change on them and on conservation and management planning in general. In doing so, I designed and applied a novel comprehensive climate change vulnerability assessment framework. I found different responses to climate change at species level and suggest that conservation and management actions should therefore be approached at the level of species, or subspecies, and not assume that multiple species will react in the same way as each other to climate change.

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The writing of this thesis extended into the COVID-19 pandemic period, the impact on mental well-being of restricted movements, confinement to a flat, the lack of normalcy and daily routine, implemented as measures to curb the spread of the virus, became real so quickly. The additional responsibilities that came with primary school closures, for me like many other parents, were significant, among others reducing productivity. The finalising of the thesis happened under the wake of the brutal murder of George Floyd by USA police, reports on the race gaps in COVID-19 deaths with high mortality rates in black and ethnic minority communities; like many these left me traumatised and concerned about my life and that of my family. My ability to perform under these challenging physical and psychological conditions was improved by the speed at which Professor Richard Washington returned constructive comments on the thesis. Prof RW, thank you for this.

This PhD was the first venture into spatial modelling, a foray that tested my determination and abilities. Many people answered basic questions about Python and R, programming softwares; these include Sebastian Engelstaedter and Jesús Aguirre-Gutiérrez; thank you. A very special thank you goes to Norbert Nthala who patiently listened and provided valuable technical advice on IT related matters I encountered in the last year of this journey. Thank you, Norbert. Catherine Walter, thank you very much for taking your time to proofread the thesis.

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Dedication:

This work is dedicated to those whom without their support and understanding over the years the thesis could probably have not been completed, my husband Phenyo and son Motheo Mauchaza. I love you both very much.

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Author's Note

The doctoral research project is made possible by the generous funding from the Botswana Government. The doctoral thesis will take the form of the "chapter route". A total of 7 chapters, of which three are analytical chapters, presents a body of research into the sensitivity of the predictions of species distribution to different spatial resolution of climatic predictor variables and the implications for conservation and management of biodiversity under climate change. The analysis I did involves first comparing climate data across different spatial scales, to establish the degree of difference in spatial distribution of climate features from climatic variables (rainfall and temperature) which would act as inputs to SDMs. The analysis then proceeds to investigate what effects the different spatial resolution of climatic predictors has on predicting species distribution under contemporary climates. It progresses to assess the potential impacts of climate change on ORB plant species and consequent implications for conservation planning given the current plans.

The thesis analytical Chapter 5; **"Climatic Drivers of Plant Species Distributions Across Spatial grains in Southern Africa Tropical Forests"** is published in Frontiers in Forests and Global Change.

Authorship contribution:

BT-M and JA-G conceived the idea and designed the study. BT-M constructed all the modelling work, carried out the statistical analyses, and interpreted the results with important discussions and input from JA-G. BT-M led the writing and produced initial drafts of the manuscripts with contribution from JA-G on revision of the manuscripts.

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List of Acronyms

AR5	Fifth Assessment Report (of IPCC)
BDMF	Basin Development & Management Framework
CBD	Convention on Biological Diversity
CCVA	Climate Change Vulnerability Assessment
CMIP	Coupled Model Intercomparison Project
CMIP3	Phase 3 of the Coupled Model Intercomparison Project
CMIP5	Phase 5 of the Coupled Model Intercomparison Project
CORDEX	Coordinated Downscaling Model Experiments
CRU	Climate Research Unit
DJF	December to February
ENSO	El Niño Southern Oscillation
GBIF	Global Biodiversity Information Facility
GCM	Global Climate Model
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Intertropical Convergence Zone
KAZA TFCA	Kavango–Zambezi Transfrontier Conservation Area
ORB	Okavango River Basin
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
SDM	Species Distribution Model

1. Introduction

Climate change is an increasing concern and an important issue for ecosystems and biodiversity conservation communities and agencies in Southern Africa (IPBES Africa, 2018). It imposes adverse impacts on species and habitats with potential consequences of extinction (Garcia et al., 2012; Midgley and Bond, 2015). Species Distribution Models (SDMs) have been useful tools in the assessment of vulnerability of species to climate change (Guisan and Thuiller, 2005; Dubuis et al., 2011; Ofori et al., 2017), as they simulate changes in suitable climate space (Stein et al., 2013; Meller et al., 2014; Foden et al., 2019). Understanding the effects of the spatial resolution of climatic predictor data in the prediction of species distribution is an important element of species distribution modelling (Radinger et al., 2015), yet it has not been widely addressed in under-sampled areas in arid tropical forests and is often not accounted for in SDMs. Variations in spatial and temporal scale in the datasets used in running SDMs remains a relevant issue for conservation practitioners. There is no consensus on the adequate spatial scale of predictors for accurate prediction (Raven, 2002; Bradter et al., 2013; Fournier et al., 2017); a full understanding of the effects of building SDMs at various predictor spatial resolutions is also lacking, and this can mislead and delay management plans and conservation decision making (Porfirio et al., 2014; Yates et al., 2018). Incorporation of climate change considerations into conservation and management planning for African biodiversity remains critical. The recently published Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES, 2018) places climate change as the third most important factor for biodiversity decline and loss. Understanding the link between climate projection estimates and species response to the projections can therefore provide useful guidelines for the design and implementation of conservation, management and adaptation strategies aimed at providing a basis for future biodiversity persistence (Guisan et al., 2013; Haddad et al., 2015).

There have been efforts to investigate the effects of global warming in African ecosystems, e.g. the Western and Central Africa rainforest ecosystems (Malhi et al., 2009; Asefi-Najafabady and Saatchi, 2013; James et al., 2013; Saatchi et al., 2013) Studies of the potential impacts of climate change have also been carried out in Sub-Saharan Africa, focusing on desertification (Oba et al., 2001), land cover change (Vanacker et al., 2005), rainfed agriculture (Mupangwa et al., 2011;

Thornton et al., 2011), deforestation, woody encroachment and forest regrowth (Rudel, 2013). The projected strong drying trend over the Southern Africa region (Kruger and Shongwe, 2004; New et al., 2006; Kusangaya et al., 2014), with a stronger warming trend for Botswana (Akinyemi and Abiodun, 2019), and implications of these projections for the sustainability of biodiversity, makes this region a priority study area. Assessments of the impacts of climate change on biodiversity over Southern Africa have however focused on bird species (Coetzee et al., 2009; Huntley et al., 2011) and only one deciduous tree species, the *Pterocarpus angolensis* (De Cauwer et al., 2014). Most of the assessment work has concentrated on the country of South Africa (Bomhard et al., 2005; Hannah et al., 2005; Ziervogel et al., 2014), where Bomhard et al. (2005) projected potential climate change threats on *Proteaceae* taxa in the Cape region of the country. Investigations of the potential impacts of climate change over the Okavango region (the thesis study area), a biodiversity hotspot and UNESCO world heritage site (UNESCO 2014), have focused on the conservation and management of the water resource of the basin (Andersson et al., 2006; Hughes et al., 2011; Weinzierl et al. 2016) and agricultural conditions and productivity (Weinzierl and Heider, 2015). Murray-Hudson et al. (2019) investigated spatial changes in the distribution of (macrophyte) aquatic plant species determined by hydrology, while Revermann et al. (2016) modelled the contemporary plant alpha diversity of the Okavango Basin. Within the Okavango River Basin (hereafter ORB), recent literature also exists on the composition of the vegetation of the Okavango Basin; Revermann et al. (2017) provide a checklist of the Miombo woodlands and geoxylic grasslands of southeast Angola, while Gonçalves et al. (2018) assessed the species diversity and vegetation structure of the tropical woodlands of Angola. However, there is a deficiency of studies assessing the potential impacts of climate change on the terrestrial plant species of the basin, despite its status as an ecoregion of global conservation priority (Botswana CBD Report, 2009).

Reviews indicate that the quantification and assessment of potential impacts of anthropogenic climate change on species is often based on the assessments of the species' exposure, sensitivity and adaptive capacity (Nicotra et al., 2015; Pacifici et al., 2015; Wade et al., 2017b). As important as these assessments are in guiding conservation actions, they lack the theoretical inclusion and reflection of the adaptation opportunity element (Berry et al., 2013; Thompson et al., 2015). Adaptation opportunity describes factors that physically hinder or facilitate species adaptive capability (Berry et al., 2013), e.g. habitat loss and fragmentation, anthropogenic and

natural barriers to dispersal (Nicotra et al., 2015). Thus, a species' ultimate adaptation capability can theoretically be evaluated in conjunction with assessment of adaptation opportunity. In an ecological context, the role the processes of adaptive evolution (Reznick and Ghalambor, 2001), phenotypic plasticity (Sultan, 1987) and migration play in species adaption to a changing climate is acknowledged; however, these processes can be limited by lack of adaptation opportunities. It is therefore critical to reconcile the concepts of adaptive capability and adaptation opportunity, as they have potential to influence and alter sensitivity of species to climate change, thus affecting their vulnerability ranking (Berry et al., 2013; Wade et al., 2017). Approaches to facilitating comprehensive frameworks for assessing potential impacts of climate change and identifying climate adaptation management actions are however lacking. Accurate projections of the potential impacts of climate change on biodiversity for climate smart conservation and adaptation strategies are critical (Vale and Brito, 2015). This thesis, therefore, in assessing the potential impacts of climate change on ORB plant species, considers how elements of adaptive capacity and adaptation opportunity can be incorporated in addition to species sensitivity to effectively quantify species vulnerability. I thus design and apply a novel comprehensive climate change vulnerability framework, which utilises projections of climate change for sensitivity assessment, and then adds elements of adaptation for the vulnerability assessment.

Projections of climate derived from climate models have thus been used to assess the potential impacts of climate change on ecosystems and humans (e.g. Niang et al. 2014: IPCC Africa.WGii). An enduring and partly untested element of this research is the general assertion that Global Climate Models (GCMs) are too coarse in spatial resolution to capture with reliability patterns of important ecological climatic variables (Diniz-Filho et al., 2009; Wiens et al., 2009), and therefore too coarse to accurately predict species occurrences when used as datasets for running SDMs (Soberón, 2007; Gottschalk et al., 2011). There are three main approaches used to downscale GCM products to higher spatial resolutions for impact studies: (i) Regional Climate Models (RCMs), described as dynamically downscaled global reanalysis (Castro et al., 2005; Sotillo et al., 2005) or GCMs run to simulate climate variability with regional refinements (Christensen and Christensen, 2003; Christensen et al., 2007) have been developed to provide solutions to the GCM coarse resolution problem. RCMs are limited area models nested within large-scale dynamics via consistent provision of lateral boundary conditions from GCMs or reanalysis to compute higher resolution outputs; a process called

dynamical downscaling (Rummukainen, 2010). Regional models typically simulate rainfall in grid boxes of a few tens of kilometres across. Even at grid boxes of 10km, rainfall is indirectly represented through the process of parameterisation. Biases present in the driving GCMs or reanalysis also affects the model skill. Although there have been major efforts to run RCMs without convective parametarisation, for example the 4.5 grid spacing over the continental scale for Africa as part of the IMPALA project (Stratton et al., 2018), these achievements are as yet experimental and are not yet available for multiple decades of the 21st century or in ensemble mode or in multi-model experiments.

(ii) Statistical downscaling (also known as empirical downscaling) (von Storch and Storch, 1999; Wilby et al., 2004), is a downscaling technique that follows the view that regional scale climate is based or conditioned on the large scale climatic state and regional physiographic features (Wilby et al., 2004; Diaz-Nieto and Wilby, 2005). Statistical or empirical downscaling grew out of the process of establishing transfer functions which link observed climate variables to climate model data. The resolution derived from the process in this approach therefore matches the original resolution of the observed data sets (Wilby et al., 2004; Benestad et al., 2008; Hewitson et al., 2014). (iii) Change factor downscaling (Wilby et al., 2004; Klausmeyer and Shaw, 2009) is the most straightforward method for generating higher spatial resolution climate scenarios from GCMs. The technique applies coarse scale climate change projections onto a higher resolution observed climate baseline, following a spatial interpolation method (Wilby et al., 2004; Fowler et al., 2007). The advantages of the change factor (or "delta-change") method is that it claims to reduce systematic biases between observed and simulated future climates.

In other impact studies, it is often inferred that the RCMs and other finer resolution data (for example generated through statistical downscaling) constitute an effective solution to data resolution problem; however, within species distribution modelling, RCMs are considered too coarse to predict species range (Seo et al., 2009). A typical spatial resolution of GCMs is 200km, whereas the resolution at which many RCMs over Africa are run is 50km×50 km (e.g.Nikulin et al., 2012). Examples of the assumption that RCMs represent an effective solution are widely evident in the literature. Gan et al. (2016), for example, in relation to water resources, partly attribute the lack of understanding of hydrological impacts of climate change in African regions

susceptible to drought, to the few climate change studies based on regional climate models. This implies that RCMs are conducive for modelling hydrological impacts; however, with no evidence offered to demonstrate that climate change derived from GCM based studies are misleading. Gan et al. (2016: p. 1217-1218) strengthen the claim, later in the same work, arguing that RCMs should be expected to perform better (Kharin et al., 2013; Sillmann et al., 2013) and thus projections based on RCMs give more confidence in climate change impact studies than those from GCMs. Similarly, Kusangaya et al. (2014), also on the theme of water, presents a nearly identical claim, noting that even though RCMs have superior spatial resolution for better temperature projections relative to GCM (e.g. Mujere and Mazvimavi, 2012), limited studies have used RCMs in the projections (e.g. Engelbrecht, 2005; Schulze et al., 2005b ; Tadross et al., 2005). More recently, Akinyemi and Abiodun (2019: p. 388) have made assertion that the resolution of GCM simulations used to project impacts of Global Warming Levels (GWLs) on climate extremes over Botswana were inadequate to investigate local features that induced extreme events. It is worth noting that the claim that GCMs are too coarse has no supporting evidence or reference as well as the suggestion that RCMs will be better has no evidence for Africa.

The Coordinated Regional Downscaling Experiment (CORDEX ; Giorgi et al., 2009; Jones et al., 2011) programme was designed to address the perceived deficiency created by the coarse spatial resolution in GCMs (see Nikulin et al., 2012; Kim et al., 2014), with Africa being declared as a domain of special interest in the World Meteorological Organisation (WMO) run programme. The programme consumed vast computing and scientific resources, meaning that in ecological modelling, it is important to assess the generally asserted claim that GCMs are too coarse to be used for predicting species occurrence and that downscaled GCM products, whether through dynamical or statistical means, are better. Studies investigating the difference made by spatial resolution in simulating climatologies and projecting future climates, as well as those that consider whether different GCMs or their dynamically and statistically downscaled products are more useful for ecological modelling are lacking. It may be the case that climate data at 200km (from GCMs) and 50km (for example from RCMs), and finer resolution data (for example generated through statistical downscaling) are *all* sufficient for impact assessments. I therefore compare different climatic data products, at different spatial resolutions, GCM against statistically downscaled and bias corrected products.

The thesis thus begins by investigating the assumptions that data of the resolution of climate models (GCMs and RCMs) are too coarse for impact studies. A first step is to compare climate data across different spatial resolutions, to establish the degree of difference in spatial distribution of climate features. I compare rainfall and 2-meter air temperature from the AFRICLIM historical baseline (WorldClim interpolated observations) and AFRICLIM future projection (statistically downscaled and bias corrected CORDEX projections, AFRICLIM v3.0; Platts et al., 2015) with the GCM historical and future data from Coupled Model Intercomparison Project phase 5 (CMIP 5) (Taylor et al., 2012), over the Southern Africa domain, covering the ORB. Similarities and differences between simulated and observed contemporary climates, where simulated climates are provided by the GCM are analysed and explored. I then proceed to analyse the variability in changes in future climate simulations from the GCM and AFRICLIM climate datasets for the late 21st Century (2071-2100). These results are presented in Chapter 4.

Next I explore the sensitivity of SDM modelling output to the spatial resolution of climatic predictor data by using extensive field sampled vegetation plots data on species occurrences and current temperature and rainfall climatic conditions (1950-2000) to (i) identify some of the main climatic determinants of the plant species distributions in the ORB and how they might change as a function of the spatial resolution of the climatic predictor data, (ii) explore the degree to which species richness estimations differ across fine to coarse spatial resolution of climatic predictor data and (iv) assess the potential impacts of climate change (2071-2100) on plants species of ORB and their vulnerability and implications for conservation and management planning. These analyses are presented in Chapters 5 and 6.

This thesis thus addresses crucial questions for understanding the importance of spatial scale in climate modelling, as well as understanding the sensitivity of SDMs to the spatial resolution of climatic variables used as input datasets, and implications for conservation management planning. Establishing the sensitivity of using coarse spatial resolution versus fine spatial resolution climatic datasets on species distribution modelling provides a useful way of establishing whether the costly laborious efforts involved in downscaling global climate model products to finer resolutions are indeed justified, at least in the context of their use for SDMs. Secondly, running models at high resolution, especially over Africa, produces model data for which there is no matching observed data set for comparison. It therefore requires a leap of faith

that the higher resolution models will grant more useful information. Testing whether the high-resolution models provide something different and better is an obvious and necessary step. The assumption is simply that they are better; this assumption is however worth testing. Another important goal is the provision of a better understanding of the effects of spatial resolution of climatic predictor variables in studies inferring niche relationships (Revermann et al., 2012; Brown et al., 2016; Connor et al., 2017; Nadeau et al., 2017). This understanding is vital for guiding and informing biodiversity conservation and management decision making (Rodríguez et al., 2007; Fordham et al., 2013).

This thesis contributes to general debates on the adequate spatial resolution of climatic predictor data for an accurate projection of species distribution and estimates of species richness. I expect that the thesis results will increase the evidence about the impact of spatial resolution of climate datasets on SDMs and advance our understanding of its implications for conservation planning. I also anticipate that the assessment of the potential impacts of climate change on ORB terrestrial flora species will result in effective conservation and management strategies and policies, fit to potentially make the region resilient to climate change.

1.1 Aims of the thesis.

The thesis seeks to advance knowledge of the sensitivity of the predictions of species distribution to different spatial resolution of climatic predictor variables used as input data sets, over the Okavango River Basin landscape, and to use this knowledge to make recommendations for enhancing conservation policy under climate change. This will be achieved through the following three sequential aims:

(i) To investigate the effects of spatial scale differences in climate models on simulating contemporary and future temperature and rainfall over Southern Africa.

(ii) To investigate the effects of spatial resolution of climatic predictor data on plant species distributions and richness estimates in ORB.

(iii) To assess potential impacts of climate change on ORB terrestrial plant species and their vulnerability and to explore the implications for conservation and management planning.

1.2 Okavango River Basin (case study)

The study is based on the Okavango River Basin located in Southern Africa and spanning three countries: Botswana, Namibia, and Angola. It is an interesting case study given its special ecological status: as a biodiversity hot spot (Myers et al., 2000), it is therefore important to understand the potential impacts of climate change for conservation planning. This is especially the case, given that Botswana is currently experiencing climate change which has been argued to be substantial – e.g., a warming signal of about +3 Celsius (see Akinyemi & Abiodun, 2019) coupled with a drying trend predicted over Southern Africa, which is one of two of the largest land-based drying trends on the planet. Therefore, to best understand these climate change impacts on ORB biodiversity, accurate models are needed, and this thesis helps to contribute to the process, by guiding model makers on the choice of spatial resolution at which to work. The Okavango Basin is also selected as it falls under an interesting Southern African landscape and climatic system, in particular the relatively flat terrain in the interior of subtropical continents (Hart, 2012; Saeed et al., 2013; Reason, 2017). This makes it an ideal test bed to investigate elements of the SDM modelling framework and methodological uncertainties; however, the region is rarely used for such studies. From a species distribution modelling perspective, having an area that is less heterogeneous is advantageous in helping to reduce some of the factors which might affect modelling outputs such as topographical variation (Stein et al., 2014). The Okavango basin therefore provides a tractable model system for addressing issues of scaling in SDM. The diversity of species and habitat types within the Okavango basin also allows for testing of a variety of plant species (about 150). Using any other area would have meant studying distribution methods using fewer species, and probably with wider tolerances to climate change.

2. Literature Review

2.1 Overview

Each analytical chapter of the thesis includes a literature review in the introduction section, giving the conceptual grounding for the chapter research. Therefore, in this chapter I provide a brief, general literature review commencing with literature on the understanding of the Southern African climate, to aid in understanding the Southern African climate under global warming. The review also draws from literature in support of and against the assumption that GCMs or their dynamically and statistically downscaled products are too coarse in spatial resolution to capture, with reliability, patterns of variation in important ecological climatic variables. A review on species distribution modelling and climatic variables is also provided, relating to drivers of vegetation composition and structure in ORB as well as current conservation and management plans for the ORB.

2.2 Understanding the Southern African Climate (0 °-51 °E, -37 ° - 0 ° S)

Investigation and comparisons of the climatology of rainfall and surface air temperature derived from the fine and coarse climate models, simulation of the future climate projections (2071-2100), and climate change signals relative to the baseline period of 1950-2000, over the broader Southern Africa region, have to be preceded by the understanding of the region's climate. This section therefore provides an overview of the climate of Southern Africa. The overview is mainly informed by the texts books of (Tyson and Preston-Whyte, 2000), on the weather and climate of Southern Africa; and by numerous relevant journal articles (e.g. Cook and Cook, 2000a; Nicholson, 2001; Rouault et al., 2003; Reason, 2016).

Located in the southern tip of the African continent, between the Atlantic Ocean and the Indian Ocean, Southern Africa is described as a semi-arid region with a generally warm climate with average annual temperatures of 17 degrees Celsius and annual rainfall of about 550mm (Tyson and Preston-Whyte, 2000).

The regional climate can be categorized into two zones following Spear et al. (2019); Haile (2011); Gasse et al. (2008): (i) the dry climate zone which comprises a semi-arid, sub-humid climate in the east and a hyper-arid climate in the west. These dry climates are in countries in the Southwestern part of the region along the Kalahari Desert: Angola, Namibia, Botswana, Zimbabwe, and South Africa; (ii) the moist mid-latitude climate zone, comprising dry to moist subtropical mid latitude conditions, in countries in the eastern part of the region: Tanzania and Mozambique.

The region has two rainfall seasons, the wet and dry seasons. The core of the wet season over much of the region is experienced in the austral summer months of December, January, and February [DJF] (Diallo et al., 2012, 2015). This wet season is a result of the tropical rainbelt (Reason and Smart, 2015) shifting south and bringing along rainfall in the form of thunderstorms. Uneven distribution of rainfall is the norm in the region. The main circulation rainfall features which influence summer rainfall are the Angola low (Munday and Washington, 2017; Howard et al., 2018), subtropical anticyclones, tropical convergence zones (Reason and Smart, 2015; Reason, 2016) and tropical temperate troughs (Macron et al., 2014; Howard et al., 2019). Being between the Atlantic Ocean and Indian Ocean, Southern Africa domain features high pressure zones on the west and east sides, resident in the ocean basins. These pressure systems are associated indirectly with oceanographic features such as the Angola Benguela Frontal zone, the Agulhas current (Stramma and Lutjeharms, 1997; Reason and Smart, 2015) and the retroflection region, the Seychelles-Chagos Thermocline ridge (Reason and Smart, 2015) which therefore also contribute, albeit indirectly, to the formation of summer rainfall. The rainfall onset occurs when tropical convection moves south from the central African convective region. A strong east to west rainfall gradient is a characteristic of this region, because the convection aligns meridionally over Southern Africa during the core of the rainfall season (Munday and Washington, 2017; Maranan et al., 2018; Howard et al., 2019), unlike the zonal configuration in the West African monsoon (Diallo et al., 2014; Diedhiou et al., 2018; Maranan et al., 2018).

Topographical features control temperature patterns across the domain. The Kalahari and Namib deserts covering southwest Botswana and south east Namibia are characterized by high temperatures (New et al., 2006; Diallo et al., 2012). High altitudes areas covering the Katanga

Plateau in Northern Zambia and Drakensberg/ Lesotho highlands in south east area experience lower temperatures. High maximum temperatures of >40°C occur in day time during the austral summer months of DJF (Lyon and Lyon, 2009) and drop at night time. The same atmospheric features responsible for rainfall over Southern Africa, outlined above, are also responsible for the timing and magnitude of temperature variability in the region. The most prominent atmospheric feature controlling inter-annual temperature patterns in Southern Africa is the El Niño Southern Oscillation (ENSO), a well-studied phenomenon described as periodic variation in sea surface temperature over the tropical eastern Pacific Ocean (Halpert et al., 1992; Nicholson and Kim, 1997; Jury et al., 2002; Jury, 2013; Kisembe et al., 2019). During the period of El Niño, the austral summer months typically experience drier and warmer conditions across the region, while La Niña years tend to produce wetter and cooler conditions (Trenberth et al., 2000). There is less spatial and temporal variability in temperature over the region than in rainfall (Daron, 2014).

2.3 Understanding the Southern African Climate under global warming

Greenhouse gas induced climate change has resulted in global warming (IPCC, 2014). A phenomenon where average air temperature near the earth's surface increases (Scholes et al., 2015), global warming leads to warming of the atmosphere, oceans and land, as well as changes in precipitation patterns (Solomon, S. et al., 2007). Despite the impacts of anthropogenic global warming being observed and felt across ecosystems functions (Malhi et al., 2009; Hegerl & Stott 2014), the rise in emissions of greenhouse gases has not been halted (Peters et al., 2012; Quéré et al., 2013). A number of studies (e.g. Hulme et al., 2001; Shongwe et al., 2009; Washington et al., 2006; James & Washington 2013) have been carried out to investigate climate change due to global warming in Africa. For the continent in general, including the region of Southern Africa, starting with the previous Coupled Model Intercomparison Project Phase 3 (CMIP3), some models in the multi-model datasets which are forced by IPCC Special Report on Emissions Scenarios, A1B, with Green House Gas (GHG) increased to 2200 (Taylor, 2010), predict a rise in temperature of 4^{o}C by 2200 (James & Washington 2013). Arid subtropical regions in the Northern Hemisphere (NH) regions, experience the highest anomalies during the season September to November (SON), during which a dry signal is projected for Southern Africa,

under A2 (A1B) (James & Washington 2013). Figure 2.1 illustrates and gives evidence for projected change in temperature and precipitation trends in Africa due to global warming.

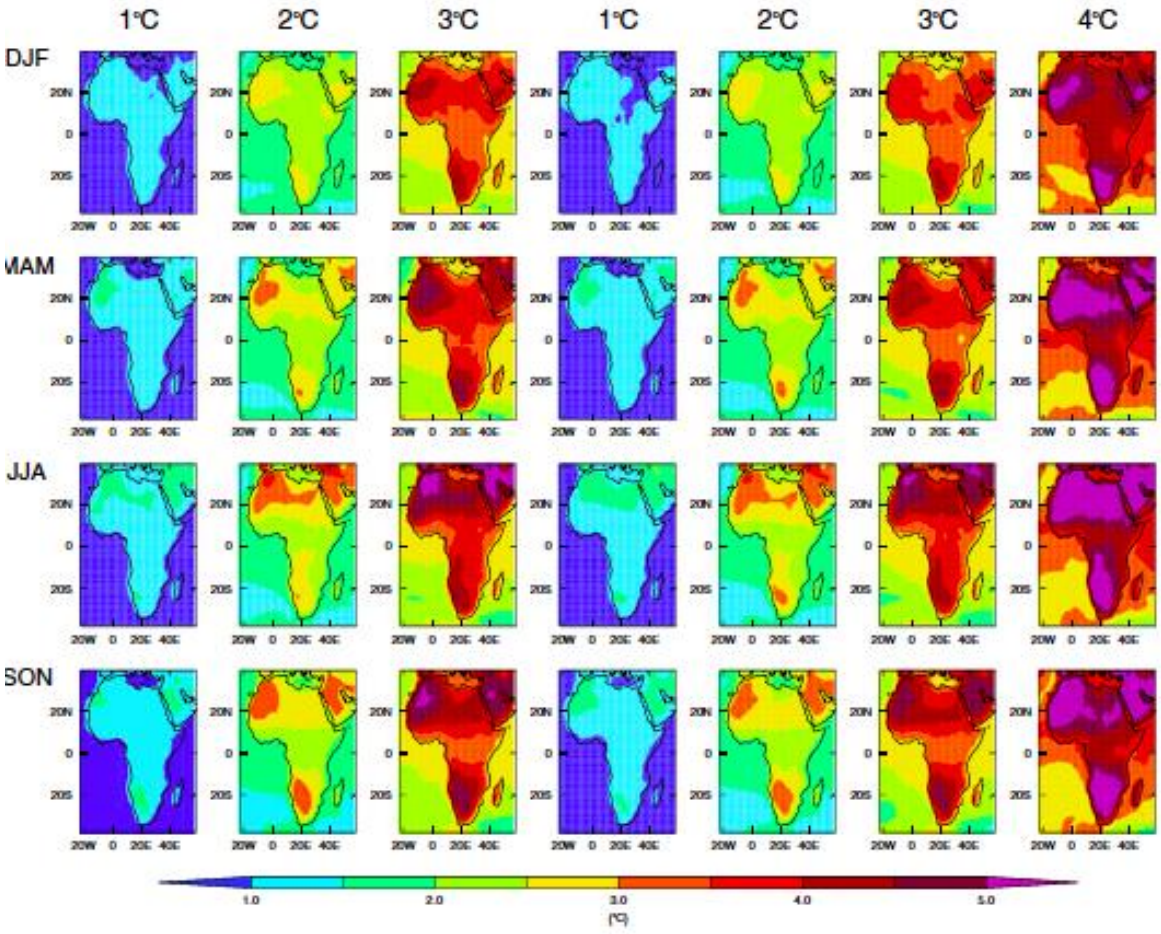


Figure 2.1:"Ensemble mean seasonal precipitation anomalies (mmday^{-1}) associated with degrees of projected global warming in A2 (first 3 columns) & A1B (last 4 columns)" the first three columns are projected A2 global warming and the last four columns are projected A1B global warming (adopted from James and Washington, 2013:p. 864).

Shongwe et al. (2009) projected the western parts of the region to have an increase in the severity of dry extremes during the summer months, due to a decrease in mean precipitation. This result is consistent with, for example Giorgi et al. (2001) and Hulme et al. (2001), who found significant decreases in mean austral summer precipitation in the area of South Africa, Botswana and Namibia. Recent climate change model simulations over the region based on CMIP5 medium and high Representative Concentration Pathway emission scenarios, [RCP4.5 and RCP8.5] (Taylor et al., 2012) continue to project signals of drying (IPCC, 2013: p. 1061) and upward trends of mean annual temperatures with projected increases between 4^{o}C and 6^{o}C by the

end of the 21st century (Engelbrecht et al., 2015; Dosio, 2016; Engelbrecht and Engelbrecht, 2016; Pinto et al., 2016).

Southern Africa, like other African regions, is vulnerable to changes in climate, due to key sectors' dependence on rainfall (Meadows, 2006). Evidence of climate change impacts have already been recorded for the agriculture sector (Vermeulen et al., 2012), water resources (Kusangaya et al., 2014), biodiversity and ecosystems (Midgley and Thuiller, 2011; Midgley and Bond, 2015b; IPBES 2018). Given their great impact on human activities and wide application, investigation of the likely patterns of future change in rainfall and temperature over the region still deserves more attention.

Even though GCMs have been used to project the climate change for Southern Africa (Giorgi et al., 2001; Hulme et al., 2001; Munday and Washington, 2017, 2018) due to their coarse resolution relative to much finer spatial resolution required for many impact studies, the utility of GCMs in regional work is often assumed to be limited (Rummukainen, 2016). RCMs, described as dynamically downscaled global reanalysis (Sotillo et al., 2005) and other finer resolution data (for example generated through statistical downscaling) have been developed to provide a solution to the GCM coarse resolution problem (see Chapter 1 and Section 3.2.3c for more details). The CORDEX initiative (Giorgi et al., 2009) has coordinated runs of RCMs over an African domain and made the output from the experiments available. These RCMs have been used in assessing climate projections for Southern Africa (Maúre et al., 2018; Akinyemi and Abiodun, 2019), and simulating precipitation over Southern Africa (Shongwe et al., 2015; Pinto et al., 2016). An increase in temperature of about 2.5 ^{o}C is projected for the region under RCP8.5 for the summer season relative to the baseline period 1971-2000 (Maúre et al., 2018), in areas of the western Kalahari Desert in Namibia and Botswana. A 0.4 mmday $^{-1}$ reduction in precipitation is projected across the Limpopo and Zambezi basin (Maúre et al., 2018), while a wetting signal of about 0.1mmday^{-1} is detected in the central and western parts of South Africa and Southern Namibia.

Literature examining the performance of RCMs over Africa is available (e.g. Crétat et al., 2012; Endris et al., 2013; Sylla et al., 2013; Gbobaniyi et al., 2014b; Ratna et al., 2014; Diallo et al., 2015); these studies conclude that RCM have greater fidelity in reproducing the basic elements and characteristics of the climate of the region, to the extent of improving the performance of the

driving global models or observations. However, studies focusing on comparisons and analysis of the performance and differences in the GCM and statistically downscaled (and bias corrected) climate products over Southern African climate are lacking. This is important as Schmidt attest that the performance of RCMs in simulating climatology and projecting climate change is not significantly better than that of the driving GCMs, a notion supported by Racherla et al. (2012). I address this deficiency in Chapter 4. The analysis of coupled, coarse models versus other forms of downscaled data in replicating characteristics of ecologically meaningful climatic variables of Southern Africa is important first and foremost to establish whether the resource demanding downscaling process of climate data derived from GCM to fine resolution is justified at least for use in SDMs, secondly to further assess and understand the differences in future climate projections which are important for impact studies, produced through statistically downscaling and bias correction method relative to the driving GCMs. Simulation of the climate change signals over Southern Africa which provides a context for the region's future climate change is also provided in Chapter 4 of the thesis.

Most studies that explore the future climates of Southern Africa at regional scale (e.g. Shongwe et al., 2015; Pinto et al., 2016b; Maúre et al., 2018b) use CORDEX (Giorgi et al., 2009) models to simulate key climatic variables (precipitation and temperature), even though biases specific to individual models, studied regions and seasons are revealed (Endris et al., 2013; Kalognomou et al., 2013; Gbobaniyi et al., 2014). Nikulin et al. (2012), notes that all ten CORDEX RCMs overestimate rainfall over the eastern escarpment region of Southern Africa. It is however still desirable to use reference runs from CORDEX regionally downscaled models to simulate climate variables over Southern Africa and assess the outputs. AFRICLIM used observational baselines to empirically downscale the CORDEX RCM outputs for Africa to resolutions assumed to be applicable for ecological modelling (Platts et al., 2014) This thesis in Chapter 4 therefore compares GCM historical and future data to AFRICLIM historical baseline (WorldClim interpolated observations) and AFRICLIM future projections (statistically downscaled and bias corrected CORDEX projections). Chapter 4 provides description of the models' ability to reproduce the regional climatic features over Southern Africa and continues to describe the projected climate-change signal in the rainfall and temperature distribution over the subcontinent it then draws attention to features of similarity and differences in the changes from the AFRICLIM and GCM simulations. The thesis thereby presents a comprehensive study on the

difference in resolution (GCMs vs statistically downscaled and bias corrected products) focusing on important characteristics of contemporary and future seasonal rainfall and temperature patterns. Through this, the thesis will contribute to the knowledge of the difference in climate simulations of GCM and statistically downscaled products.

Of importance also is that the value of climate change scenarios is understood and a discussion on how best they should be used in local and regional vulnerability and adaptation assessments brought to the forefront. Chapter 6 of this thesis assesses the vulnerability of plant species to the medium (RCP4.5) and high (RCP8.5) climate change scenarios; the Chapter then proposes adaptation measures.

2.4 Species distribution modelling and climatic variables

As evident from the previous sections, Southern Africa is a region vulnerable to climate change, with potential devastating impacts on humans, ecosystems and biodiversity, resulting in species range shifts (Midgley and Bond, 2015; Pacifici et al., 2015). The understanding of environmental conditions determining current species occurrence and figuring out how the species habitat, distribution and richness might change as the climate envelope changes is critical for maintaining ecosystem functioning and biodiversity conservation and management planning.

Species distribution modelling (SDM) is one of the techniques currently used for projecting impacts of climate change on the spatial patterns of habitat and species distributions, for both ecological research and conservation management. SDMs statistically quantify the relationship between species presence and absence records to gridded layers of environmental predictors data (Thuiller et al., 2009). Despite their wide use in ecological research, SDMs have well known and documented limitations (Allouche et al., 2006; Heikkinen et al., 2006; Wiens et al., 2009). A critical limitation of the technique that is of interest to my study is the use of coarse climatic variables (De Marco et al., 2008; Diniz-Filho et al., 2009; Buisson et al., 2010). Climatic variables are responsible for determining the distribution and ecology of plant species (Aguirre-Gutiérrez et al., 2015). The climatic predictor data used as input datasets in the prediction of the species distribution come at multiple spatial resolutions, this potentially influencing the prediction abilities of the models (Connor et al., 2017; Kosanic et al., 2018). Modelling of the

species projections under current and changing climates therefore requires spatially explicit climatic predictor datasets.

The main output of an SDM fitted with climatic variables is referred to as the bioclimatic envelope (Araújo and Peterson, 2012) for the species under investigation. The raw probability outputs of the bioclimatic envelope give values of the environmental conditions in a given geographic location, indicating suitability or unsuitability for the species (Thuiller et al., 2009). As an output, SDMs also yield Variable Importance values (VI) for each variable involved in the models. These VIs reflect the relative contribution of environmental predictor variables to the model outputs. The favourable and unfavourable conditions for a species, therefore, are determined by the variable importance of the SDM (Aguirre-Gutiérrez et al., 2017a), which has the potential to be affected by the predictor spatial resolution at which the species distributions are modelled (Thuiller et al., 2003). The likely dependence of variable importance on spatial resolutions, therefore, adds to the SDM's well-known limitations (Guisan and Thuiller, 2005; Araújo and Guisan, 2006).

Examination of the sensitivity of prediction of species distribution to the spatial resolution of climatic predictor data is therefore an important factor to consider in the planning of an SDM. The relationship between the spatial resolution of environmental predictors and the species under investigations has been well studied (Revermann et al., 2012; Connor et al., 2017; Nadeau et al., 2017). The spatial resolution effects of environmental predictors on model performance has also been extensively assessed. Guisan et al. (2007b), Gottschalk et al. (2011), Franklin et al. (2013), and Bean et al. (2014) concur that predictor spatial resolution can under-estimate or overestimate distribution probabilities, and the coarser the predictor spatial resolution, the poorer the model performance results for some species, and for other species the better the model performance; thus there is no clear picture and results may be species dependent. Wan et al. (2016) in a global study found climate data spatial resolution significant in altering species distribution probabilities. Khosravi et al. (2016), evaluated the sensitivity of predictive models to varying spatial resolutions and spatial extent, and asserted that prediction model accuracy increased with spatial resolution. The above noted variations in results indicate the importance of a consensus on the effect of predictor spatial resolutions on the projection of the probabilities of species occurrence. The reaching of this consensus is critical for both conservationists and

resource managers (Rodríguez et al., 2007) for guiding selection of the level of spatial resolution of climate data or scenarios needed for modelling the impacts of climate change on biodiversity.

To address this issue, emerging studies have focused on investigating how model transferability for invasive plant species is influenced by spatial resolution, and found that accurate transferability is achieved at fine spatial resolutions (Manzoor et al., 2018). Morán-Ordóñez et al. (2017) examined effects of predictor spatial and temporal scales on models' predictive performance across time. However, studies rarely aim to investigate and test the effects of different spatial resolution of climatic predictors on SDMs model outputs in African tropical forests and climatic landscape, a deficiency that this thesis seeks to address by testing the sensitivity of the predictions of species distribution to different spatial resolution of climatic predictor variables used as input data sets, over the Okavango River Basin landscape.

Even though climate is not considered a significant driver of species range shifts at fine spatial resolutions, Revermann et al. (2016) reported a good model performance for Okavango plant alpha diversity calibrated on climatic predictor variables. Fordham et al. (2018) state that species niche models built with climatic variables only perform reasonably well at predicting the magnitude of species range shifts, while Bucklin et al. (2015) attest to the efficiency of sole climatic variables SDMs in the assessment of environmental suitability for species distribution. Effective conservation strategies rely on the understanding and incorporation of the complete effects of the variation in the spatial resolution of climatic data in SDMs (Rodríguez et al., 2007). This thesis uses relevant bioclimatic variables to investigate and evaluate the effects of spatial resolution of predictor data in the prediction of SDMs of the ORB plant species.

2.5 Drivers of vegetation composition and structure in ORB (for a physical description of the river basin/case study see Chapter 5, section 5.3.1)

Spatial heterogeneity of the vegetation cover in semi-arid savannas vary with physiography, parent bedrock material, rainfall variability and soil type (Fritz & Duncan 1994; Skarpe et al., 2004; Ramberg et al., 2006; Skarpe et al. 2014) . In ORB, vegetation composition and variability are largely determined by resource availability [mainly nutrients, i.e. soil characteristics and water] (Aarrestad et al., 2011, 2014). Fire as a common phenomenon in African savanna systems (Gandiwa and Kativu, 2009) is understandably categorised as one of the determinants of ORB ecosystem structure.

The ORB is described as a flood pulsed system, with flooding experienced annually (Ramberg et al., 2006). The flood frequency, time passed since preceding flood, duration and depth have varied ecological effects (Murray-Hudson et al., 2014). ORB experiences varied hydrologic events because of its dependence on upper Zambezi River system events (VanderPost et al., 2005). When the Zambezi River system floods the Chobe River, results are heavy flows into the upper area of the delta, causing flooding (Scudder, 2008). The flood regime of the river basin may have an effect on plant species richness, cover, and community composition. A positive correlation between flood pulsing and high plant productivity and diversity has been determined (Junk & Piedade, 1993; Murphy et al., 2003). Despite the understanding of the ORB hydrology, the relationship between plant species composition and hydrology has not yet been quantified (Murray-Hudson et al., 2014). However, the understanding of how distribution may change in response to hydrological change is imperative for sustainable conservation and management efforts. This study will seek to investigate plant species distribution in relation to hydrological parameters by use of climatic variables responsible for hydrological processes i.e., rainfall and temperature related climatic variables, across ORB plant species, including those in the floodplain habitat type of ORB. This will be achieved by identifying the main climatic determinants of the plants' distribution (whether rainfall or temperature driven) and how these might change as a function of the spatial resolution of the climatic predictor data used in the modelling process. The investigation also covers how the changes in rainfall (affecting hydrology) under climate change scenarios will impact on the plant species distributions (Chapter 6).

3. Data and Methods

3.1 Overview

The interdisciplinary nature of the thesis necessitated use of multiple methods and data. Datasets and statistical methods used to compute and visualise representation of the studied climatic variables and to model the flora species distribution were determined by the questions the chapters seek to answer. I thus present detailed description and discussion of the methods and datasets used in each of the analytical chapters. To avoid repetition, the aim of this short chapter is to provide brief overview of the datasets used and their construction. Discussion of the necessary datasets modifications that have been carried out to effectively answer the research questions is also given. Section 3.3 focuses on the discussion of statistical tools/methods used in the analysis of the datasets in order to provide answers to the research questions.

3.2 Data

To answer the climate questions of the thesis, I derived datasets from Global Circulation Models (GCM), statistically downscaled and bias corrected data and the gridded rainfall dataset and 2-meter air temperature. These are datasets recognised and commonly used in climatological research. To answer the species distribution modelling questions, I used datasets sourced from Vegetation Database of the Okavango Basin (GIVD ID: AF-00-009, http://www.givd.info/ID/AF-00-009) (Revermann et al., 2016), Global Biodiversity Information Facility (GBIF) and bioclimatic variables from the AFRICLIM v.30 database (https://webfiles.york.au.uk/KITE/AfriClim/). Table 3.1 gives a summary of the climate data products used in each empirical Chapter, 4, 5 and 6.

Table 3.1: Summary of climate data products used in each empirical chapter. For Chapter 4, CMIP 5 GCM historical and future data compared to AFRICLIM historical baseline (WorldClim interpolated observations) and AFRICLIM future projection (statistically downscaled and bias corrected CORDEX projections). For Chapter 5 bioclimatic data products sourced from AFRICLIM baseline data i.e., WorldClim v.1.4 observations at different resolutions. For Chapter 6 bioclimatic data products are sourced from AFRICLIM future projections – statistically downscaled and bias corrected projections from one CORDEX model (SMHI) forced by one CMIP5 model (EC-EARTH) at a coarse spatial resolution of 50km×50km.

Chapter 4: CMIP 5 models for rainfall and 2-meter air temperature AFRICLIM: SMHI-RCA4_v1 (driven by the 10 GCMs)	**Chapter 5: Bioclimatic data** (2km×2km,5km×5km,10km×10km,20km×20km,50km×50km)	**Chapter 6: Bioclimatic data** (50km×50km)
CanESM2	Temperature Seasonality mm (standard deviation*100)	Temperature Seasonality mm (standard deviation*100)
CNRM-CM5	Mean temperature warmest quarter (◦C)	Mean temperature warmest quarter (◦C)
CSIRO-Mk3-6-0	Potential evapotranspiration (mm)	Potential evapotranspiration (mm)
EC-EARTH	Rainfall driest quarter (mm)	Rainfall driest quarter (mm)
GFDL-ESM2M	Moisture index moist quarter (%)	Moisture index moist quarter (%)
HadGEM2-ES		
IPSL-CM5A-MRIPSL-CM5A-MR		
MIROC5		
MPI-ESM-LR		
NorESM1-M		

3.2.1 CRU gridded rainfall dataset

Evaluating model seasonal mean climatology requires the use of observational datasets (Diallo et al., 2012, 2015; Gbobaniyi et al., 2014). Here the evaluation is achieved by comparing contemporary model climatology with the observed climatology. This however is only a partial

test since models may produce a climatology with minimal bias for the wrong physical reasons (Diallo et al., 2016). I use the CRU gridded rainfall data to evaluate the model output.

The Climate Research Unit version TS3.22 (CRU) from the University of East Anglia https://catalogue.ceda.ac.uk/uuid/4a6d071383976a5fb24b5b42e28cf28f (Harris et al., 2014), is here used in model validation. The data come in monthly gridded fields based of monthly observational data, covering the period January 1901-December 2013. These data are computed from daily or subdaily data by National Meterological Services, on a spatial resolution of 0.5 by 0.5 degrees longitude/latitude grids.

Climate variables of interest from the data for this study are the rainfall and air temperature, for the period January 1950- December 2000. This is the target period used as the baseline for climate change projections. The data files I used in this thesis are the netcdf data files, containing monthly mean values for parameters of interest.

Production of the CRU TS 3.22

Construction of the CRU datasets is based on the Climate Anomaly Method described in Peterson et al. (1998a). The gridding processes use station series that has a minimum of 23 non-missing values (over 75%) for a base period average or a normal to be computed. Input data at each time step are the station anomaly values and the station locations. This therefore entails a complex gridding process, for a detailed discussion of the production process refer to (New et al., (2002; Harris et al., 2014).

Dataset Modifications

Horizontal grid interpolation of datasets is a common process in climate research (Jones and Jones, 1999). Quantitative evaluation of data based on the research questions and thesis aim required the regridding of the original CRU datasets from a fine spatial resolution of 0.5 by 0.5 degrees longitude/latitude grids to a coarser data global grid box of 2.5 x 2.5 degrees. Selection of the regridding size was informed by the spatial resolution of the subset of CMIP5 models used in the study. Gridding data is necessary in order to compare observations with climate model outputs. I used the coarser CRU dataset grid size to allow efficient comparison of the representation of the seasonal long term mean of the observed climate variable climatology to that of the models. I also used the coarser CRU dataset grid size to facilitate evaluation of model

fidelity against observed data, as well as for subtraction of the CRU observed climate variable climatology from the model simulated climatology, to obtain representation of the difference in climatologies. The gridded observed data also facilitates calculations of the difference between the future and historical climatology in order to project climate change, Chapter 4.

Numerous grid interpolation methods are used in climate research, bilinear (Chang, 2009), nearest neighbour (Berndt and Haberlandt, 2018) and inverse distance. For creation of the coarse observed gauge rainfall data grid box, I used the interpolation to the nearest - neighbour remapping technique using the CDO remapnn operator. I did the remapping in Climate Data Operators (CDO 2018: Available at: http://www.mpimet.mpg.de/cdo). Since the data to interpolate is observed data, to avoid imposing weights to the data points or unintentionally averaging the observed data points which can then change the distribution of the error in the new remapped data (e.g. through the use of bi-liner interpolation method), (Berndt and Haberlandt, 2018) the nearest neighbour remapping technique was the best approach to employ. The structure (grids in spherical coordinates) and distribution of the variables of interest (rainfall and air temperature) in the CRU data also meant interpolating to a nearby grid point was ideal.

3.2.2 WorldClim version 1.4 baseline dataset

The data layers for the WorldClim baseline were generated through interpolation of average monthly data from weather stations on a 30 arc-second resolution grid. The climate surfaces were then aggregated to a 10 arc-min resolution. The variables included were monthly precipitation and mean, minimum and maximum temperature. These were mostly calculated for the period 1950-2000. The interpolated climate layers were constructed using monthly averages from weather stations sourced from global, regional, national and local sources as compiled by the Global Historical Climatology Network (GHCN),the Food and Agriculture Organisation (FAO), the World Meteorological Organisation (WMO), the International Center for Tropical Agriculture (CIAT) and the Regional, Electronic Hydrometeorological DataNetwork (R-HydroNET) (Hijmans et al., 2005). The interpolation of the data was done using the thin-plate smoothing splines, in the ANUSPLIN software program. Latitude, longitude and elevation were used as independent variables. This resulted in creation of global land areas climate surfaces for

monthly precipitation and minimum, mean and maximum temperatures. Uncertainty arising from the climate input data and the interpolation process was quantified by mapping weather stations density, elevation bias in the weather stations and elevation variation within the grid cells and through data partitioning and cross validation (Hijmans et al., 2005). The data is referred to as WorldClim database and are available for download from http://www.WorldClim.org. The data was used to derive nineteen historical bioclimatic variables (Platts et al., 2014).

3.2.3 Future Climate Projections

Numerical models are the only way of calculating projections of future climate. From these numerical model simulations of future climate it is possible to create dependent data sets of future climate with different characteristics, notably higher spatial resolution (Diaz-Nieto and Wilby, 2005; Spak et al., 2007). Since the large scale climate system features close connectivity and coupling between atmosphere, ocean, ice and land, and because regional climate depends on large-scale drivers of climate, it follows that simulations of future climate require coupled global models (Wilby et al., 2004; Hewitson and Crane, 2006). These models are referred to as coupled global climate models or global climate models or general circulation models. Owing to the demand on computing to simulate the coupled climate system at global scales, such models are typically of coarse spatial resolution, often with grid boxes of around 150 km x 150 km or more (Randall et al., 2007). Such coarse resolution can lead to missed controls or processes which may be important to regional climate. As a result, several methods have been developed to downscale climate data to higher spatial resolution.

Limited area models or regional models are a widely used method of downscaling (Wilby et al., 2004). The essential approach is that available computing power can be dedicated to higher spatial resolution within a model but with the constraint that the domain of the simulation is not global but regional. Regional climate depends on global climate drivers, therefore information on the evolution of the global climate needs to be passed to the regional model in order for the regional climate model to keep track of the changing climate system (von Storch and Storch, 1999; Wilby et al., 2004). This information is passed on to the boundaries of the regional model at regular time steps throughout the simulations. A drawback of the regional model simulations is that they are mostly unable to feedback on to the global climate since the forcing from the

global model to the regional model is often one-way. Even in the case of two-way nesting, the feedback is only permissible to a slightly expanded domain beyond that of the RCM and therefore the RCMs are unable to truly feedback on the global climate system-or even the hemispheric system. Although regional models have been run at high resolutions, ecological studies have been argued to require information at far higher spatial resolution (Kremen et al., 2008; Connor et al., 2017). Empirical or statistical downscaling is a method by which global climate models and regional models have been downscaled. Global models are discussed in Section 3.2.3a, AFRICLIM in Section 3.2.3b and dynamical and empirical downscaling in Section 3.2.3c

3.2.3a Global Climate Models (GCMs)

I used the Coupled Model Intercomparison Project 5 (CMIP5) ensemble (Taylor et al., 2012), to derive the model data used in Chapter 4 to assess the performance of the models both in the historical and future periods. The ensemble is a collection of Atmosphere-Ocean General Circulation Models (AOGCM) made freely accessible through the Program for Climate Model Diagnosis & Intercomparison (PCMDI) via https://pcmdi.llnl.gov/mips/cmip5/. Ensemble mean for rainfall and temperature variables, were achieved through picking simulations from the first experiment (r1i1p1) of each of the subset of 10 models of interest (Table 1; Chapter 4) from both historical and future experiments.

I interpolated the GCMs to a global grid of 2.5x2.5 degrees longitude/latitude grids. The interpolation spatial resolution was informed by the Chapter 4 aim of examining the difference in climate simulations between two scales typical of climate information in order to establish the degree of difference in spatial distribution of climate features.

The historical data is available for the period 1850-2005 for various variables. This experiment is forced with twentieth century estimates of forcing agents including greenhouse gases (Taylor et al., 2012). The historical climatology period I use in Chapter 4 to compare the climatic variables climatologies, against the observed data is 1950-2000, the variable of interest are the rainfall and air surface temperature in historical period (long term mean rainfall over Southern Africa).

In the CMIP5 suite, the future experiments are based on four Representative Concentration Pathways (RCPs) providing varying time dependent scenarios of projections of atmospheric greenhouse gas concentrations (Vuuren et al., 2011). The future experiment data availability runs from 2005-2100. I used the high emission future scenario experiment RCP8.5, which comes with atmospheric carbon dioxide (CO_2) equivalents of 1370 ppm by the end of the 21 century, [2100] (Moss et al., 2010), in Chapter 4 to simulate future projected climate. The variables of interest in this analysis are the rainfall change (ΔP) and temperature change (ΔT). For the chapter, the future climate projection (2071-2100) and climate change signals were simulated relative the baseline period (1950-2000). Africa is one of the regions exhibiting greater vulnerability to the impacts of climate change (Collier et al. 2008), it is therefore appropriate to select an extreme emission pathway for projection of future climate change in the region.

3.2.3b AFRICLIM datasets

The CORDEX initiative (Giorgi et al., 2009) has made available RCM data for Africa. AFRICLIM used observational baselines to empirically downscale the RCM outputs to resolutions assumed to be applicable for ecological modelling. To recover spatial variations at local scales, as well as correct for differences between observed and simulated baseline climates, the change factor downscaling was used (Fig. 3.1) (Platts et al., 2014c). Through this, the AFRICLIM project has produced climate projections in Africa (Platts et al., 2015). The AFRICLIM historical baseline (WorldClim interpolated observations, see section 3.2.3) and AFRICLIM future projection (statistically downscaled and bias corrected CORDEX projections, see section 3.2.3c) data I use in the comparison of climatologies and climate projection estimates across the coarse and fines spatial scales (Chapter 4) is therefore sourced from the AFRICLIM V3.0 database. This is so that the comparison made in Chapter 4 and the subsequent ecological work, draws on the same collective data set. The data comes from the regional climate model SMHI-RCA4 (Rossby Center regional model) forced with the ICHEC-EC-EARTH global circulation models from CMIP5. This regional model was used as it had a decent climatology of Southern Africa.

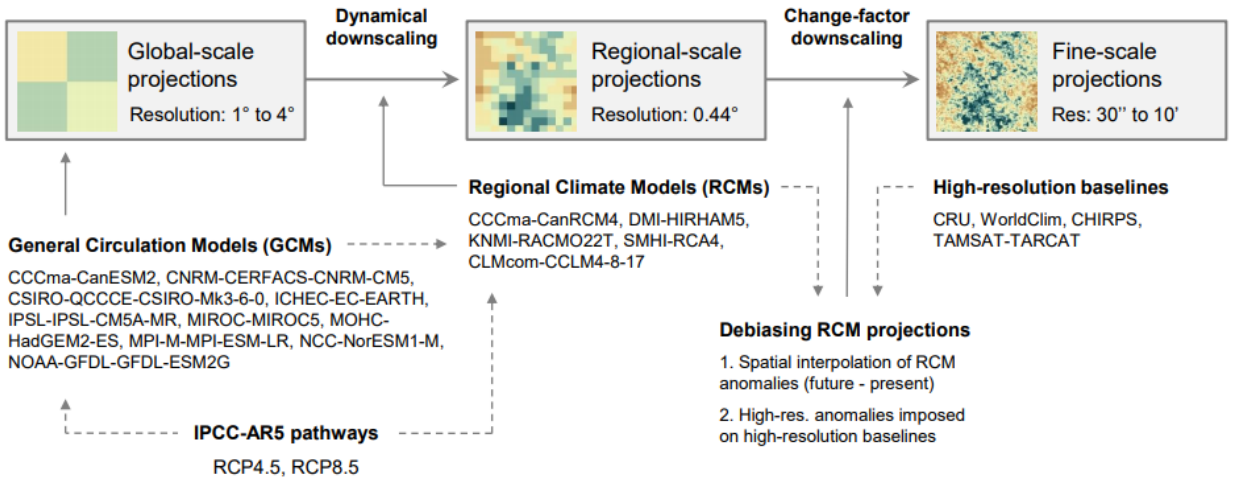


Figure 3.1: AFRICLIM 3.0 schematic of the AFRICLIM database spanning ten GCMs, downscaled using five regional climate models (RCMs) and four contemporary baselines, under two representative concentration pathways of the IPCC-AR5 (RCP4.5 and RCP8.5) adopted from (Platts et al., 2014c)

3.2.3c Dynamical and Empirical/Statistical downscaling

Dynamical downscaling refers to the use of regional climate models. RCMs are limited area models embedded within large-scale dynamics via consistent provision of lateral boundary conditions from GCMs to compute with higher resolution outputs (Rummukainen, 2010). Like GCMs, RCMs are based on fundamental equations and parameterise atmospheric processes such as convection, orographic precipitation, and surface atmosphere interactions. Models are often run at ~0.5° latitude and longitude scale but can be run at a high enough resolution for some parameterisation schemes to be turned off (though this was not done in the CORDEX programme). Dynamical downscaling is thought to be sufficiently skilful to represent / simulate regional climate features (Fowler et al., 2007; Rummukainen, 2016). Regional models simulate rainfall in gridboxes of a few tens of kilometres across. Much higher spatial resolution down to a few kilometres is possible in regional models but the computational costs are generally not affordable, particularly if an ensemble of model runs is involved as is generally recommended. Even at gridbox sizes of 10 km, rainfall is indirectly represented through the process of parameterisation. Biases present in the driving GCMs also affects the model output.

Statistical downscaling techniques grew out of the empiricism of transfer functions between explicitly resolved variables in climate models and outputs such as rainfall which were required at high resolution (Wilby et al., 2004; Benestad et al., 2008; Hewitson et al., 2014). These transfer functions can take the form of statistical relationships determined from observational data and GCM simulation to project regional scale climate characteristics. This downscaling technique follows the view that regional scale climate is based or conditioned on the large scale climatic state and regional physiographic features (Wilby et al., 2004; Diaz-Nieto and Wilby, 2005). There are numerous approaches to empirical downscaling, (i) regression modes, (ii) weather typing schemes and (iii) weather generators; a detailed description of these methods are in Wilby et al. (2004). A caveat of the empirical downscaling method is the assumption that the developed current day climate relationships remain stationary under forcing conditions of future climates, while an advantage of the technique over RCM is its low computational demand.

The simplest of all the approaches is the change factor downscaling (Wilby et al., 2004; Klausmeyer and Shaw, 2009). The technique applies coarse scale climate change projections onto a higher resolution observed climate baseline, following a spatial interpolation method (Wilby et al., 2004; Fowler et al., 2007). The interpolated anomalies are applied to baseline observations by adding and scaling the mean climatic change factor, thus producing downscaled and debiased future climate projections. Bias correction was applied to the model fields so that the change factor is controlled for the current climatology and the divergence of the model simulation from that climatology (Tabor and Williams, 2010). Bias correction means correcting the systematic differences between the observed and simulated climates. If the systematic differences between the observed and simulated climates is not corrected, the 21st century simulations would result in either too warm or wet (depending on the bias) projections, this leading to extreme outcomes of assessment of climate change impacts. It is therefore useful to correct for model bias between the present simulated and observed climates. One of the advantages of the change factor method is embedded within the delta-change approach in that it claims to reduce systematic biases between observed and simulated future climates.

The future bioclimatic variables used in this study are AFRICLIM projections which are downscaled & bias corrected using WorldClim 1.4 baseline, following this simple method where the projected change in a variable is computed as the difference between the output of the models

run for the baseline years 1950-2000, for future climate studies and for the targeted years 2071-2100. These changes were then interpolated to a grid with a high resolution of ~1km, assuming that the change in climate is relatively stable over space (high resolution autocorrelation). These high-resolution changes were then applied to high resolution interpolated climate data for the current period (the WorldClim dataset). The RCM outputs were therefore downscaled, and bias corrected using WorldClim 1.4 as baseline/current climate. AFRICLIM, (Platts et al.,2014) used the change factor approach (Fig. 3.1) to derive downscaled data to resolutions of 2, 5, 10 and 20 km×km (see section 3.2.3b for details). These data are used in Chapter 5.

3.2.4 Vegetation Species Sample

The limited knowledge on the vegetation composition and plant diversity of the Okavango River Basin, led to the establishment of the, The Future Okavango (TFO) project. TFO initiated a $100m^2$ plot nested in the centre of a $1000m^2$ plot vegetation survey in 2011 (Revermann et al., 2016). Existing major vascular vegetation units were identified through a random, stratified sampling design, using unsupervised classification of MODerate Resolution Imaging Spectroradiometer (MODIS) land surface phenology metrics (Revermann et al.2016). This resulted in the Vegetation Database of the Okavango Basin (GIVD ID: AF-00-009, http://www.givd.info/ID/AF-00-009) (Revermann et al., 2016a) from where the plant species samples I used in Chapter 5 to model the species distribution and richness estimates across different spatial resolutions were sourced. The database contains a wide range of terrestrial vegetation, such as *Miombo* woodlands and forests, geoxylic grasslands, *Baikiaea-Burkea* woodlands, and *Colophospermum mopane* woodlands. The terrestrial vegetation data I used was sourced from 194 plots. To ensure maximum inclusion of species across the sampled geographic and environmental space, and to avoid dealing with the impacts of extremely few samples, I based the selection of the species on the occurrence of >10 records, resulting in a total of 150 species with presence and absence data. The vegetation data was merged with occurrences from GBIF database (Chapter 6).

3.2.5 Climatic variables

The second aim of the thesis of investigating the effects of the spatial resolution of climatic predictor data on plant species distribution and richness estimates in ORB meant the use of climatic variables (rainfall and temperature) only, excluding other environmental variables known to drive plant species distribution in the region (Ramberg et al., 2006; Kreft et al., 2007; Wisz et al., 2013). For coherence with Chapter 4, the bioclimatic variables used in Chapters 5 and 6 was sourced from the AFRICLIM v.30 database (https://webfiles.york.au.uk/KITE/AfriClim/), at the following four different spatial resolutions 2km×2km, 5km×5km, 10km×10km and 20km×20km (Table 5.1: Chapter 5). The EC-EARTH model from CMIP5, (Pinto et al., 2018) was used as, based on model performances (see section 4.3.2), (Libanda and Nkolola, 2019), it is one of the models that performs better in reliably simulating features evident in the Southern African climatology the domain's climatology. Following on from this, within the AFRICLIM V3.0 database the study uses products from the EC-EARTH_SMHI-RCA4 model (Tshwene-Mauchaza and Aguirre-Guiterez 2019).

Datasets modifications

Coarse spatial climatic variables are considered inefficient in ecological modelling (Diniz-Filho et al., 2009; Field et al., 2009; Corney et al., 2013). Therefore, they are not readily available. To achieve the aim of the thesis of testing the sensitivity of the projections of species distribution to different spatial resolution of climatic predictor data of up to 50km×50km, applying the bilinear interpolation method, I interpolated the mean values of the 20km×20km climatic variables to a 50km×50km grid size. I used Climate Data Operators (CDO 2018: Available at: http://www.mpimet.mpg.de/cdo) for the remapping. Differences in spatial resolutions represents spatially scaled up predictor variables.

3.3 Statistical methods used in the datasets' analysis.

General statistical and visualisation methods in climate research including long term mean, frequency distributions, mean spatial bias and standard deviation are used in the climatology and future climate change analyses of this thesis. These metrics are computed over the Southern Africa domain. Here I present in brief statistical methods I used to explore, draw inferences and

analyse bivariate data in answering the climate questions of Chapter 4 and analysis of the sensitivity of species distribution models to spatial resolution of climatic predictor data in Chapters 5 and 6.

I computed the coefficient of variation, defined as the standard deviation divided by the mean rainfall (Wilks, 2011) in Chapter 4 to infer the differences between model rainfall climatologies. Given the strong rainfall gradient of Southern Africa (Cook, 2000a), the coefficient variation is an appropriate descriptive statistic. The statistic is particularly useful in constraining differences across a domain where the mean rainfall varies by a large amount. In the case of Southern Africa, where rainfall along the west coast is close to a mean of 10 mm a year whereas in parts of eastern Southern Africa it may be as high as 2000 mm per year, simple bias plots may disguise important issues. A standard deviation of 10 mm per year in a rainfall region which has a mean of 10 mm per year is a variation of 100%. However, a standard deviation of 10 mm per year in a region where the mean is 2000 mm per year is a variation of only 0.05%. The coefficient of variation is therefore a useful descriptive statistic in the case of a domain with a strong rainfall gradient.

Linear correlation coefficient (Persons, product moment correlation); to measure the model agreement in replicating the observed rainfall over the region of Southern Africa in Chapter 4, I used the linear correlation coefficient. The correlation coefficient r, between x: model rainfall and y: observed rainfall uses the standard equation as follows from Wilks (2011):

$$r = \Sigma (xy) / \sqrt{[(\Sigma x^2) * (\Sigma y^2)]}$$

where:

Σ is the summation symbol,

$x = x_i - x$, x_i is the x value for observation i, x is the mean x value,

$y = y_i - y$, y_i is the y value for observation i, and y is the mean y value

Bivariate correlation (scatter plots)

To visually display the relationship between the CMIP5 models rainfall and observed rainfall (Chapter 4), I plotted a scatter plot consisting of models simulated data in the X axis (horizontal

axis) and the CRU observed data in the Y axis (vertical axis). Since the interest in this analysis is determining whether there is a relationship between models' rainfall and observed rainfall (bivariate data), in order to deduce model agreement performance with observed rainfall (i.e. whether is linear, strong or has a positive slope), the use of a scatter plot is necessary. The scatter plots display how different patterns of the models and observed data produce varied degrees of correlation.

Generalised Linear Model (GLM)

I fitted GLM (Venables and Ripley, 2002) to investigate how the relative importance of climatic predictor variables changes as a function of spatial resolution of the predictor data (Chapter 5). The variable importance of the climatic variables was modelled as a function of the spatial resolution interacting with the climatic variable identity. I used the logistic regression analysis to (i) interpret and examine whether the relationship between the variable importance scores and the bioclimatic predictors is significant; and (ii) to establish the contributions and roles of the different sets of bioclimatic variables. The analyses therefore aid the understanding of how the VI scores (dependent variables) change when the bioclimatic predictors (independent variables) are varied according to spatial resolution, while holding the climatic predictors, identity fixed. This is to investigate which among the climatic predictor spatial resolution are related to the variable importance scores as well as to explore the types of relationships.

I modelled the observations of the variable importance scores as percentages (continuous variables bounded between 0&1), with the binomial exponential family of error. The model was tested, and no suggestions of over dispersion was found. I selected the default logit link function following a test of both the default and the user specified complementary log-log, where the model with the lowest deviance fit was then chosen. I built the GLM in the R platform (R development core team, 2007), with the MASS package (Venables and Ripley, 2002).

Multiple Comparison Analysis (*Post-hoc analysis*)

Performance of a likelihood ratio test of the built GLM (Venables and Ripley, 2002) against the model without the predictor spatial resolution conditions (fixed effects), yielded significant

differences in the group means. All effects being significant, necessitated computation of a multiple comparison analysis in order to test for significant differences between the climatic variables and spatial resolution. This is to provide a robust analysis of the interactions between variables importance and spatial resolutions, and the contrasts of the interaction. I performed the multiple comparison analysis using the Least Square means; lsmeans package for R (Lenth, 2016).

4. Comparison of Model Climatologies and Climate Projections over Southern Africa

4.1 Introduction

Rises in atmospheric greenhouse gases are already resulting in changes in the earth's climate (Stocker et al., IPCC, 2013:WG1AR5). The evidence is seen in sectors such as agriculture (Vermeulen et al., 2012) and ecosystems and biodiversity (IPBES, 2018). The Southern Africa region is particularly vulnerable to the effects of a changing climate (Niang et al., 2014b), due to low adaptive capacity that hinges on limited access to technology and financial resources among others (Boko et al., 2007). Understanding projected changes in climate from different data products (coarse resolution versus statistically downscaled/bias corrected climatic products) is therefore important for adaptation planning and policy making across all sectors, including ecosystems and biodiversity.

GCMs and downscaled products from GCMs are widely used to describe climate behaviour and draw conclusions about past and future climate systems (e.g.Engelbrecht et al., 2009; Dedekind et al., 2016). Previous research based on the Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al., 2012) has shown that global scale climate simulations have the ability to reproduce features of general circulation with reasonable fidelity (Blázquez et al., 2012; Rupp et al., 2013; Gulizia and Camilloni, 2015). Thus past and recent studies have evaluated the use of CMIP5 GCMs to understand the Southern African climate system, e.g. Joubert and Hewitson (1997), simulated the present and future climate of the region using GCMs, Dieppois et al. (2015) assessed the impact of ENSO on Southern Africa rainfall in CMIP5 GCMs, Munday and Washington (2017) used CMIP5 GCMs to investigate and understand the role of the Angola Low in Southern Africa rainfall and Munday et al. (2018) studied the nature of projected future drying over Southern Africa, also in CMIP5.

It is, however, frequently argued that global climate model data is too coarse to be of use in a wide variety of applications, including ecological research (Field et al., 2009; Fordham et al., 2011; Corney et al., 2013), and that the resolution typical of regional climate models are an important step to resolving the scale issue in climate applications (e.g. Akinyemi and Abiodun, 2019). Thus, RCMs have been used to produce possible scenarios of future changes based on their added value and skill over GCMs (Dosio and Panitz, 2016; Fotso-Nguemo et al., 2017b, 2017a). In ecological research, the implication is that there is a difference in SDM modelling outputs when using coarse versus fine resolution climate data, although this is a partially untested element of research. The content and output of SDMs at different spatial resolutions can only be adequately understood once the inputs at different resolutions have been contrasted with each other.

Even though the value of GCMs in regional work is deemed limited (Feser et al., 2011), a gap in literature exists in studies that analyse whether different GCMs might be important for ecological analysis as well as analyse the variation between different climatic data products; coarse resolution against statistically downscaled and bias corrected products. Here I employ the AFRICLIM historical baseline (WorldClim interpolated observations) and the AFRICLIM future projections (statistically downscaled and debiased CORDEX projections) to investigate whether the contemporary climate and climate change projected for the end of the 21st Century (2071-2100) centred around 2085 is consistent with that of GCMs historical and future data, and also to identify where there are striking differences.

Thus, the aim of this chapter is to lay the foundation work to evaluate the issue of scale in climate data over the Southern African region and the effects it has on SDMs. The chapter focuses on comparing the output of global climate models (referred to as coarse resolution) with statistically downscaled and bias corrected data obtained from AFRICLIM (referred to as fine resolution) (Platts et al., 2015), to establish the degree of difference in spatial distribution of climate features. I compare the seasonal mean climatology of rainfall and surface air temperature derived from the fine and coarse climate datasets over the broad Southern African domain (0°-51°E, -37°-0°S). The season of analysis is the austral summer, covering December, January February (DJF). This season is chosen as it is the period in which Southern Africa receives the bulk of its rainfall (Engelbrecht et al., 2009) and which is associated with the green growth

period of most plant species in this region (Adole et al., 2018). The chapter goes on to investigate and comment on the fidelity of the climate models from the perspective of their biases and the structure of climate features that they either resolve, miss altogether or falsely represent. I base the analyses on the long term seasonal mean rainfall and temperature of contemporary model climatology from 1950-2000 derived from the CMIP5 GCM and AFRICLIM models' simulations. These are compared with the CRU observed data (also over the period 1950-2000).

A vital initial point in any climate modelling task is the assessment of the model's ability to accurately simulate the observed climate, especially within the domain of interest. Achieving good simulation of current climate with the observed climate will then reduce the uncertainty bound up in using the models for impact studies (Sushama et al., 2006). The chapter thus goes on to investigate and establish the models' ability to simulate features evident in the observed temperature and rainfall climatology. I note differences in the ability of the data sets at contrasting scales to simulate climate features across Southern Africa. The large Southern African domain is chosen rather than the smaller study domain over the Okavango river basin so that the origin of any differences between the model and the observed data sets can be more easily traced. In a limited domain, such as the Okavango, it would be difficult or impossible to know whether, for example, a cold bias on the western edge of the Okavango was part of an extensive model bias covering much of the South East Atlantic and relating to factors such as the simulation of sea surface temperatures, or whether it was simply a local model grid box which turned out to have a temperature bias because of minor errors such as cloud simulation in models at that specific part of the domain. The larger Southern African domain is therefore conducive to more thorough assessment of model error and bias.

Given Africa's vulnerability to global warming, with climate change listed as one of the major threats to biodiversity in the continent (IPBES 2018), it is important to understand the future changes of climate over Southern Africa. In this chapter I therefore also investigate future rainfall and temperature over Southern Africa, under the RCP 8.5 emission scenarios (Solomon et al., IPCC 2007:WGIAR4), by the late 21st Century (represented by decades surrounding 2085), as simulated by the GCM future data and AFRICLIM future data (AFRICLIM future projections – statistically downscaled and bias corrected projections from CORDEX models. I base analyses on model simulated future climate projections (2071-2100) and climate change

signals relative to the baseline period (1950-2000). I continue to describe the climate change signals of Southern Africa, by providing an evaluation and comparison of the projected rainfall and temperature pattern of changes derived from the fine and coarse spatial resolution models' future climate projection simulations.

The chapter therefore focuses on addressing the following questions:

(i) What are the effects of spatial resolution differences in climate models on simulating contemporary and future temperature and rainfall over Southern Africa (SA)?

(ii) What is the difference between coarse GCM (CMIP) and observations (CRU/WorldClim)?

(iii) How much variation is there between different GCMs?

In answering the questions, the first step was computation and visualisation of the representation of the long-term seasonal GCM model climatologies, the AFRICLIM historical baseline (WorldClim interpolated observations) and the CRU observed mean climatology over the broader SA domain. Following this, through a study using correlation coefficients and the coefficient of variation, I assessed the strength of association between models' simulations and the observed climatologies. Therefore, section 4.2 gives a summary of the methods and data used to answer the chapter question. Results and discussion are then presented in section 4.3.

I conclude the chapter by summarizing the results to answer the main chapter question of comparison between different climate data products at fine and coarse spatial resolutions, (statistically downscaled/bias corrected products). In this chapter I use scale descriptor "coarse" to refer to GCM (CMIP5) products and "fine" to refer to AFRICLIM historical baseline and future projection data. Within this section, further specific research questions on how the value of simulating contemporary climates on fine spatial resolutions translates to modelling species distributions are posed. Investigations on the effects of the use of contemporary climate datasets at different spatial resolution in species distribution modelling experiments are then carried out in Chapter 5.

4.2 Methods and Data

The study area domain used is over broader Southern Africa (0 °-51 °E, -37 ° -0 ° S).

4.2.1 Data

Gridded data derived from station or point data and model data derived from GCMs and AFRICLIM historical baseline (WorldClim interpolated observations, see section 3.2.2) and AFRICLIM future projection (statistically downscaled and bias corrected CORDEX projections, see section 3.2.3c) are used in this study. A brief description of each of the datasets is given below. Detailed discussion and information on necessary dataset modifications that have been carried out to answer the research questions effectively is given in Chapter 3 (Methods and Data) of the thesis.

4.2.1.1 CRU rainfall dataset

Gridded and interpolated observational datasets are widely used in evaluating climate model seasonal mean climatology (Diallo et al., 2015) in part because the comparison between gridded observed and gridded model data is easier to undertake than station to gridded model data. Here I used the Climate Research Unit version TS3.22 (CRU) from the University of East Anglia (Harris et al., 2014), in model evaluation. Climate variables of interest from the data for this study are rainfall (pr), and 2-meter air temperature (Tas), for the period January 1950 - December 2000. This period is used to calculate future change.

4.2.1.2 Global Circulation Models (GCMs)

I used a ten-member subset from the Coupled Model Intercomparison Project 5 (CMIP5) (Taylor et al., 2012) [Table 1]. The selection criteria for the ten-member sample was dictated by the fact that these were the driving GCMs from the AFRICLIM version 3.0 database (Platts et al., 2015). I interpolated all the data to a common grid of 2.5 degrees latitude-longitude.

The historical climatology period used in this chapter to compare the climatology of rainfall and temperature against the observed data was 1950-2000. The period from 1950-2000 is generally used to infer conditions at the commencement of the impacts of anthropogenic climate change (Le Treut et al., 2007; Pacifici et al., 2015). I used the high emission, RCP8.5 future scenario experiment to simulate future projected climate (Moss et al., 2010).

Table 4.1:Ten driving GCMs from CMIP5 used in this study

Model	Institute	Original Horizontal Resolution	Reference
CanESM2	Canadian Centre for Climate Modelling and Analysis (CCCma-)	2.81° x 2.79°	Ji et al., 2014
CNRM-CM5	Centre National de Recherches Meteorologiques / centre Europeen de Recherche et Formation Avancee en Calcul Scientifique (CNRM-CERFACS)	1.4° x 1.4°	Voldoire et al., 2011
CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organisation in collaboration with Queensland Climate Change Centre of Excellence (CSIRO-QCCCE)	1.9° x 1.9°	Jeffrey et al., 2013
ICHEC-EC-EARTH			
IPSL-IPSL-CM5A-MR	Institut Pierre-Simon Laplace (IPSL)	2.50° x 1.26°	Dufresne et al., 2013
MIROC5	Atmosphere and Ocean Research Institute (University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (MIROC)	1.40° x 1.40°	Watanabe et al., 2010
HadGEM2-ES	Met Office Hardley Centre (MOHC)	1.9° x 1.3°	Jones et al., 2011
MPI-ESM-LR	Max-Planck-Institut fur Meteorologie (MPI-M)	1.9° x 1.9°	Marsland et al., 2003
NorESM1-M	Norwegian Climate Centre (NCC)	2.5° x 1.9°	Bentsen et al., 2013
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory (NOAA-GFDL)	2.5° x 2.0°	Dunne et al., 2013

4.2.1.3 AFRICLIM data

The GCM historical and future data are compared to AFRICLIM historical baseline which are interpolated observations from WorldClim and AFRICLIM future projection (statistically downscaled and bias corrected CORDEX projections). The original future projections are derived from the regional climate model RCA4 (Rossby Center regional model), forced with each of the ten global circulation models from CMIP5 (Table 4.1).

4.2.2 Methods

A brief description of the methods used to characterise, plot, and visualise climatologies and future climate change in this chapter is presented. I give detailed discussions and explanation of

the techniques and methods used, as well as statistical methods/tools used in the analysis of both historical and future time model outputs in order to provide answers to the research questions in Chapter 3 of the thesis.

4.2.2.1 Model description and simulation design

To investigate differences in spatial resolutions amongst climate models in simulating contemporary temperature and rainfall over Southern Africa, and to characterise the models' climatologies, I obtained the current climate/baseline climate by computing and plotting the long term mean over a 50-year period (1950-2000), from individual GCMs from the CMIP5, AFRICLIM historical baseline data (WorldClim interpolated observations) and CRU observed climatologies dataset. Visualisation and characterisation of the models and observed climatologies is therefore based on the long term mean state. The 50-year period was predetermined by the AFRICLIM v3.0 dataset (Platts et al., 2015) used for plotting the GCM-driven RCM simulations, to be compared with the GCM simulations. I converted the precipitation data values from historical experiment (CMIP5) from kg m-2 s-1 to mm.day^{-1} (multiplying all values by 86400.0), while temperature values were converted from Kelvin to Celsius ($T_{(°C)} = T_{(K)}$ - 273.15) in CDO. I calculated the summertime seasonal (DJF) long term means over the Southern Africa domain.

In order to facilitate comparisons of the climatologies, I computed absolute value gridded plots. The spatial resolution of the individual mean state climatologies is regridded to a (2.5x2.5°) grid using the nearest neighbour interpolation method for rainfall and bilinear interpolation method for temperature, in order to do the ensemble, mean over the 10 subsets of models.

4.2.2.2 Evaluating ability of models to simulate the region

It has been well established that climate model simulations have systematic biases (e.g.,Christensen et al., 2008). To evaluate and correct the rainfall models biases, I used an anomaly approach where the spatial distribution, pattern and magnitude of rainfall are evaluated as departures from the observed seasonal rainfall climatology. Comparison of the AFRICLIM historical baseline (WorldClim interpolated observations) and future projections with the comparable CMIP5 (GCMs) models allows for exploring and quantifying any added value/information brought by a higher spatial resolution.

I used the coefficient of variation, (Wilks, 2011), in this analysis to deduce the differences between model rainfall climatologies. This was an appropriate descriptive statistic to use (see section 3.3) considering the strong rainfall gradient of Southern Africa (Cook, 2000).

Linear correlation coefficient (Pearsons product moment correlation), is a commonly used statistical method to measure the strength of the linear relationship or association between two variables (Schober et al., 2018). In this chapter, I used linear correlation coefficient to measure the model agreement in replicating the observed rainfall over the Southern African domain. The CRU observed summer rainfall is correlated with the GCM simulated summer rainfall, with each observation being a matching grid box in the domain. Visual inspection of the relation is provided by standard scatterplot, with least-squares regression showing the best fit line between model and observed data.

4.3 Results interpretation and discussion

4.3.1 Observed historical DJF rainfall climatology

Figure 4.1 and Figure 4.2; show the mean observed DJF rainfall distribution for 1950-2000 in $mm.day^{-1}$ from the CRU TS3.22 dataset, after a nearest neighbour interpolation onto the analysed set of CMIP5 models' grid (2.5x2.5°) and the AFRICLIM observed DJF rainfall distribution. The AFRICLIM (1950-2000) data is observational data interpolated from WorldClim. I have reproduced the fine resolution AFRICLIM historical plots in each row for easier comparison with the coarse resolution model fields (Figure 4.1 and 4.2). I used the rainfall patterns as baselines to assess the models' performance in replicating the observed climatologies (CRU and WorldClim). The CRU observed climatology (Figure 4.1 and Figure 4.2) shows a clear rainfall gradient from the hyper arid climate of the Namib Desert to the moist sub-tropical climate of Mozambique. The rainfall ranges from less than 90mm/season to 900mm/season. The organisation of the rainfall gradient reflects the main circulation features responsible for summer rainfall in this region. The cold Benguela upwelling regime on the Atlantic coastline is associated with a drier climate in the west of the domain, whereas moving eastwards, the East coast, which is influenced by the Southward flowing Mozambique and Agulhas current bringing in warm water from tropical latitudes, has a moist climate (Tyson and Preston-Whyte, 2000).

Tropical convection (e.g.,Macron et al., 2014) dominates the rainfall regime over the southern Congo Basin, extending southwards into Zambia and eastwards across Malawi into Mozambique.

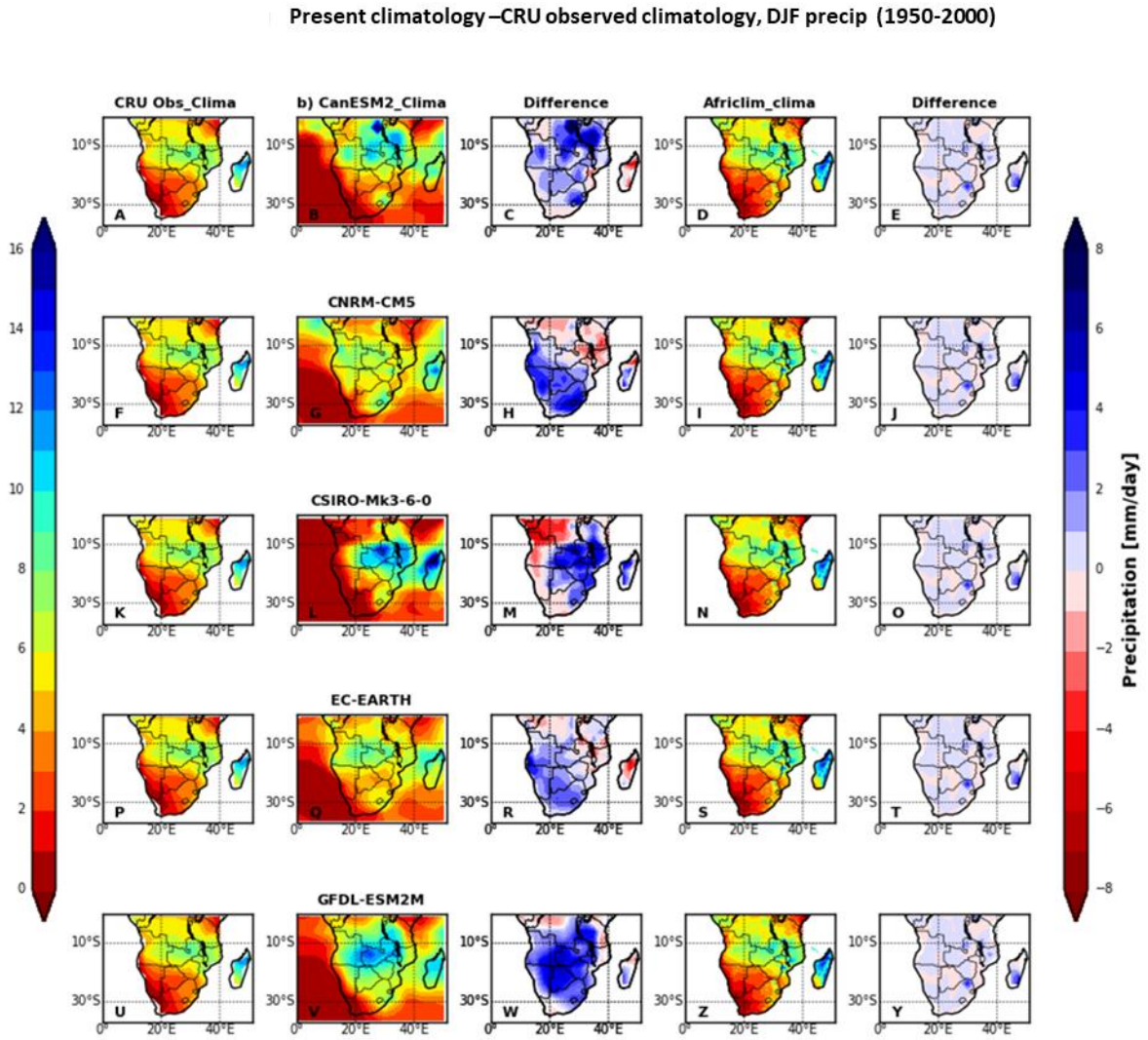


Figure 4.1: DJF Rainfall climatologies and differences from observations in mm.day^{-1}. 1st column shows CRU observed climatology (1950-2000), 2nd column shows the CMIP5 historical/present day climatology (1950-2000), 3rd column is the absolute difference; CMIP5 minus CRU observed climatology. 4th column is the AFRICLIM historical/present day observational climatology and 5th column is the absolute difference; between AFRICLIM and CRU (column 4 minus column 1). The AFRICLIM plots have been reproduced in each row for easier comparison with the coarse resolution model fields.

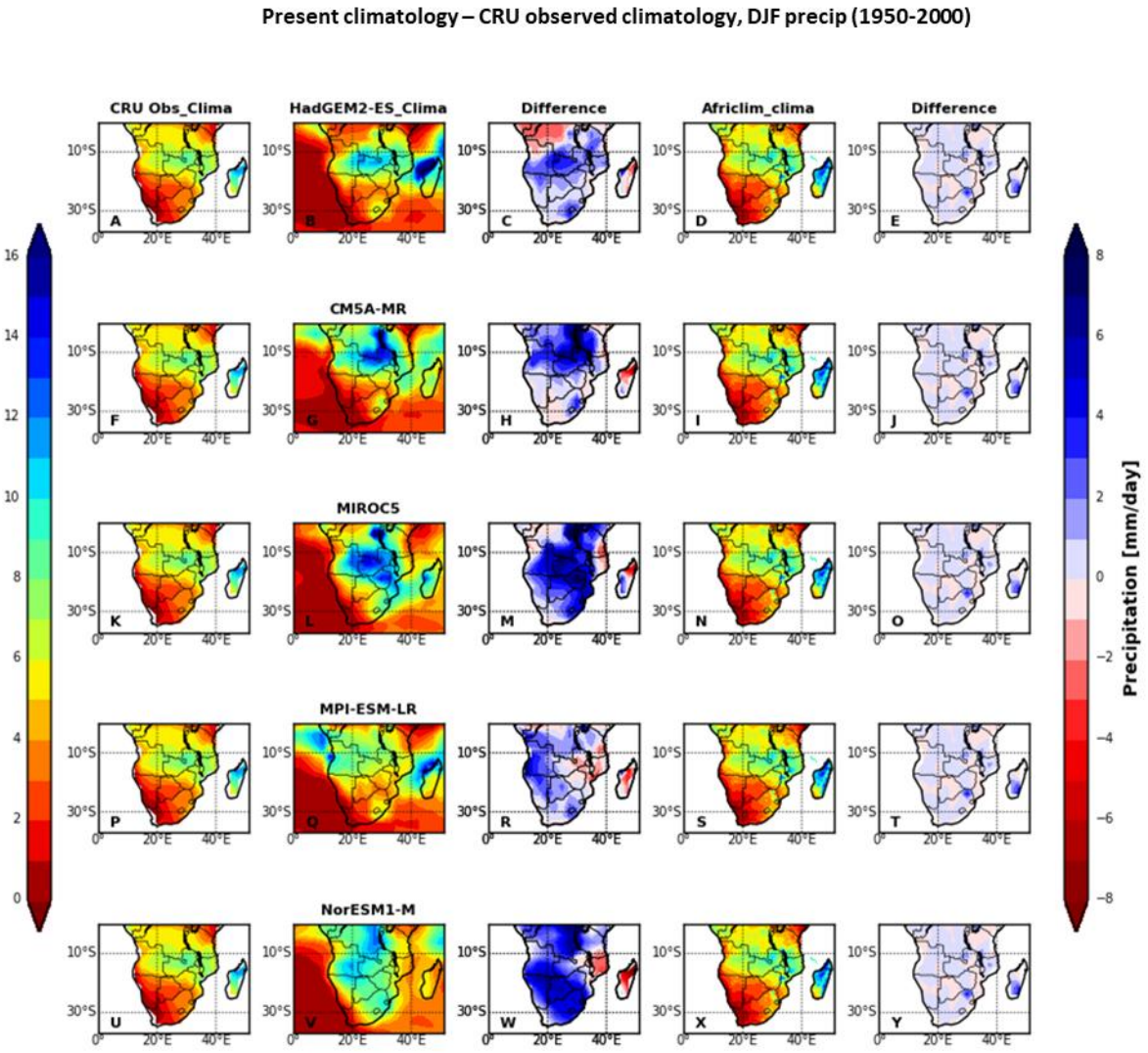


Figure 4.2: DJF Rainfall climatologies and differences from observations in mm.day^{-1}. 1st column shows CRU observed climatology (1950-2000), 2nd column shows the CMIP5 historical/present day climatology (1950-2000), 3rd column is the absolute difference; CMIP5 minus CRU observed climatology. 4th column is the AFRICLIM historical/present day observational climatology and 5th column is the absolute difference; between AFRICLIM and CRU (column 4 minus column 1). The AFRICLIM plots have been reproduced in each row for easier comparison with the coarse resolution model fields.

4.3.2 The differences between coarse resolution models and observed present-day rainfall mean.

Before analysing the representation of the present-day rainfall features in the coarse resolution GCM (CMIP5) models, it is important to evaluate and compare the relationship between the performances of GCM models and CRU observed data in simulating the present-day rainfall mean (1950-2000) over Southern Africa (0 °-51 °E, -37 ° -0° S). Each model's seasonal mean rainfall against CRU is presented in Figure 4.3. In this subsection I go on to examine the difference between coarse resolution GCM (CMIP5) and observations (CRU/WorldClim) by assessing the performance of GCM in simulating spatial rainfall patterns during the austral summer rainy season (DJF). The assessment includes comparisons of the rainfall spatial distribution, and the magnitude, with the observed seasonal mean rainfall patterns. The section also examines the difference between observations at different spatial resolutions (CRU versus WorldClim). Rainfall biases as departures from the contemporary DJF climatology are also examined (Figures 4.1 and 4.2).

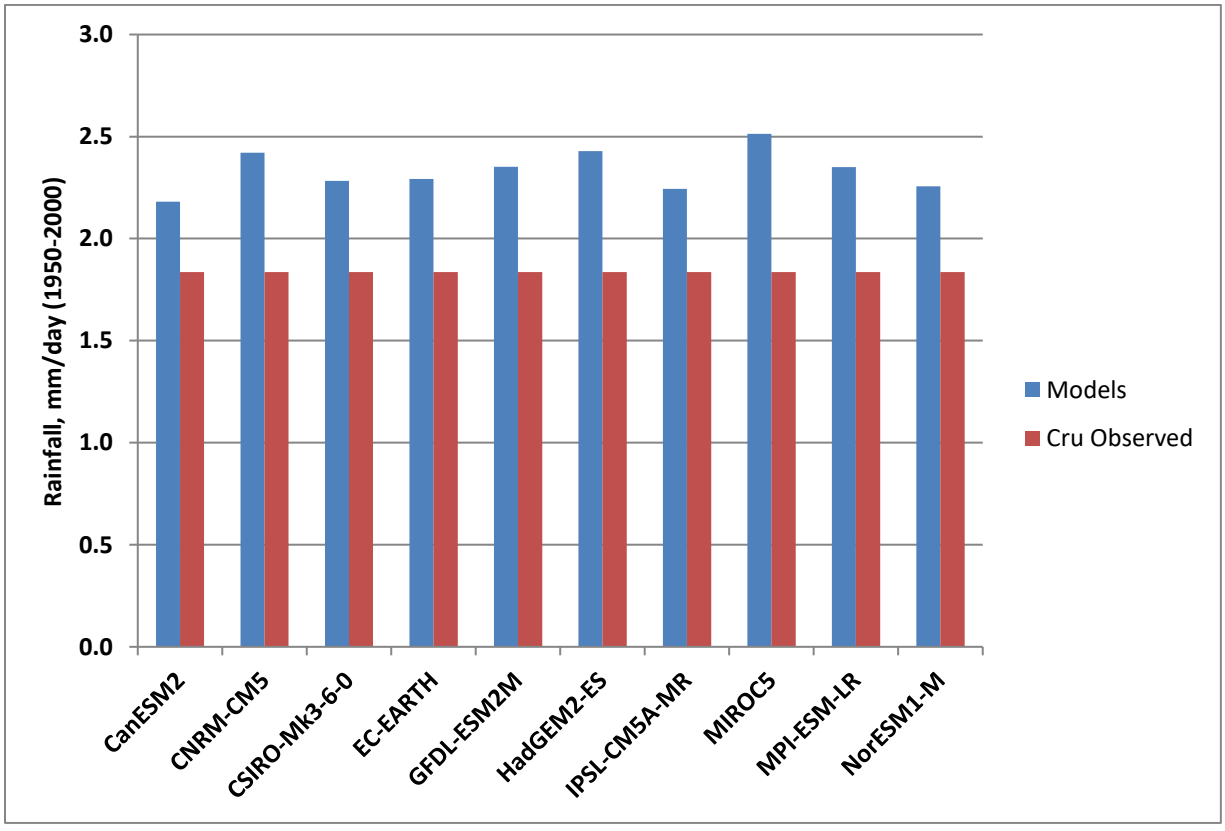


Figure 4.3: CMIP5 present day Rainfall summer (DJF) mm.day^{-1} against CRU Observed for Southern Africa (1950-2000) for 10 CMIP5 GCMs

It is clear that the GCM (CMIP5) models simulate too much present-day austral summer mean rainfall over Southern Africa compared with the CRU observed. MIROC5, HadGEM2-ES and CNRM-CM5 perform similarly in presenting a wetter seasonal long-term mean rainfall of about 225 mm/season. CanESM2 has the driest seasonal mean of 207mm. This large difference in models' simulation of the summer rainfall is a cause for concern, considering the dependency on CMIP5 models in projecting future regional climate change information used by impact research. These kinds of uncertainties have been shown to be associated with model resolution, which in the case of coarse resolution models allows excessive transport of water vapour over the mountains of southern Tanzania that otherwise would be expected to block the flow. The excessive convergence of that water vapour over the interior of Southern Africa then leads to excessive rainfall (Munday and Washington, 2018).

The climatologies obtained from the coarse resolution climate models listed in section 4.3.1 reflect the CRU observed climatologies in varying degrees. The rainfall gradient displayed in the coarse resolution/global models is smoother along the southeast of Southern Africa, where steep topography leads to a sharp gradient in the observed field. The evaluated GCMs generally simulate low rainfall around the southwest region of Southern Africa, likely reflecting the stabilisation of the atmosphere by the Benguela upwelling system described in the previous section 4.3.1 as well as subsidence from the South Atlantic anticyclone. Seven out of the ten coarse scale models (Figure 4.1 and Figure 4.2) simulate excessive rainfall relative to the CRU observed climatology over the humid subtropical region, this corresponding with the core of convective activity, which appears at that location during the austral summer (Nicholson, 2001). In particular, the models IPSL-CM5A-MR and MIROC5 simulate too much rainfall within the tropical rainbelt stretching further to Madagascar while CISRO-Mk3-6-0 simulates intense drying in the central Congo area along the west coast (Figure 4.1L). In the remaining three models, CNRM-CM5, EC-EARTH and MPI-ESM-LR, the rainfall gradient across the interior of Southern Africa from east to west is not sufficiently strong owing to the wet bias along the western coast.

With the exception of the EC-EARTH model, which captures the summer rainfall distribution with greater fidelity, and displays the gradient across the interior of Southern Africa more

realistically, (the model therefore simulates the CRU observed summer rainfall most closely, (Figure 4.1Q), it can be determined that the capability of the rest of the studied global models in simulating the key elements of the summer rainfall climatology identified in the preceding paragraphs is therefore relatively weak. The assumption is that this misrepresentation of the GCM models' simulated climatologies in reference to the observed climatology gives less confidence in the climate projections they produce (Randall et al., 2007). I will explore this notion in subsequent sections.

When considering the difference between observations at different resolutions, that is the CRU coarse climatology relative to the fine resolution AFRICLIM climatology (WorldClim v1.4 interpolated observations), the fine resolution climatology simulates the main climate rainfall elements alluded to in section 4.3.1 with much higher fidelity. The AFRICLIM simulated climatology (Figure 4.1 and Figure 4.2) shows a clear zonal gradient going from the Kalahari (Southern Namibia) to central Botswana, in agreement with the key rainfall elements. However, both the coarse CRU and fine AFRICLIM observed rainfall climatologies, display similar rainfall pattern, distribution and magnitude.

However, the agreement between the observed seasonal rainfall climatologies is not perfect. There are minor discrepancies between the climatologies (Figure 4.1 a & d), as the AFRICLIM climatology shows seasonal mean increased wetting relative to the CRU climatology of about 180 mm, around the Madagascar region.

In general, it can be attested that the mean seasonal rainfall characteristics over Southern Africa are realistically captured by the fine resolution AFRICLIM dataset, especially around the subtropical areas. The AFRICLIM dataset benefits from addition of spatial detail such as more structure reflecting the topography of the region, which is not well represented in the coarse resolution global model. Further into the study I will test whether this seeming added value presents any worth in modelling species distributions under current climate envelopes by using AFRICLIM projections which are statistically downscaled & bias corrected using WorldClim and GCM future projections.

Assessment of the similarities in the climatologies of both the coarse resolution GCM and fine resolution AFRICLIM (WorldClim interpolated observations) is evident in that the humid

subtropical region of wetting which corresponds with the core convective activity is captured by both, albeit at differing magnitudes. The region of wetting in the middle of the domain has a higher magnitude in the global scale models, with a maximum seasonal rainfall of about 1,200 mm relative to 990mm in the fine resolution AFRICLIM climatology.Figure 4.1 and Figure 4.2; 3rd and 5th columns show the seasonal rainfall biases for the CMIP5 global scale models and the AFRICLIM dataset. Although I have already discussed these biases here, they are explicitly quantified. The CRU dataset and the AFRICLIM dataset were interpolated onto the global scale models' grid of 2.5x2.5 degrees prior to computing the biases. I evaluate the spatial distribution, pattern, and magnitude of the rainfall patterns as departures from the observed DJF climatology. This anomaly approach facilitates assessment of the models' associated biases (Patricola and Cook, 2011).

Over-all CMIP5 evaluated models (Figure 4.1 and Figure 4.2, 3rd column), have wet biases, although with differing magnitudes and spatial distributions. This intense wet bias is especially evident in the models MIROC5, HadGEM2-ES and IPSL-CM5A-MR. The wet bias could be associated with excessive convection over the SW Indian Ocean and, in particular, the warm Agulhas current which brings about latent heat fluxes, increasing moisture in the atmosphere water cycle (Reason and Smart, 2015). Assessment of the spatial distribution of the wet bias across the models shows varied distribution with no clear pattern. Some models have a wet bias in the centre of the domain within the zone of tropical convection (Figure 4.1 & Figure 4.2h), while others depict a large wet bias over the Kalahari Desert area (Figure 2h, CNRM-CM5) and along the west coast to Angola (Figure 4.1h & r and 4.2w). The mean rainfall gradient weakens as the wetting bias intensifies. An exception occurs in the case of CSIRO-Mk-3-6-0, which is characterised by a dry bias over the central Congo Basin area extending to Northern Angola. This could be owing to the representation of the cold Benguela upwelling regime on the Atlantic coastline being associated with a drier climate in the west of the domain, although analysis of the causes of these biases lies beyond the scope of this study.

In comparison with the global scale models, the fine resolution AFRICLIM dataset (WorldClim) seems to significantly reduce the spatial variability of the rainfall bias and correct the exaggerated rainfall bias. The AFRICLIM data depicts a wet bias is in the range of 270-540mm/season, whereas that of the driving GCMs falls within the range 1080-2160mm/season.

The wet biases are spread across the entire domain, with large wetting bias shown in the eastern part of the escarpment area (the Drakensburg-Maluti Mountain region). In terms of dry biases, the AFRICLIM dataset produces weak drying biases over the Kalahari Desert area of Botswana, in the northeast of the domain, and along the west coastline. Accurate simulation of the spatial characteristics of seasonal rainfall patterns is achieved by the fine spatial scale AFRICLIM dataset.

Quantification and further evaluation on the conditions associated with a strong wet bias in most of the global scale models is needed (Munday and Washington, 2018). This will among other things determine whether the disagreements between the coarse scale models and fine scale climatology simulation rainfall biases are due to rainfall intensity and/or spatial distribution issues. However, some literature suggests that the strong wet bias could happen as a result of overestimation of the number of wet days (Van Pelt et al., 2009; Sylla et al., 2012). The fine spatial resolution simulations detect some systematic biases, for example, overestimation of wetting in the tropical rainbelt. It is important to understand the cause of the systematic biases in order to correct them, a call for further research.

4.3.3 Model agreement performance measured by linear correlation coefficient.

In this section I statistically analyse the GCM performance in simulating the observed seasonal long term mean rainfall based on linear correlation and associated scatterplots. The category of GCMs is chosen because, relative to AFRICLIM, the GCM bias is large. Further analysis of the bias is therefore warranted. Figure 4.3 and Table 4.1 below show the strength of agreement between maps of model and CRU observed rainfall – the so-called pattern correlation. Reassuringly, a significant positive linear correlation is observed between all of the models' summer simulated rainfall and the CRU observed summer rainfall, such that the dry/wet grid boxes in the CRU are similar to the dry/wet grid boxes in the models. Therefore, even though the performance of the global scale models in simulating the key elements of the observed summer rainfall climatology is qualitatively low, according to the pattern correlation, the CMIP5 models' summer simulated distribution of rainfall correlates significantly with the observed rainfall.

The scatterplot permits an easy examination of the relationship between models' simulated present day mean seasonal rainfall and the observed seasonal rainfall, with the diagonal line

separating wet and dry bias. When considering the fitted regression line, the pattern depicted in the figure corresponds with the previously derived information that the global scale models overestimate rainfall (section 4.3.1, & Figures 4.1,4.2 and 4.3). This is mostly emphasised in models NorESM1-M and MIROC5, which have the lowest pattern correlation, and the poorest visual agreement with the observed climatology (Figure 4.1 and Figure 4.2). Models CNRM-CM5, HadGEM2-ES, and EC-EARTH show a regression line slope that is close to the reference (one to one) black line, this also emphasising the model's better ability to simulate observed rainfall. CNRM-CM5 and EC-EARTH displayed the best visual agreement with the observed climatology (Figure 4.1 and Figure 4.2). EC-EARTH shows a closer to perfect fit with the one-to-one line, supporting the overall model's good performance in simulating Southern Africa rainfall seasonal mean and general climate elements of the domains' contemporary DJF mean rainfall (4.3.1).

Table 4.2: CMIP5 Model agreement to CRU observed for seasonal mean rainfall based on pattern correlation coefficient

Model	**Correlation Coefficient (r_value) **=significant at p=0.01 or better**
CanESM2	0.701**
CNRM-CM5	0.568**
CSIRO-Mk3-6-0	0.74**
EC-EARTH	0.706**
GFDL-ESM2M	0.735**
HadGEM2-ES	0.782**
IPSL-IPSL-CM5A-MR	0.715**
MIROC5	0.64**
MPI-ESM-LR	0.702**
NorESM1-M	0.278**
Average of ensemble	0.657**

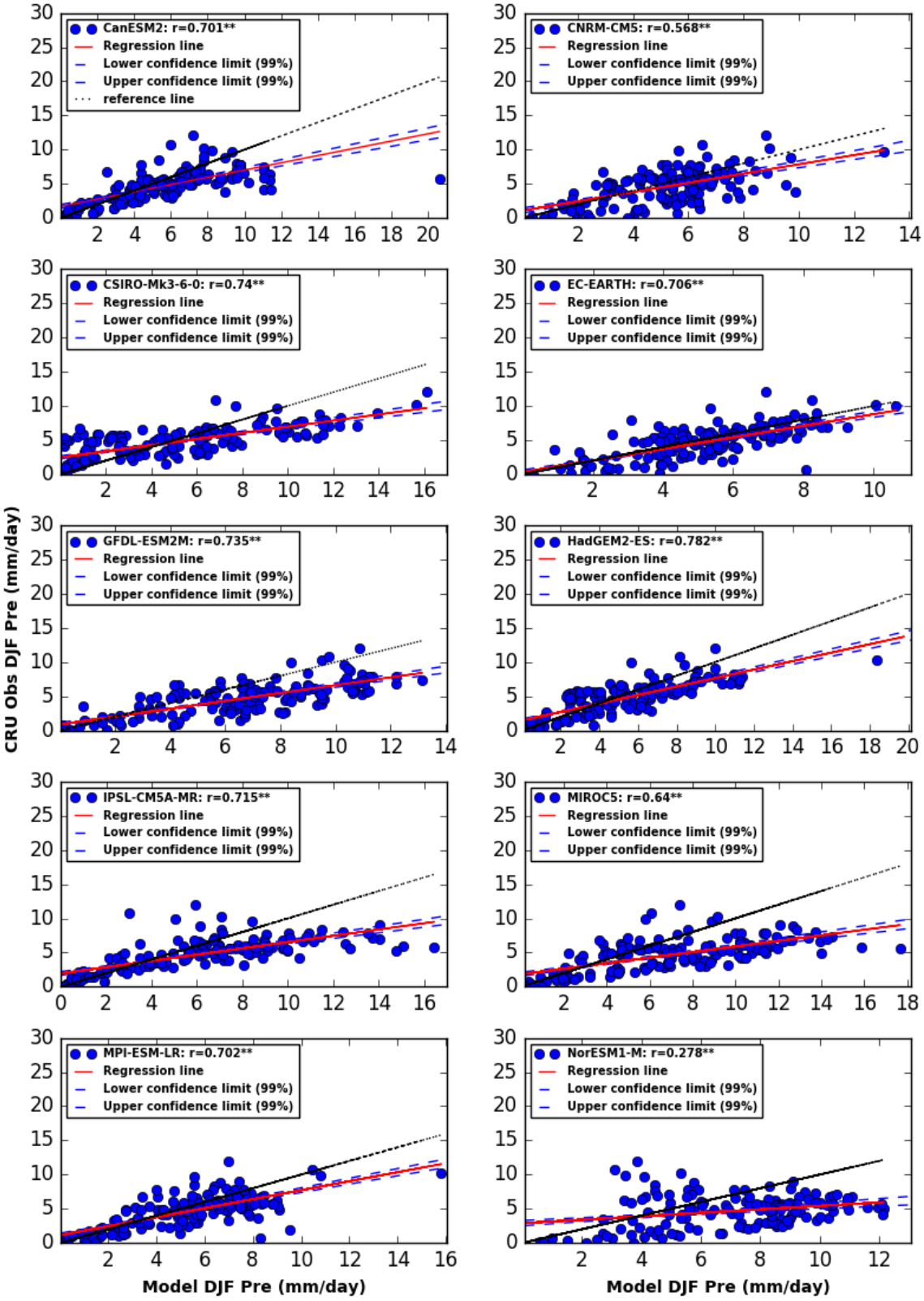


Figure 4.4: Scatterplot of CMIP5 models simulated summer rainfall (1950-2000) and CRU observed rainfall (1950-2000) . Vertical axis is the CRU observed data, horizontal axis is the model simulated data. Each blue dot is one grid box with CRU CRU observed summer rainfall long-term mean (mm/day^{-}1) and model simulated summer rainfall long-term mean. Significant r_values (p<0.01) indicated by. The red line is least-squares regression showing the best fit line between model and observed data while the black line is the reference (one to one) line.**

4.4 Models' simulation of observed temperature over the summer season

Few studies over Southern Africa have evaluated models' simulation of mean temperature climatology relative to observed temperature climatology (Mariotti et al., 2014; Diallo et al., 2015). To date, recent studies over the African continent, and the Southern Africa region in particular, still place emphasis on the evaluation of rainfall models' performance relative to observed rainfall (Sylla et al., 2013; Dedekind et al., 2016; Munday and Washington, 2017). Given that outputs from climate models are key for projecting future climate change estimates used in the assessment of climate change impacts on biodiversity, it is important to evaluate how the ecologically meaningful both rainfall and temperature simulate observed climate at coarse and fine scales.

To address this, in this section, using coarse GCM products and fine resolution AFRICLIM (WorldClim interpolated observations), I evaluate and compare the simulated GCM seasonal (DJF) climatology of 2-metre air temperature with that from the observed contemporary temperature (1950-2000) from the CRU dataset, over the broader Southern Africa domain (0-51E,-37-0S). Later in the chapter, I use this ensemble model chain to produce future temperature projections over the region. I base the evaluation of the simulations on the magnitude of temperature spatial distribution and patterns. This evaluation approach based on model ensemble means is widely used in climate research (Engelbrecht et al., 2016; Munday and Washington, 2017). Assessment of the added value of the AFRICLIM (WorldClim interpolated observations) compared to the driving GCM is also carried out.

Assessing the ability of climate models to simulate observed temperature over Southern Africa is an initial step towards evaluating model projections of future temperature change. This section thus commences by examining the observed distribution of temperature.

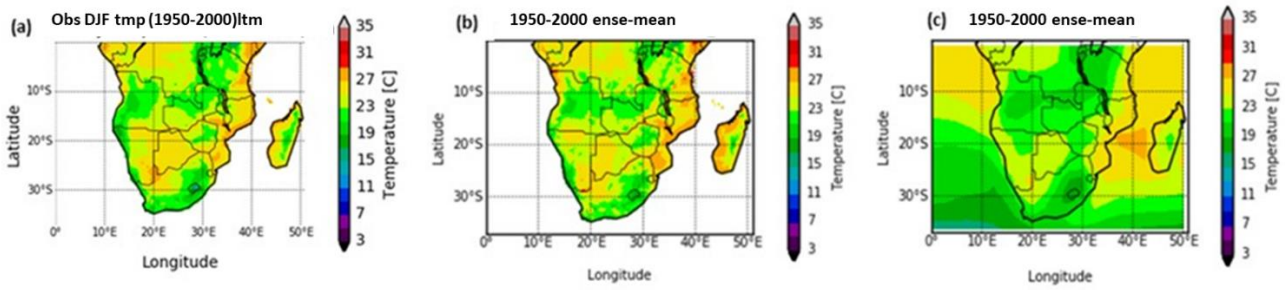


Figure 4.5: Observed and model simulated DJF 2-meter temperature (T2m; in °C) climatologies over Southern Africa domain, (a) observed climatology (1950-2000), (b) AFRICLIM climatology, (c) Coarse GCM climatology (ensemble mean of 10 CMIP5 models).

4.4.1 Observed contemporary austral summer (DJF) temperature climatology

Figure 4.5a shows the observed contemporary DJF 2-meter air temperature 1975 (1950-2000) from the CRU TS3.22 dataset. The climatology exhibits hot temperatures over the interior of the domain, and cooler temperatures around the coastal zones where the temperatures along the coastal zones are moderated by oceans. Cooler temperatures of a range between 15°C - 19°C are experienced around the Namib and Angolan coastlines, in response to the Benguela upwelling regime in that region (Andrews and Hutchings, 1980; Hutchings et al., 2009; Ismail et al., 2015). An exception in coastal zone cooling is seen around the east coast along the Mozambique region, with warmer temperatures of a range between 25°C-29°C experienced. The warming along the east coast relates in part to the influence of the Mozambique current transporting in warm water and humid air from the tropical Indian ocean. Unlike much of the rest of Southern Africa, Mozambique is largely a low-lying coastal plain. Whereas altitudes more than 1000 m keep much of the interior of Southern Africa somewhat cooler than would otherwise be expected for the subtropical latitude, Mozambique's low altitude is an exception.

The spatial distribution of the T2m in the interior of the domain, around the Kalahari and Namib desert region, experiences warm temperature conditions despite the altitude. The high temperatures in the semi-arid region can be attributable to clear skies (Hart et al., 2012) which result in a large flux of short-wave radiation. The southeast edge of the sub-continent displays cooler temperatures, which is largely a result of topography. because of high altitude along the Drakensberg /Lesotho highlands. Similarly, the Angolan highlands result in cooler temperatures

in the western region of Angola. Factors such as cloudiness (Diallo et al., 2012; Sylla et al., 2012), in the region around the northern side of Zambia can be associated with regulation of temperatures in that region. This region coincides with the area of the tropical rainbelt which is associated with intense convective activity in DJF. This tropical region benefits from the convection which increases the albedo, resulting in the region experiencing lower solar heating, and subsequent cooler conditions (Nkemelang et al., 2018).

4.4.2 Key differences and similarities between the coarse GCM and Fine resolution AFRICLIM (WorldClim interpolated observations)

The AFRICLIM climatology (Figure 4.5b) shows an improvement in simulating the temperature ranges over the domain, relative to the coarse GCM climatology (Figure 4.5c). The fine AFRICLIM (WorldClim interpolated observations) from here forth AFRICLIM (Figure 4.5b) reproduces the main features of the spatial distribution of temperature well (Figure 4.5a). However, the fine resolution AFRICLIM climatology shows slightly cooler conditions in the northeast side of Namibia and the east side of Botswana relative to the observed climatology (Figure 4.5a). The coarse resolution GCM model climatology (Figure 4.5c), also features the same basic climate elements as the fine resolution AFRICLIM climatology (Figure 4.5b). The figure captures well the Angola highlands, the Lesotho highlands, and the region of cloudiness around the Zambia area; however, the interior of the Kalahari Desert shows cooler conditions relative to the observed climatology (Figure 4.5a), with a temperature difference of about 2˚C. The coarse resolution GCM model climatology (Figure 4.5.c) exaggerates cooling in the high topographical areas around the Katanga Plateau (Northern Zambia) and the Drakensberg mountains (South east area).

The spatial extent of lower temperatures displayed in the centre of domain covering the Angola and Zambia region in coarse resolution GCM (Figure 4.5c) is wider than in AFRICLIM (Figure 4.5b), while the extent of high temperatures displayed around the Kalahari Desert is narrower in Coarse resolution GCM relative AFRICLIM. This demonstrates that the spatial resolution causes discrepancies in simulated present day climatologies against observed estimates. AFRICLIM reproduces the spatial distribution and magnitude of the T2m better than coarse resolution GCM model. The coarse resolution GCM exhibits a cooler climatology, as it underestimates the warm

temperatures across both the Kalahari and Namib desert regions. The coarse resolution GCM also overestimates the minimum temperatures in regions with high topography (Drakensberg mountain area, south east region). The AFRICLIM better replicates these minimum and maximum temperature spatial distributions. This result demonstrates the added value brought about by finer topographical representation from the high-resolution AFRICLIM dataset. The results correspond with that of Diallo et al. (2016), who reported greater skill of fine resolution models in simulating observed climatology.

4.5 Section Conclusion

In laying the foundation work for this interdisciplinary study, the preceding sections of Chapter 4 have filled a gap in knowledge, by examining the ability of an ensemble of coupled coarse resolution climate models and fine AFRICLIM (WorldClim interpolated observations) to simulate summer rainfall and temperature fields over a broad Southern African domain. The pattern correlations between the coupled coarse resolution models all return significant correlation coefficients with the observed climatology, with the strongest correlations around $r=0.78$ ($p<0.05$) and the weakest around $r=0.27$ ($p<0.05$). Plots of the climatologies reveal that the coarse coupled climate models all simulate the rainfall gradient from the dry western side to the wet eastern side of Southern Africa; but overall, the gradient is much weaker than observed. This is in part because much of the interior of Southern Africa is predicted to be very wet compared with observations. A notable feature of the models' wet bias is the extent to which coupled coarse resolution models simulate too much rainfall in the core convective region along the tropical edge of Southern Africa, particularly over Zambia and the south-west Indian Ocean. In general, the finer scale dataset captures the summer rainfall distribution with much greater fidelity. Biases are lower and the gradient across the interior of Southern Africa is more realistic. Temperature is a field which is much better simulated in the coarse coupled models than rainfall. The fine AFRICLIM (WorldClim interpolated observations) is also able to capture the detailed features of observed temperature. A notable deficiency of the coarse coupled models in their simulation of temperature is a cold bias over the interior of Southern Africa, which is very likely linked through excessive cloud to the positive rainfall bias.

The emerging intriguing question from this is, given that the datasets of different resolutions vary in their representation of key climate variables, what effect do they have in species distribution modelling? These are not questions, that have received much attention in the literature and are therefore questions which are interesting to investigate. This is the focus of Chapter 5, which investigates the effect of the seeming added value in finer topographical representation from the fine spatial resolution of climatic predictor variables (rainfall and temperature) in Species Distribution Modelling (SDMs). It tests the sensitivity of the predictions of species distribution to varied spatial resolutions of climatic variables inputs. However, before I discuss testing the sensitivity of SDM outputs to different spatial resolutions of climatic predictor variables, since there are differences in the characterisation of the basic elements of rainfall and temperature climatologies over Southern Africa, across the coarse CMIP5 models compared to the fine scale AFRICLIM and the observed, the next step in this chapter is to explore the projections of future climate from these models.

4.6 Southern Africa under Increased Greenhouse Gas Emissions

Assessment and understanding of future climate projections is vital to inform climate change mitigation and adaptation plans across various sectors, including biodiversity.

Here I evaluate possible future changes in seasonal mean rainfall and temperature, and their variability for 2071-2100, centred around 2085, under RCP8.5, by focusing on model simulations from the studied coarse GCM CMIP5 and fine, AFRICLIM future projection (statistically downscaled and bias corrected CORDEX projections). This evaluation follows many studies that have used model simulations from CMIP 3 & 5 to understand and project future African climate change (James and Washington, 2013; Gibba et al., 2018). The aim of this section is to provide an evaluation and comparison of the projected pattern of changes in rainfall and temperature variables derived from the coarse and fine future climate projection simulations.

The section seeks to answer the following question:

1. How much difference between coarse projections (GCM/CMIP5) and downscaled projections (AFRICLIM)?
2. How much difference between different GCMs? How much difference between different versions of AFRICLIM based on different GCMs?

Within this section, I provide an evaluation and comparison of the projected rainfall and temperature pattern of changes from the fine and coarse scale models. I then progress to explore the spread in the climate change signals for the end of the 21st Century under the RCP8.5 emission scenario pathway. Inter-model variability as a source of uncertainty (Fu et al., 2013) in projections is also evaluated. In this section I use scale descriptors "coarse" to refer to the GCM/CMIP5 future data and "fine" to refer to the AFRICLIM future data.

4.6.1 Methods

To obtain the future climate projections, I computed and plotted long term mean over a 30-year period (2071-2100), covering the end of the late century period under a radiative forcing scenario of RCP 8.5. To attain the climate change signal, I computed absolute change of the projected future climate relative to the simulated current climate. This gives rainfall and temperature future anomalies of averages taken over a 50-year period (1950-2000). This anomaly approach is extensively used in climate change research (Collins et al., 2013), because the approach removes the mean climatology, which helps to correct bias (Lafon et al., 2013). The future change was thus calculated as:

$$\Delta X = Xfut - Xhist$$

4.6.1.1 Reliability of projections

To evaluate reliability of the projections derived from the CMIP5 models and the AFRICLIM, I used a projection difference approach, where the climate projections of the seasonal mean rainfall for the end of the 21st century (2071-2100) from CMIP5 models is subtracted from the AFRICLIM projections (Africlim projections minus the CMIP5 projections). Metrics based on the agreement in the sign, whether positive or negative, magnitude and distribution of change signals is used to assess model agreement between CMIP5 and AFRICLIM. To facilitate

subtraction of the fields, I interpolated AFRICLIM future projections to a horizontal resolution of 2.5˚x2.5˚ (Diedhiou et al., 2018) to match the CMIP5 projections.

4.7 Results and discussion

4.7.1 Climate change projections of the GCM and AFRICLIM simulations

The projection of future seasonal mean summer rainfall from CMIP5 models in comparison with the model climatology is presented in Figure 4.6.

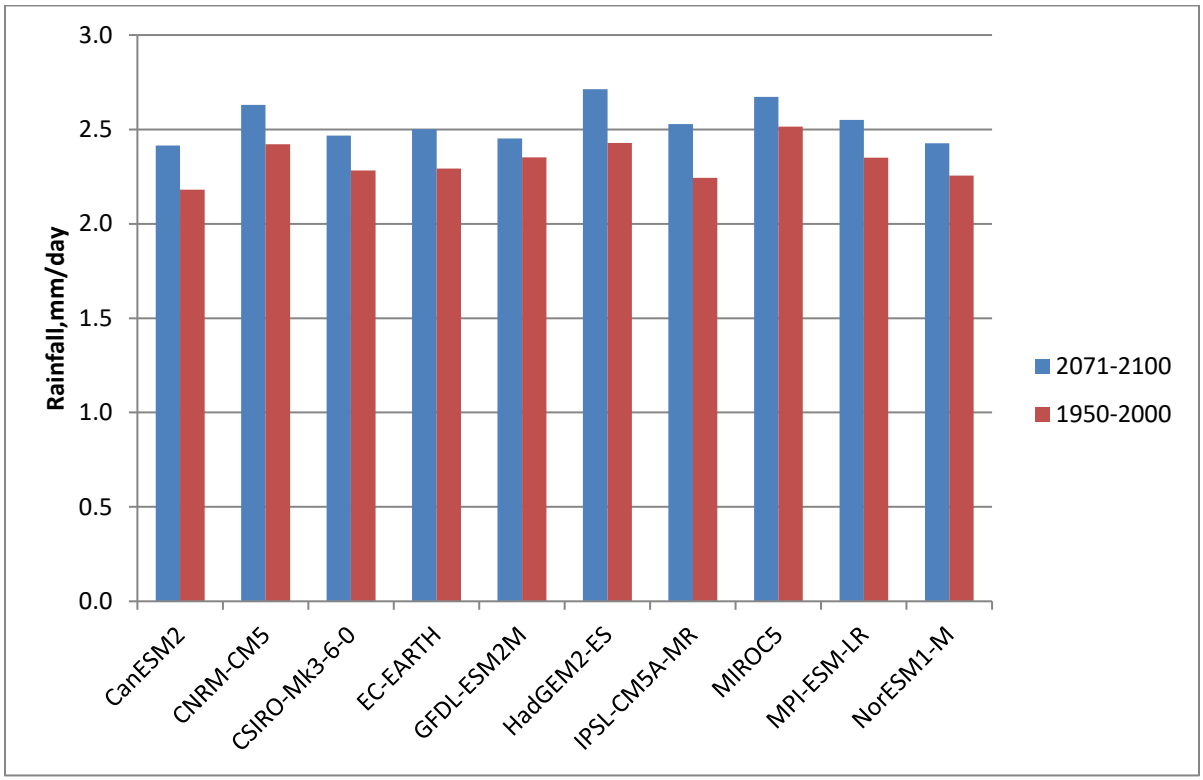


Figure 4.6: Projected rainfall summer (DJF) mm.day^{-1} Southern Africa long term mean (2071-2100) for each GCM against the present day mean climatology.

All models get wetter over the domain in the future (Figure 4.6). This result corresponds with the visual pattern of climate change signals relative the present-day climatology displayed in Figure 4.7 & Figure 4.8. Models HadGEM2-ES, IPSL-CM5A-MR, and MIROC5 project high seasonal mean future rainfall of about 270 mm, an increase of about 45mm relative the highest simulated

present day seasonal mean rainfall (Figure 4.3). For these models, the results indicate a high seasonal mean rainfall change by the end of the 21st century. To further explore the future rainfall, change over Southern Africa Figure 4.7 & Figure 4.8 show representation of the seasonal mean spatial distribution and pattern as simulated by the GCMs and the AFRICLIM datasets.

Considering the description of the climate of Southern Africa given in Chapter 2 section 2.2, all the coarse resolution models simulations of future climate change correspond with the main rainfall elements of the domain, in the sense that the projected wetting is displayed in the humid subtropical climate / tropical savanna climate responding to the tropical convergence zone. This rainfall response appears to follow the "rich get richer" mechanism (Chou et al., 2009) where rainfall is projected to increase in currently wet areas such as convergence zones.

The GCM future climate projections displayed in Figure 4.7 & Figure 4.8 also capture the intense wetting in the southeast, along the Drakensberg escarpment / Lesotho highlands. The intense wetting links with the topography of the region, where altitude and exposure to moist air from the Indian Ocean produces strong rainfall in the region (Washington and Preston, 2006; Lucas and Buque, 2007; Munday and Washington, 2018). While there is a clear signal of wetting in already wet regions, dry areas show no major change, as the projected intense drying is exhibited along hyper arid Namib Desert in the west ward region in similar magnitudes to the baseline climatology (Figure 4.1 and Figure 4.2). This region of intense drying represents the cold Benguela current from the Atlantic Ocean, which brings stable atmospheric conditions (Hutchings et al., 2009).

Overall, the GCMs project an increase in rainfall in the centre of the domain (the region of core tropical convection) towards north eastern tropical regions (Figures 4.7 & Figure 4.8 b,h,n). Based on the analysed models' projections, the future changes in rainfall for the close of the 21st century are not spatially uniform. This finding corresponds with that of Mizuta et al. (2014) . The lack of uniformity is expressed in the degree of variation in space of the rainfall changes among the models. The CMIP5 models also differ in the projected magnitude of rainfall (Figures 4.7 b-z & Figures 4.8 b-z). The variation is prominent in the case of models MIROC5 and IPSL-CM5A-MR, where the intense convective area intensifies North eastwards across the domain (~270mm wetting), in association with the large region of enhanced convection over the tropical and

subtropical SW Indian Ocean, also known as the South Indian Ocean Convergence Zone (Lazenby et al., 2016). The intensity of rainfall in this area is determined by surface conditions (Cook, 2000) as opposed to the tropical rainbelt, where the rainfall intensity is driven by wind convergence in the moist environment (Cook, 2000). The low-level circulation current brings in warm water and humid air from the tropics, creating higher energy in the lower atmosphere, which acts as a source of energy for convection and for the rainfall.

When considering the AFRICLIM future climate projection Figure 4.7 e-w and Figure 4.8 e-w, similar rainfall elements/characteristics to the GCMs are exhibited, although differing in magnitude. As should be expected, in contrast, the bias corrected fine resolution AFRICLIM future climates have lower rainfall over the tropical savanna climate of the Zambia/Congo region in comparison to the coarse resolution future climate. There is less increase in both dryness and wetness displayed, relative to the observational climatology (Figure 4.1 and Figure 4.2); for example, the highest wetness is about 180mm/season with the highest dryness of about -90mm/season. However, in comparison with the coarse resolution models simulations, the AFRICLIM projects more rainfall over the Madagascar region.

The AFRICLIM future climate also exhibits a broader spatial distribution of drier conditions in the Kalahari Desert region relative the GCMs, especially in the case of models CNRM-CM5 vs CNRM-CM5 driven SMHI-RCA4 (Figure 4.7 h & k) and NorESM1-M vs NorESM1-M driven SMHI-RCA4 (Figure 4.8 z & c last row).

Both fine spatial resolution bias corrected future climate and coarse spatial resolution models simulate similar futures. The gradient across the region of tropical convection, which makes that area wet, is displayed on both datasets' future climates. Also similar is the gradient across the region of Kalahari convection making that region dry, which is displayed on both the coarse resolution future climate projections and the fine resolution projections. In general, given the high forcing scenario, the magnitude of the rainfall change is large.

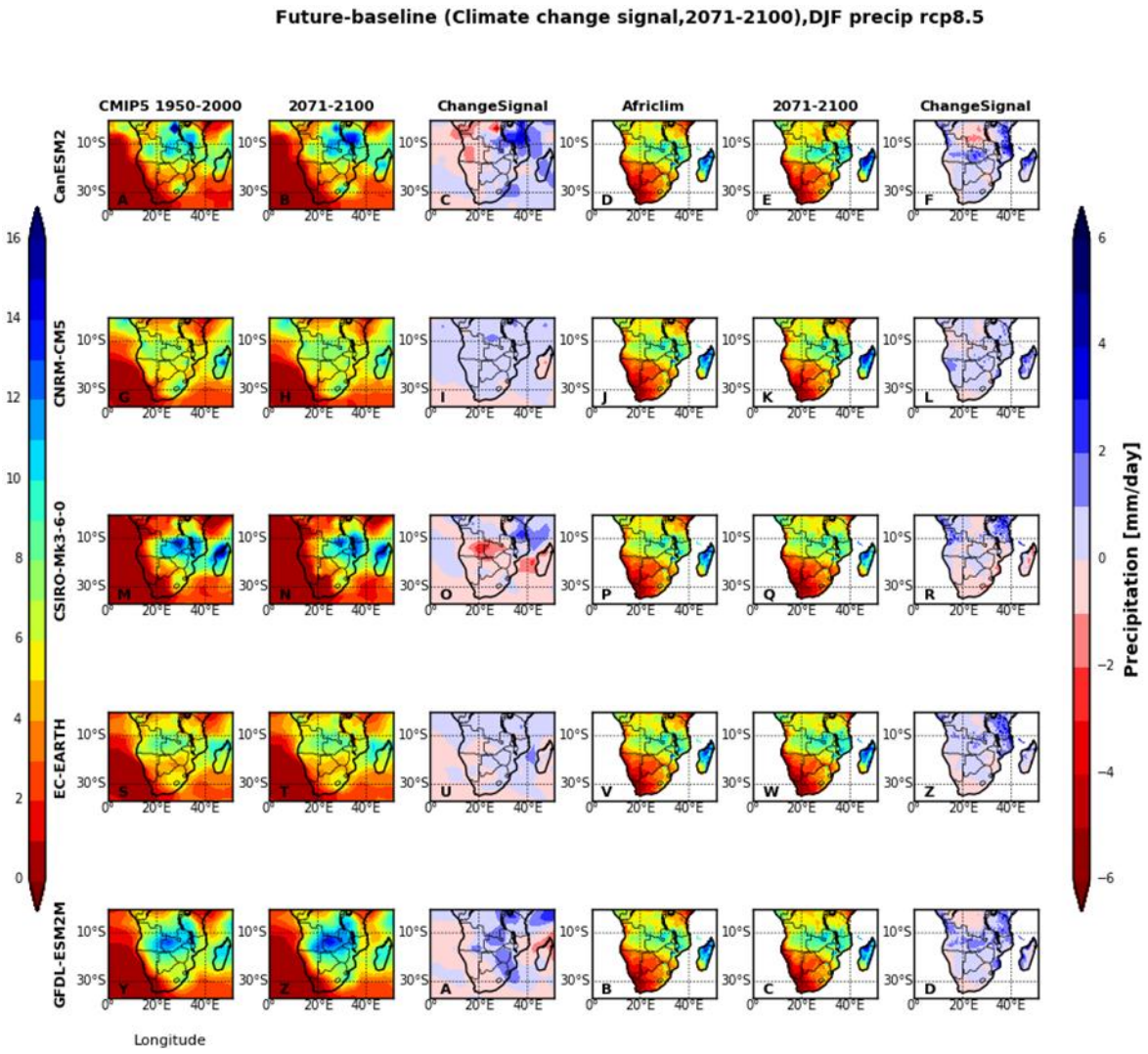


Figure 4.7: Climate change signals relative the present day climatology mm.day^{-1}.1st column is the first set of CMIP5 present day climatology (1950-2000), 2nd column is the future climate projection (2071-2100) and 3rd column is the climate change signal (column 2 minus column 1).4th column is the AFRICLIM present day climatology (1950-2000), 5th column the future climate projection (2071-2100) and 6th column the climate change signal (column 5 minus column 4).Rows correspond to individual climate models as labelled.

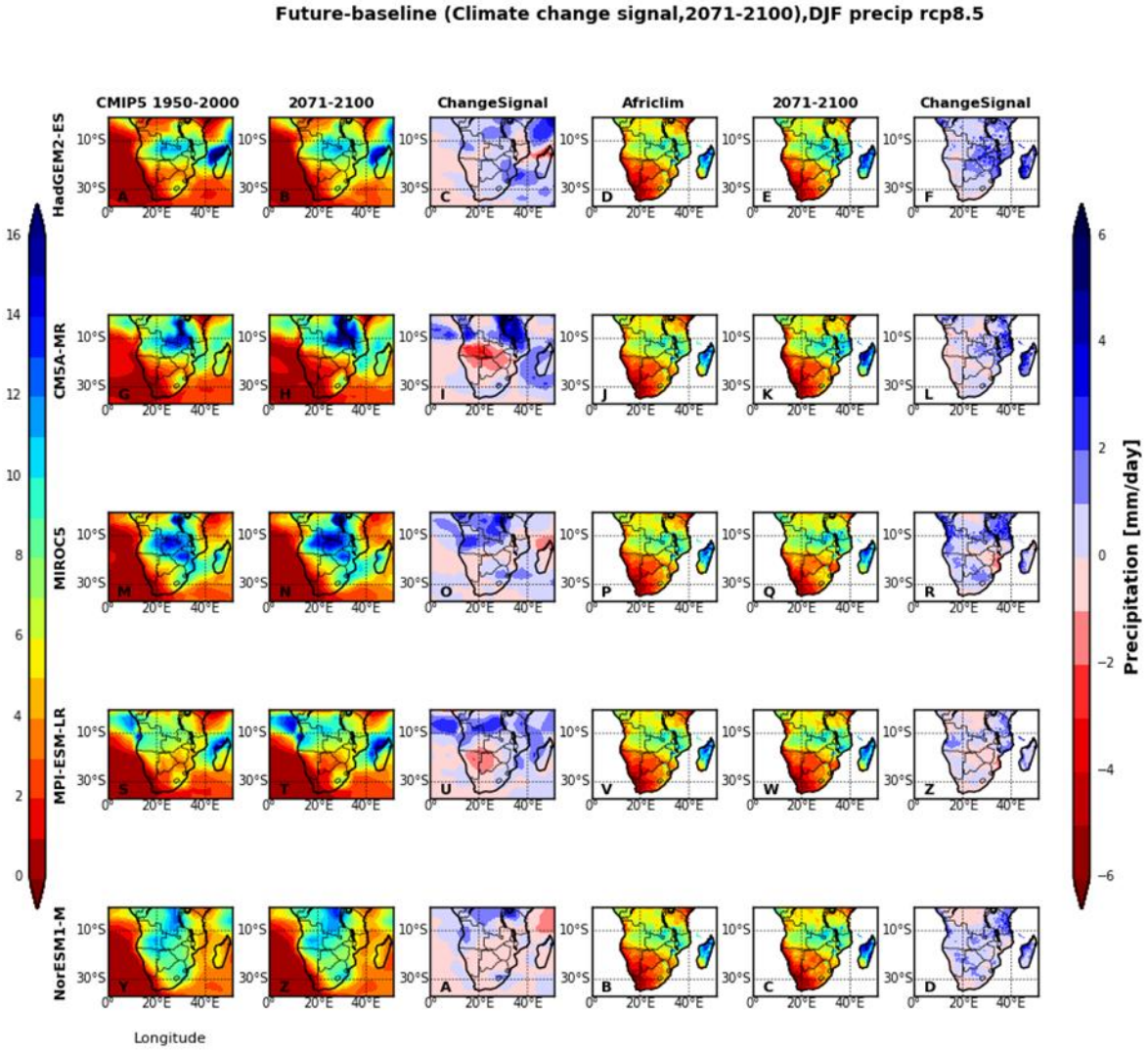


Figure 4.8: Climate change signals relative the present-day climatology mm.day-1. 1st column is the second set of CMIP5 present day climatology (1950-2000), 2nd column is the future climate projection (2071-2100) and 3rd column is the climate change signal (column 2 minus column 1).4th column is the AFRICLIM present day climatology (1950-2000), 5th column the future climate projection (2071-2100) and 6th column the climate change signal (column 5 minus column 4). Rows correspond to individual climate models as labelled. Note that IPSL-CM5A-MR has been shortened to CM5A-MR for font size clarity.

Following upon the previous section, where the focus was on the relationship between the performances of CMIP5 and AFRICLIM future datasets in projecting future changes in rainfall, here I focus on assessing how strong and widespread the projected change signals are over Southern Africa from the GCM models and AFRICLIM. I base the assessment of the change signal on the spatial distribution and the magnitude and pattern of change.

The domain in both the coarse and fine spatial resolution data displays both wetting and drying signs of responses, depending on the region, the model and the data product albeit differing in amplitude (Figure 4.9 and Figure 4.10).

Evaluating the coarse resolution models, there are robust positive rainfall anomalies of values of about +540mm/season. This gives the GCMs an intense wetting signal relative to the baseline climatology Figure 4.7 and Figure 4.8. A closer look at the pattern of the intense wetting shows more rainfall distinctly regionalised in all the GCM models, this partly owing to the different activities forming rainfall in Southern Africa (i.e thunderstorm activities and movement of coastal warm moist air) (Hart et al., 2012). Hence a variation in the climate system's response to climate change is shown.

In all the subsets of the CMIP5 models used, negative rainfall anomalies are projected across the Namib Desert spreading towards the dry climate of the Angola region. The negative anomalies are of a low amplitude relative to the wetting signals.

Focusing on both the coarse and fine models, there is a clear variation in the magnitude, pattern and spatial distribution of the wetting response projected in the GCM simulations. For instance, looking at the example of the seasonal mean rainfall of the MIROC5 model (Figure 10; e), a large magnitude wetting response is exhibited in the humid subtropical and monsoon climates of the Zambia, Angola, and Congo region. Within the same model simulation, an intense wetting response is displayed around the moist subtropical mid-latitude climates of the Lesotho Drakensberg mountains.

When considering the wetting response exhibited in the AFRICLIM projections; MIROC5 driven SMHI-RCA4 simulation (Figure 4.10; f), a different wetting pattern and distribution is displayed. A high magnitude of wetting is displayed along the west coast covering Angola, the hyper arid area of the Namib Desert and the Kalahari Desert. A similar magnitude of wetting is

then exhibited in the tropical convergence zone (Zambia area), extending over a large space across the moist mid-latitude climates of the Malawi, Mozambique coastlines. Previous research suggests that this result discrepancy is due to the internal model physics and dynamics, which affect the output of the nested simulations (Paeth and Diederich, 2011; Paeth et al., 2011).

The region across the central convective around the core of the tropical rainbelt shows increases in the future in both the coarse and fine models. The wetting over the East Africa through to central Kenya to Tanzania is exhibited on both datasets. Both climate change signals (Figure 4.9 & Figure 4.10) depict similar features, for example, the increase in the tropical convection over the Zambia area. A wetting climate change signal around the East coast is exhibited on both the GCM simulations (Figure 4.9 & Figure 4.10; 1st column) and the AFRICLIM simulations (Figure 4.9 & Figure 4.10; 2nd column) but the amplitude, is muted in the AFRICLIM models.

Both the AFRICLIM and GCMs models depict similarities in that there is a wet response in the Zambia, Congo region. The wet response corresponds with the tropical convergence zone, characterised by convective activities producing summer rainfall in the region.

Key differences are that the spatial distribution of drying signal is different among the GCMs climate change signal simulation (Figure 4.9 & Figure 4.10) and the AFRICLIM change signal simulation. For instance, amplified drying response of about -360mm/season is depicted along the hyper arid area of the Namib desert, intensifying towards the dry climate of the Angola, Congo region, in the CanESM2 (Figure 4.9a) simulations, whereas the region of drying in the west coast is only evident around the Namib area, but in a subdued form, in the CanESM2 driven SMHI-RCA4 (Figure 4.9b) fine resolution regional scale simulations. A high magnitude of drying of about -144mm/season is experienced south of Congo region in the CanESM2 driven SMHI-RCA4 (Figure 4.9b), regional scale change signal simulation.

The drying in the west coast of Angola, towards Congo in the CMIP5 global scale simulations (Figure 4.9 & Figure 4.10) is not evident in the AFRICLIM fine resolution simulation. A completely different climate change response of wetting is mostly projected along the same area in the high-resolution regional scale simulation.

Continuing key differences, an intense wetting climate change signal is projected in the Madagascar region in the CMIP5 simulations, while there is a less intense wetting signal in the same region depicted by the AFRICLIM regional scale simulations.

Of interest in the future climate, the Kalahari region which is a desert is projected to experience wetting, in the case of SMHI-RC4 driven by MIROC5 and SMHI-RC4 driven by NorESM1-M (Figure 4.10 f & j).

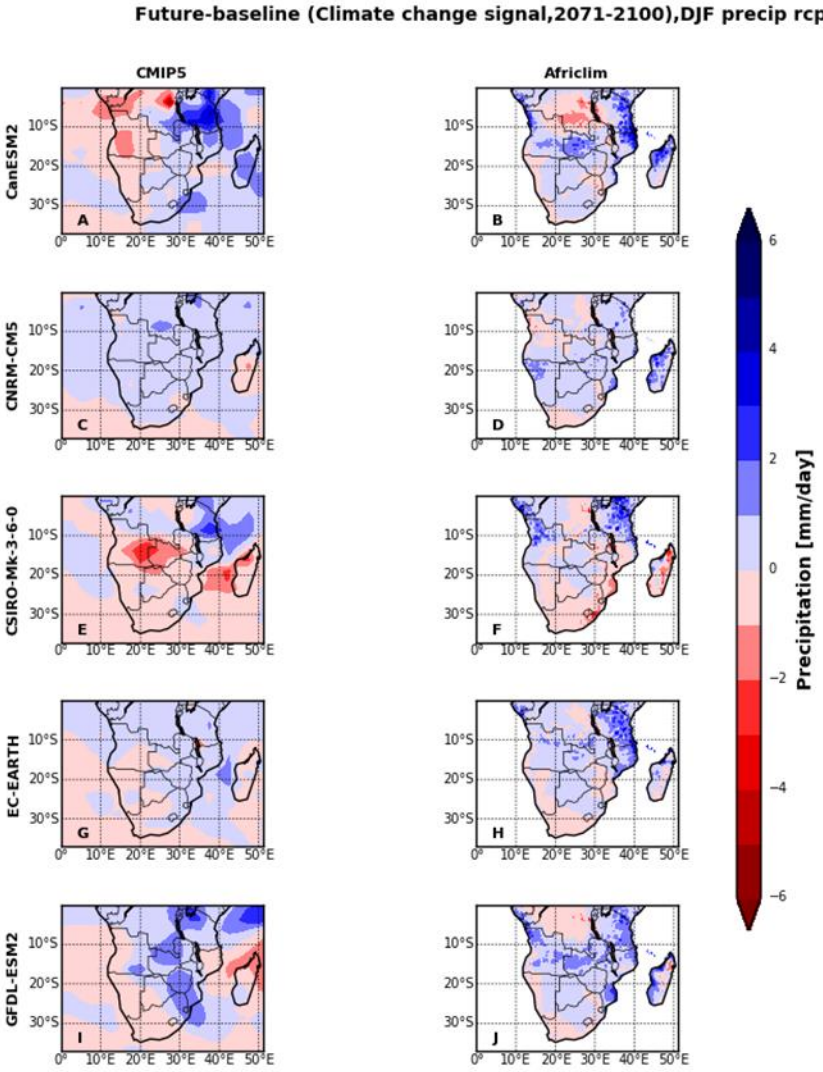


Figure 4.9: Shows the absolute summer rainfall change (2071-2100) relative the baseline climatology (1950-2000).1st column is the first set of CMIP5 climate change signal, 2nd column is the AFRICLIM climate change signal. Figure C is IPSL-CM5A-MR.

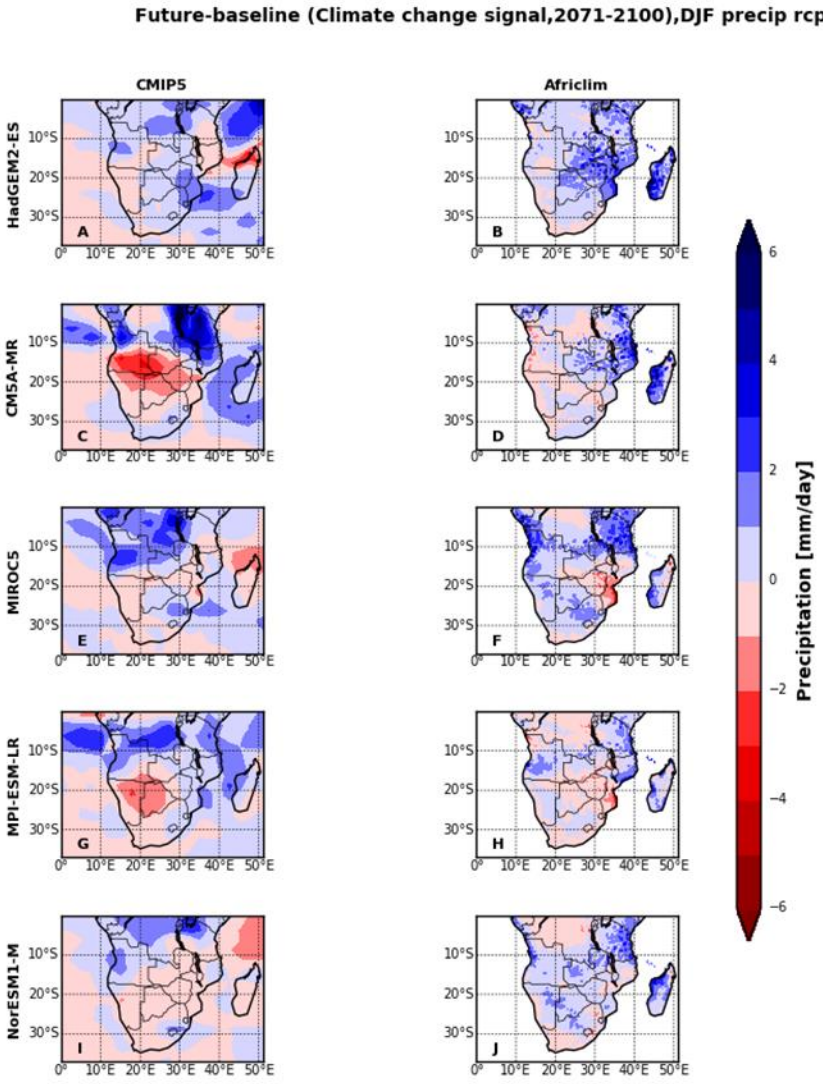


Figure 4.10: Same as Figure 4.9, except 1st column is the second set of studied CMIP5 climate change signal, 2nd column is the AFRICLIM climate change signal. Figure C is IPSL-CM5A-MR.

4.7.2 Effects of the capacity of the models to simulate observed climatology in deriving future climate projections.

Following on from previous sections, especially section 4.3.3 which explored whether model simulations of mean rainfall is consistent with gridded observations data, in this section I aim to explore whether models that simulate the observed climatology of rainfall will have a different projection of future climate compared with models that simulate the observed climatology poorly. Do models with intense wetting climatology with respect to the observed climatology, for example, simulate futures that are wetter than those models with a relatively less wet/ drier climatology? This analysis is therefore aimed at assessing the impacts of the bias in climate variable/parameters (contemporary climate model departures from the observed climatology) on the future projected climate change of the GCM and fine AFRICLIM future projections (statistically downscaled and bias corrected CORDEX projections) simulations over Southern Africa.

I begin this section by giving a brief interpretation of the present day and future representations of the rainfall seasonal mean patterns and variability. A detailed account of models' abilities to simulate the observed climate over Southern Africa is given in section 4.3.2; section 4.6 discusses the derived projected changes in rainfall and temperature of the coarse and fine scale models. I conclude the section by giving a discussion on what uncertainties and what rainfall change might be in the future.

As determined in section 4.3.3 and pattern correlations (Figure 4.4), most of the studied coarse resolution GCM models have reasonable capacity to simulate the observed climatology. Also observed is the minimal change in the organisation of the main climate features; both the historical/present-day climate and simulated future climates (Figure 4.11) display similar climatological spatial patterns. The simulated future climate shows less evidence of a radical change in the distribution of the main rainfall elements relative to the historical/present-day climatology. The CanESM2, CSIRO-Mk-3-6-0, GFDL-ESM2M, IPSL-CM5A-MR, MIROC5 and HadGEM2-ES model climatologies feature a gradient across the region of tropical convection (area around the interior down to Madagascar), which produces intense wetting in the

area. This main rainfall element: the gradient across the region of tropical convection are replicated in the simulated future climates, although with larger magnitude of wetting in the future climate. This model response agrees with the rich-get-richer mechanism, where increased rainfall is yielded following moisture increase in a climatological convergence zone (Chou et al., 2009). This moisture increase feature matches the climatology to expect in the domain of analysis as described in section 4.3.1.

Results of the AFRICLIM shows a higher performance in matching the observed climatology (Figure 4.1 & Figure 4.2). When considering the simulated future climates, similar to the GCM models, the gradient in the region of the tropical convection is displayed in the observed climatology, the present-day climatology and is also apparent in the simulated future climate. The magnitude of the wetting displayed in the gradient falls within the same range of about 720-900 mm per season, across all three climatologies, for all the AFRICLIM models. A slightly wetter climate than the observed and present day climatologies is however projected at the end of the 21st Century, especially in the case of the Madagascar region. The drying gradient of the Kalahari region is depicted in both the observed climatology and present day-climatology. This drying gradient is projected in the future climate, however with much intensity. Overall, the 21st Century future climate shows less evidence of a fundamental change in the pattern and distribution of the main rainfall features relative to the baseline climatology (Figure 4.11 & Figure 4.12).

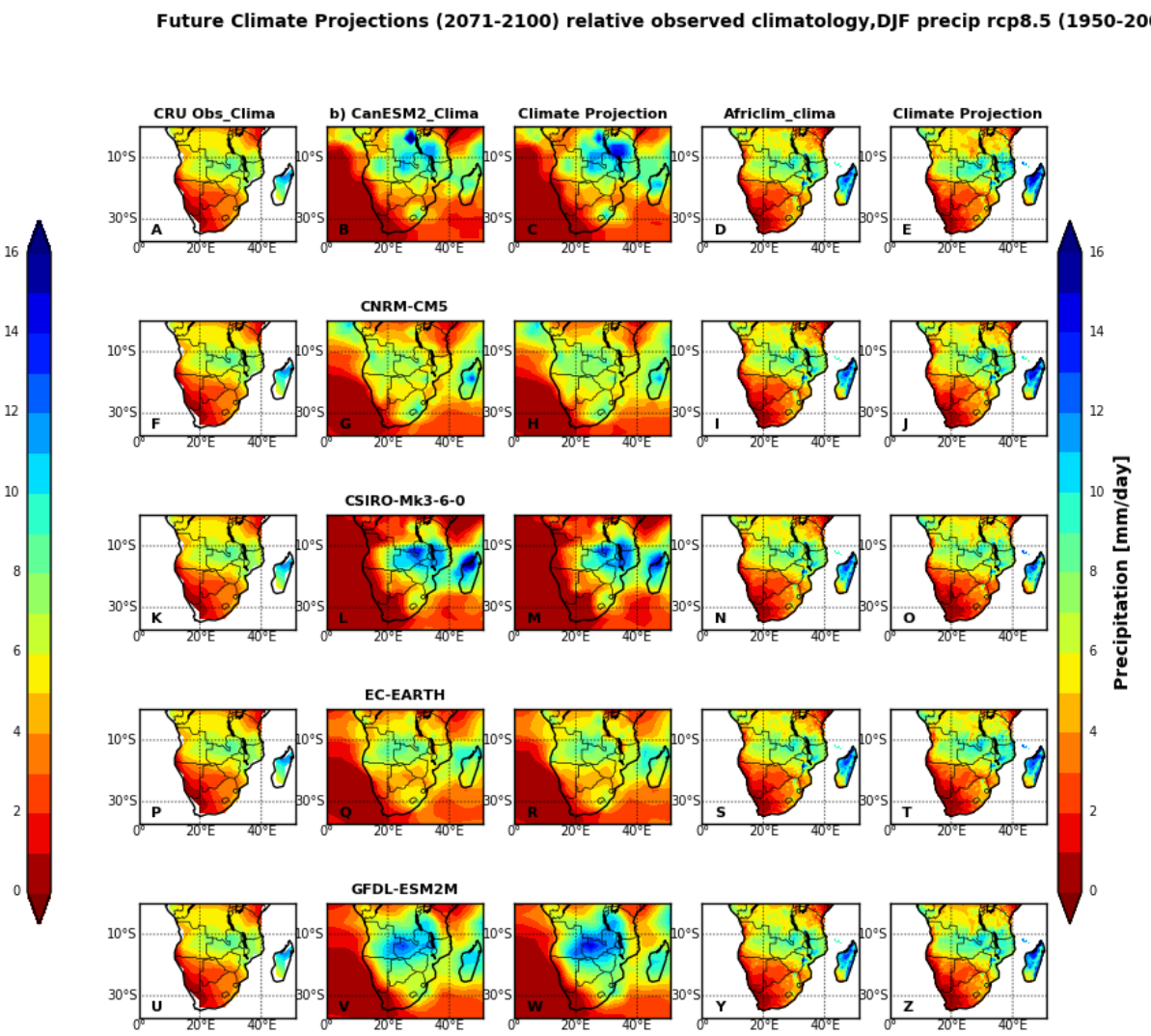


Figure 4.11: Future climate projections relative observed climatology. 1st column CRU observed climatology (1950-2000), 2nd column the first set of CMIP5 historical/present day climatology (1950-2000) and 3rd column the future climate projection rcp8.5 (2071-2100), 4th column the AFRICLIM historical/present day climatology and 5th column the future climate projection rcp8.5 (2071-2100). Please note Figure 4.11G is IPSL-CM5A-MR it has been shortened to CM5A-MR for font size clarity.

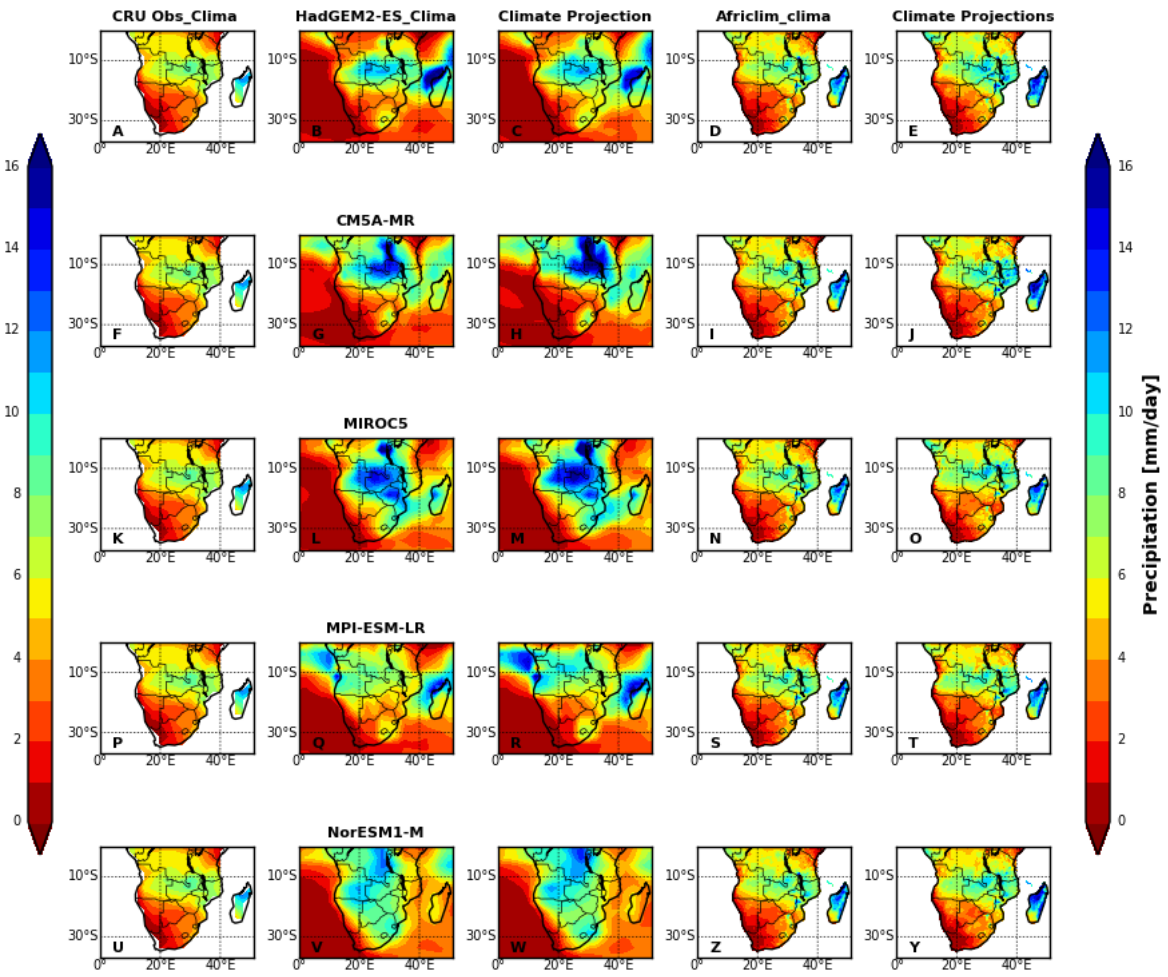


Figure 4.12: Future climate projections relative observed climatology. 1st column CRU observed climatology (1950-2000), 2nd column the second set of CMIP5 historical/present day climatology and 3rd column the future climate projection rcp8.5 (2071-2100). 4th column the AFRICLIM historical/present day climatology and 5th column the future climate projection rcp8.5 (2071-2100).

4.7.3 Southern Africa Temperature change and distribution under increased greenhouse gas emissions

Here I analyse potential 2-meter air temperature changes over Southern Africa under future greenhouse emission scenarios, using an ensemble of coarse resolution GCM and fine AFRICLIM future projections (statistically downscaled and bias corrected CORDEX projections). The projections are forced under the RCP8.5 comparatively high greenhouse gas emission scenario (Moss et al., 2010; Meinshausen et al., 2011; Riahi et al., 2011), for the end of the 21st Century (2071-2000), relative to the present-day climatology (1950-2000). The ensemble mean approach, which characterises models' average response to external forcing (Collins et al., 2013), is a widely used approach in projections of temperature and rainfall changes (Engelbrecht and Englebrecht 2016).

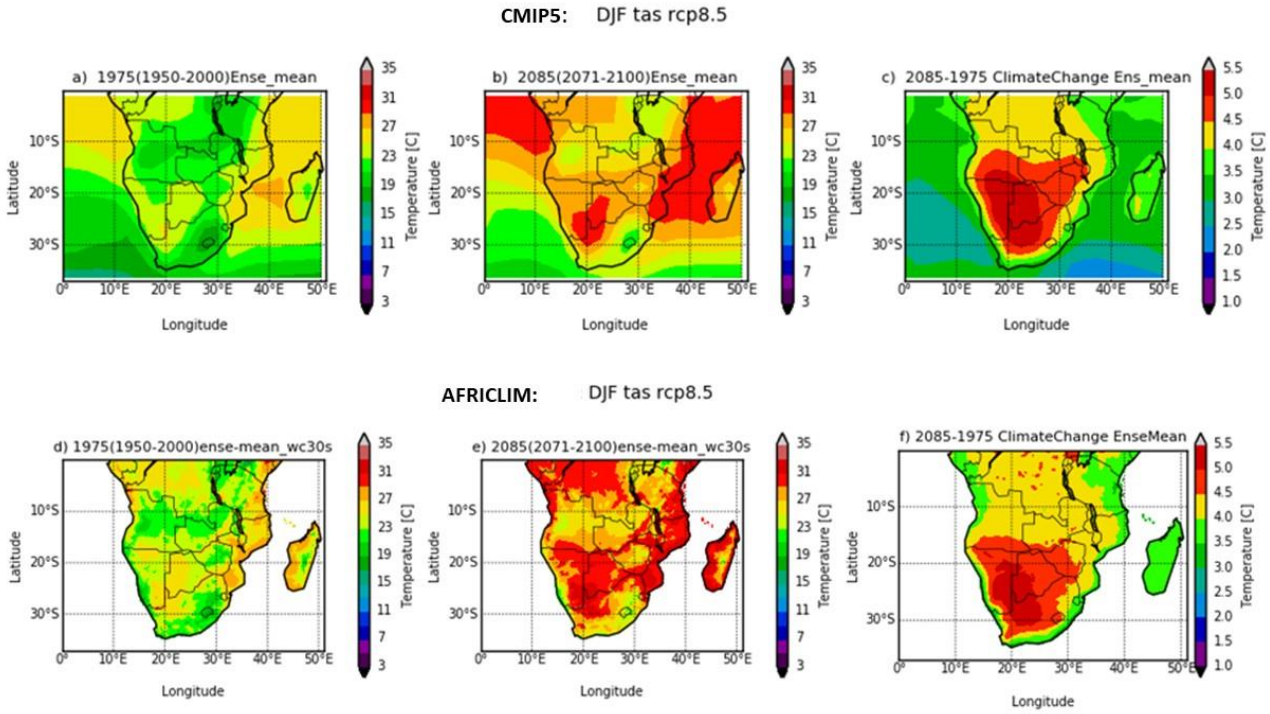


Figure 4.13: 2-meter temperature (T2m: in °C) DJF Climate change signals relative the present-day climatology under rcp8.5 for late century (mean over 2071-2100). (a) CMIP5 Climatology (1950-2000), (b) simulated future climate (2071-2100), (c) climate change signal (absolute change relative to 1950-2000). (d) AFRICLIM climatology (1950-2000), (e) simulated future climate (2071-2100), (f) climate change signal (absolute change relative to 1950-2000.

4.7.3.1 CMIP5 coarse resolution GCM Climate Projection

The CMIP5 coarse resolution model simulated future climate shows positive anomaly values for the entire domain (Figure 4.13b), signifying intensified warming relative to the climate baseline period (Figure 4.13a). The spatial scale of warming has expanded in comparison to the climatology (Figure 4.13a). Amplified warming response is projected in the subtropics, around the Kalahari and Namib Deserts due to their conduciveness to extreme warming as alluded to in section 4.7, with the tropics projecting a cooler climatology, due to the region benefiting from great convection cloudiness. The highest mean maximum temperature projected from one grid box is 35˚C, relative 27˚C observed in the climatology; a projected increase of about 8˚C by the end of the 21 Century.

4.7.3.2 AFRICLIM future projections (statistically downscaled and bias corrected CORDEX projections)

The fine resolution AFRICLIM model simulated future climate shows warming over the entire domain, with intense warming projected around the eastern coastal regions. This response can be associated with the Mozambique current bringing in warm water and humid air from the equator. Amplified warming is also projected in the Kalahari Desert relative to the climatology (Figure 4.13d). The surface temperature change range is between 3.2-5.2˚C with a large scale projecting a mean maximum temperature warming of 4˚C.

4.7.3.3 Comparison between the coarse scale (CMIP5) and fine resolution (AFRICLIM) temperature projections

The signature of climate change in the local-scale models (Figure 4.13e) is similar to that of the global-scale models (Figure 4.13b), with positive temperature anomaly values projected for the entire domain. Both simulated future climates depict a warming signal, albeit with differing magnitude and spatial patterns. In both the fine and coarse scale future projections, there is high warming in the Kalahari Desert region, with cooler temperatures projected along the edges of the Namib coastline and the region of great convection cloudiness. The AFRICLIM future climate (Figure 4.13e) with the same topography, has much more structure as expected, given the high resolution.

4.7.3.4 AFRICLIM Vs CMIP5 Climate change signal

When considering the representation and main distribution of features responsible for a warming signal over Southern Africa, between the coarse scale (Figure 4.13c) and fine scale (Figure 4.13f), relative to the contemporary climatology, both models' projected warming seems plausible. Projected warming in the entire domain is displayed in both models, with a noticeable intensification of the Kalahari heat-low region relative to the climatologies. The tropical convective area in both the fine and coarse scale change maps gets warming as well, albeit with a larger magnitude in the GCM scale (Figure 4.13c). However, some key differences can be observed in the fine and coarse scale climate projections and change signals, warming that is manifest in the fine scale change signal (Figure 4.13f) is in a different chart in the sense that it produces a muted warming response.

The coarse scale model CMIP5 (Figure 4.13c) change signal produces a greater expanse of the Kalahari heat-low region extending further than the fine scale AFRICLIM (Figure 4.13f). The Fine scale model (Figure 4.13f) shows least warming along the coast, where temperatures are moderated by Sea Surface Temperatures, than the coarse scale model. Highest seasonal mean maximum temperature projected by the coarse scale (Figure 4.13c) is 5.6˚C whereas for the fine scale (Figure 4.13f) the maximum temperature is at 5.2˚C, a slight difference of 0.4˚C.

4.7.3.5 Standard deviation of seasonal (DJF) temperature change (°C) expected by 2071-2100 for the GCM simulations

To estimate the variance response, and assess change in variability, I compute Standard Deviation of seasonal 2-meter temperature over time for the GCM. Figure 4.14 depicts the temperature standard deviation for each grid box. The region across the gradient of Kalahari convection in the contemporary climatology (Figure 4.14a) has a maximum standard deviation of about 0.8, whereas the simulated future climate (Figure 4.14b) across the same region features a large standard deviation of about 1.2 over time. Therefore, the simulated future climate of the end of the 21st Century, has a large spread in DJF air temperature values relative to the contemporary climate (Figure 4.14a). There is a small DJF temperature variability over time in the baseline period compared to the future climate. The Kalahari Desert region in the observed temperature data (Figure 4.14c) has a standard deviation of 1.0; this value is close to that of the

simulated future climate (Figure 4.14b). These results suggest that the global scale simulated future climate has credibility in projecting DJF temperature variability in this domain.

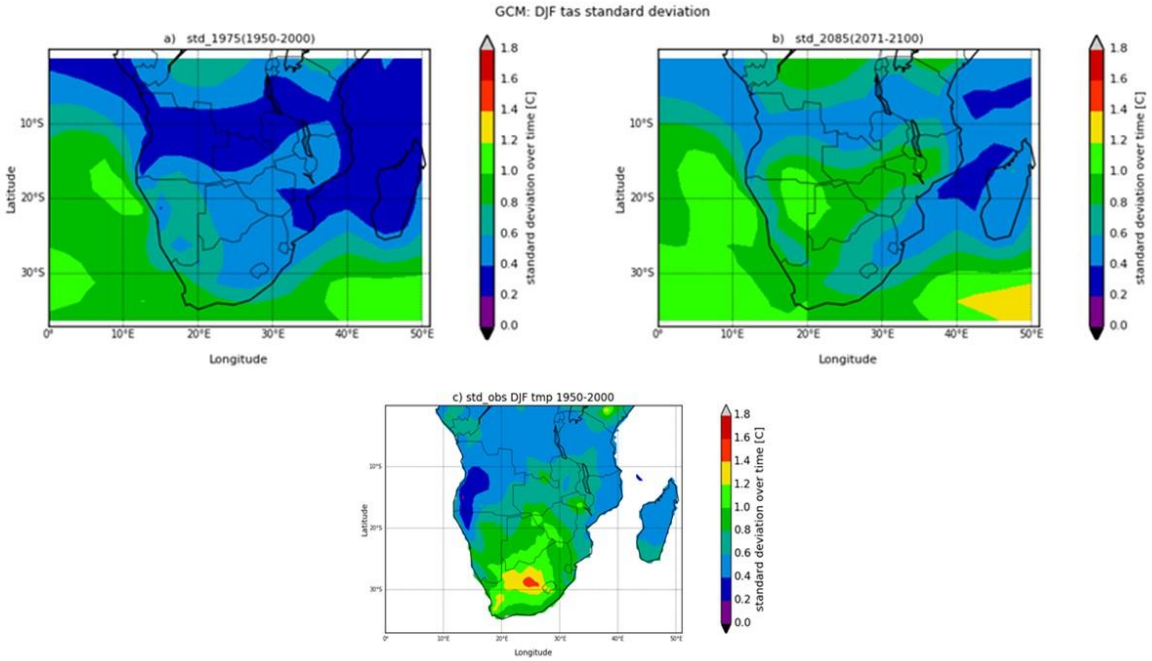


Figure 4.14: DJF 2-meter temperature standard deviation; (a) contemporary climate 1950-2000, (b) future climate 2071-2100, (c) observed 2-meter temperature data

4.8 Section Conclusion

This section documents climate change projections that have potential to cause species range shifts (Garcia et al., 2012) and changes in the phenology and physiology of the species (Scheiter and Higgins, 2009; Prober et al., 2012a, 2012b). Changes in rainfall, distribution and magnitude pose challenges to the functioning of tropical savanna habitats (Zeng et al., 2000) and promote conversion of the savannas to grassland (Hoffmann et al., 2000). Section 4.7.1 predicts an uncertain rainfall change over Southern Africa in the mid-late 21st Century. The studied GCM CMIP 5 models project both a wet and dry future across the domain under RCP8.5 climate change scenario with models such as the IPSL-CM5A-MR and the EC-EARTH depicting a dry future. Models MIROC, NorESM-M and HadGEM2-ES show a wet future. However, there is variation in the magnitude of wetting across the models, for example models HadGEM2-ES and MIROC project a higher summer rainfall relative the observed, by the end of the 21 century.

Models do project different climate changes, whether wetting or drying depending on the region, the model and target period. The future wetting projection result from the analysed wet models contradicts with Dunning et al. (2017, 2018) who found decrease in rainfall by the end of the 21st century under RCP8.5 in CMIP5 models.

The fine scale bias corrected projections, the resolution for ecological modelling, projects variations between regions with an intense gradient of drying at the end of the century over the region of ORB. The identified uncertainty in the projection of summer rainfall (a rainy season for Southern Africa), is larger than in the months of June, July, August (winter dry season) and September, October, November months, across these months other studies (e.g. Dosio et al., 2019) have found that there is model consensus on drying. The understanding of the credibility of model projections is therefore important in impact studies.

The possible increase in aridity projected by the fine AFRICLIM data across the region of ORB is one of the factors which could control the distributions of tropical woodlands and Savanna grasslands (Shanahan et al., 2016), with species responding by shifting their distributional ranges leading to expansions of tropical grasslands. This kind of response has been shown to affect the species richness, spatial patterns, and turnover, as well as ecosystem functions (Midgley and Bond, 2015), with implications for conservation and management of biodiversity. The potential wide-ranging impacts of climate change on biodiversity as briefly reviewed above make a compelling case for the need to assess vulnerability of biodiversity to climate change, especially in regions of biodiversity hotspot such as the Okavango river basin. I seek to achieve this in Chapter 6.

5. Climatic Drivers of Plant Species Distributions Across Spatial Grains in Southern Africa Tropical Forests

5.1 Overview

In the previous chapter I investigated how different climate data products at different spatial resolutions (global scale versus statistically downscaled/bias corrected products reliably capture patterns of important ecological climatic variables (temperature and precipitation), by establishing the degree of difference in spatial distribution of climate features from the model's simulation and climatologies.

From the analysis, in general it can be attested that the mean seasonal rainfall characteristics over Southern Africa is realistically captured by the fine resolution AFRICLIM baseline data (i.e. WorldClim observations) models, especially around the subtropical areas. Results proved that contemporary climate gets more detail at varied spatial resolutions. However, the AFRICLIM fine resolution datasets (AFRICLIM historical baseline [WorldClim interpolated observations] and AFRICLIM future projection [statistically downscaled and bias corrected CORDEX] projections) benefit from addition of spatial detail such as more structure reflecting the topography of the region which is not clear in the coarse resolution dataset as well as bias correction. In this chapter I test whether this seemingly added value presents any worth in modelling species distribution under contemporary climate envelopes obtained from fine and coarse models at grid spacing of 2km×2km, 5km×5km, 10km×10km, 20km×20km and 50km×50km.

To achieve the aim of the chapter, I run species distribution modelling experiments, to test the sensitivity of predictions of species distribution to different spatial resolutions of climatic predictor variables used as input data sets. I model species distributions of 150 terrestrial plants of the Okavango River Basin, spanning, Angola, Namibia, and Botswana to project their current distribution across spatial resolutions, at 2km×2km, 5km×5km, 10km×10km, 20km×20km and 50km×50km.

I give a systematic study comprising of general introduction (section 5.2) to the topic of species distribution, the dynamics of the use of climatic predictor data at multiple spatial resolutions in ecological modelling is also given. Section 5.3 presents the methods and data used i.e. stacked species distribution modelling software (SSDM) in building contemporary species distribution maps under the different spatial resolution of climatic predictor variables. In the same section I also give a description of the statistical approaches used to analyse any effects of the spatial resolution of climatic predictors on the prediction of species distribution and richness (i.e Generalised Linear Models and Tukey's Multiple Comparison post-hoc analyses). While subsequent sections present results interpretation, analyses, and discussion of the effects of spatial resolution of climatic predictor variables in species distribution modelling. I conclude the chapter in Section 5.6 by synthesizing the results and addressing the research questions of the chapter.

A version of this chapter is published as Tshwene-Mauchaza and Aguirre-Gutiérrez, 2019, **Climatic drivers of plant species distributions across spatial grains in Southern Africa tropical forests,** in Frontiers in Forests and Global Change.

5.2 Introduction

Species Distribution Models (SDM) have been a critical technique for investigating a variety of ecological, conservation and management issues (Garcia et al., 2012; Hannah, 2015; Van Echelpoel et al., 2015; Dellasala et al., 2018) as well as in studies of paleoclimate (Reichgelt et al., 2018). The technique relies on statistically associating contemporary species occurrence data with climatic and environmental predictors (Elith and Leathwick, 2009). Since its inception, the SDM technique has advanced from simple correlative ecological niche models (Araújo and Peterson, 2012) to more complex mechanistic models, incorporating range (Fordham et al., 2013; Zurell et al., 2016) and population dynamics, dispersal abilities (Fordham et al., 2013) and community dynamics (Singer et al., 2016). However, ecologists and conservation practitioners are still faced with problems of spatial and temporal scale variations in the datasets used in operating SDMs. There is no consensus about the most suitable spatial resolution for predictor data that can improve the accuracy of SDM prediction (Raven, 2002; Bradter et al., 2013; Fournier et al., 2017) and there is a lack of full understanding of the effects of building SDMs at multiple spatial resolutions of predictor variables, although this has an impact on management planning and conservation decision making (Porfirio et al., 2014; Yates et al., 2018).

The ecology and distribution of terrestrial plant and animal species are influenced by climatic conditions (Aguirre-Gutiérrez et al., 2015) across various spatial resolutions (Connor et al., 2017; Kosanic et al., 2018). Modelling of the species distributions under current and a changing climate requires spatially explicit environmental predictors. It is not surprising that one of the frequently documented sources of uncertainty in SDMs is insufficiency in the spatial resolution of the climate data used, often originating from low resolution global climate models (GCM) or from downscaled by-products of those models (Weibull et al., 2003, Dunford & Freemark 2005, Wang et al., 2016). Uncertainty in predictor variables can result from instrumental errors or methods used to collect the variables. In the case of climatic variables, this would include resampling of weather station data and gridded climate reanalysis products. The uncertainty in predictor variables can also emanate from spatial scaling (Scott, 2002), brought about by the disparity between the spatial resolution of the climate data and that of the species modelled, which may lead to uncertainty in the magnitude, rate and direction of changes of biodiversity imposed by the changing climate (Garcia et al., 2011; Wan et al., 2016).

The intrinsic properties of species occurrence data and their spatial resolution affect model performance and prediction abilities (Thuiller et al., 2003; Guisan et al.,2007a), they affect species occurrence probabilities (Garcia et al.,2012; Wan et al.,2016) and transferability of SDMs (Manzoor et al., 2018) Differences in spatial resolution of datasets have also been found to affect variations in the relative importance of environmental predictors determining plant distribution (Thuiller et al.,2003; Radinger et al.,2015). Investigating how the spatial resolution of environmental predictors in SDMs affects a model's variable importance can provide ways to use expert or theoretical knowledge in the decision-making process of what climatic variables input datasets to use in SDM's. Testing the sensitivity of predictions of species distribution models to the spatial resolution of predictor variables is, therefore, an important component to consider in/before applying SDMs. There is a lack of consensus on the direction and magnitude of effects of spatial resolution in SDMs, but it is important for practical use of this technique that consensus is reached (Rodríguez et al., 2007).

Africa is predicted to be highly vulnerable to the impacts of climate change. Extensive areas of the region are projected to have warming exceeding 2°C by the end of the 21st Century with a likely decline in precipitation (Collier et al., 2008). Different climate changes, whether wetting or drying can be projected depending on the region, the model and the target period, the studied CMIP5 GCM models in Chapter 4 depict variation in climate change based on the models, some show a wet future (increase in precipitation)) some a dry future (decline in precipitation). These changes in temperature and precipitation are already negatively impacting ecosystems and biodiversity, (Biggs et al., 2008) with evidence of species ranges shifts and changes to ecosystems (Garcia et al., 2012, 2014). Despite the continent's vulnerability to a changing climate, with a potential high loss of biodiversity (IPBES 2018), the likely impacts remain largely unstudied. In addition, the African arid tropical forests landscape has not yet been utilised to investigate intrinsic sensitivities of SDM modelling. Given the continent's vulnerability to climate change, effective, reliable, and high performing SDMs within the arid forests of Africa is critical.

Recent studies have aimed to increase confidence in species occurrence projections by tackling methodological uncertainties of ecological models (Diniz-Filho et al., 2009; Buisson et al., 2010). The Southern African landscape, climatic system and plant species diversity (Revermann et al.,

2016; Reason 2017), presents an ideal setting to investigate if and how the importance of environmental drivers for determining species distributions change across spatial resolutions. In this study I use 194 unique intensively sampled vegetation plots (nested design of 100-m^2, at the centre of 1000-m^2 plot) in the Okavango River Basin, and relevant climatic information to investigate and evaluate the effects spatial resolution of predictors has on SDM predictions. I then explore if and how the variation in spatial resolutions affects the patterns and estimations of species richness distribution. I specifically tackle the following questions:

1. Which are some of the main climatic determinants of the plant species distributions in the Okavango river basin?
2. What are the effects of spatial resolution on the importance of the climatic variables determining suitable climate space/species distribution? and,
3. What is the degree to which species richness estimations differ across fine to coarse spatial resolutions of climatic predictor data?

5.3 Methods and Data

5.3.1 Study Area

The study is based on the Okavango River Basin (hereafter ORB) located in Southern Africa (Figure 5.1) and spanning three countries: Botswana, Namibia, and Angola. An interesting and important case study given its special ecological status: as biodiversity hot spot and UNESCO world heritage site (UNESCO, 2014), as well as an ecoregion of global conservation priority (Botswana CBD report, 2009). Its relatively homogenous climatic and topographic background (Figure S5.1), also provides a tractable model system for exploring issues of spatial resolution in SDM. The ORB covers an area of approximately 1,860km^2 including the delta. The basin is comprised of distinctive landscape units starting with the semi-humid Angolan highlands in the north where the Okavango river originates, South of this are lowlands, followed by the Okavango Delta in Northwest Botswana (Revermann et al., 2016a). The Okavango Basin has a strong rainfall gradient with a mean annual precipitation of 1,300 mm in the north east and >500 mm in the southwest. The wet season is between the austral summer months of December, January, February. Climatic, geological and soil conditions control the flow regime of the river. The Okavango basin is a key conservation region as it is a major wetland system and harbours

vital seasonal habitats that support a high diversity of species. The basin features a latitudinal gradient of a transitioning wet/dry type of tropical climate and landscape where the vegetation can be clustered into 13 vegetation communities (Revermann et al., 2016a). This plant community composition appears to be driven by variations in wetness and soil texture and fertility (Ramberg et al., 2006).

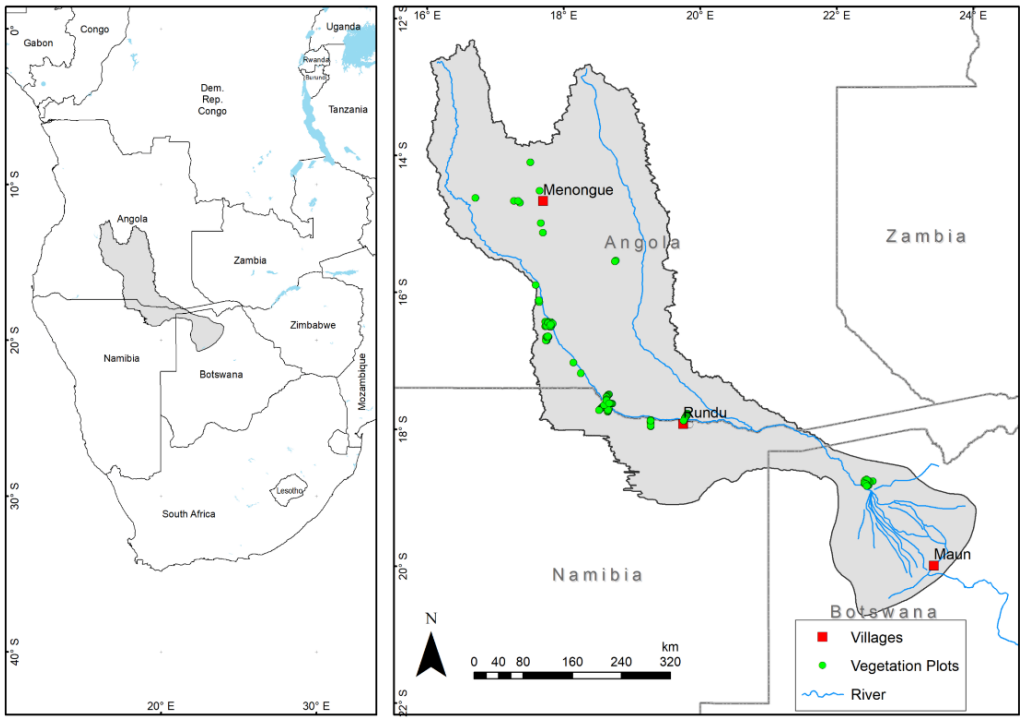


Figure 5.1: Location of the Okavango Basin in Southern Africa with the map of the Okavango Basin showing the location of vegetation plots used for this study

5.3.2 Vegetation Species Sample

In this study I used the Vegetation Database of the Okavango Basin (GIVD ID: AF-00-009, http://www.givd.info/ID/AF-00-009) (Revermann et al., 2016a) collected through The Future Okavango (TFO) project. The database contains samples from a wide range of terrestrial vegetation, such as *Miombo* woodlands and forests, geoxylic grasslands, *Baikiaea-Burkea* woodlands, and *Colophospermum mopane* woodlands. The terrestrial vegetation presence/absence data comes from a plot network consisting of 194, 1000m^2 plots.

5.3.3 Climate Data

The CORDEX initiative (Giorgi et al., 2009) has made available Regional Climate Models (RCM) for Africa. The RCM outputs have been empirically downscaled by AFRICLIM to resolutions applicable to ecological modelling. Through this, the AFRICLIM project has produced high resolution climate projections for ecological application in Africa (Platts et al., 2015). The climate data I used for this study was different resolutions of AFRICLIM baseline (observations interpolated from WorldClim). The WorldClim v1.4 datasets were generated through interpolation of average monthly climate data from weather stations and the averages were calculated for the period 1950-2000 (Hijmans et al., 2005). Variables included are monthly total precipitation, monthly mean, minimum and maximum temperature. Nineteen (19) bioclimatic variables then derived from the monthly data. For this study I selected 10 bioclimatic variables as detailed below. The period from 1950-2000 is commonly used to represent conditions at the beginning of the impacts of anthropogenic climate change and is therefore used as the present period.

Climatic conditions are critical to plant physiological function and survival (Becklin et al., 2016), and are therefore among the most important agents in determining the distribution of vegetation. The seasonally arid tropical region of the ORB calls for variables that measure and include the intensity of the dry or wet season**.** I therefore selected the bioclimatic variables based on their significance to plant physiology. Used is a combination of coldest and warmest quarter mean temperatures (mtwq), annual ratio of actual to potential evapotranspiration (pet) and a measure of the rainfall intensity of the dry /wet season (moisture index moist quarter [mimq], rainfall driest quarter [rdq], temperature seasonality [tempSea]), see Table 1. The bioclimatic variables were used at the following four different spatial resolutions 2km×2km, 5km×5km, 10km×10km and 20km×20km [from the AFRICLIM v.30 database (https://webfiles.york.ac.uk/KITE/AfriClim/] Applying the bilinear interpolation method, I interpolated the mean values of the 20km×20km climatic variables to a 50km×50km grid size. The remapping was done in Climate Data Operators (CDO 2018: Available at: http://www.mpimet.mpg.de/cdo). In this chapter I use scale descriptors “finest” to refer to spatial resolution at 2km×2km, “fine” to refer to 5km×5km, “intermediate” to refer 10km×10km & 20km×20km and “coarse” to refer to 50km×50km.

Prior to model calibration, I conducted a sensitivity analysis in order to identify and remove highly correlated variables, while retaining variables that are known to be important determinants of plant distribution (Braunisch et al., 2013). A Variance Inflation Factor [VIF] (Zuur et al., 2010; Naimi et al., 2014) with a threshold of 3 was used and highly collinear variables were excluded through a stepwise procedure. From the original ten variables, five had a collinearity problem: mean temperature coolest quarter, rainfall seasonality, rainfall wettest quarter, moisture index arid quarter and length of longest dry season. The remaining five variables that represent climate variability and extremes were retained for use in the study (Table 5.1).

Table 5.1: Bioclimatic variables used to generate contemporary species distribution models of the vascular plant species (bioclimate data products sourced from AFRICLIM baseline data i.e., WorldClim v.1.4 observations at different resolutions)

Variable's acronym	Description	Units
tmpSea	Temperature Seasonality	mm (standard deviation*100)
mtwq	Mean temperature warmest quarter	◦C
PET	Potential evapotranspiration	mm
rdq	Rainfall driest quarter	mm
mimq	Moisture index moist quarter	%

Climatic variables represent annual trends and seasonality.
They are derived from monthly temperature (units: ◦C) and rainfall (mm)

5.3.4 Fitting Species Distribution Models

I fitted SDMs for the current period (1950-2000) across five climatic predictor spatial resolutions from local to regional scale (2km×2km, 5km×5km, 10km×10km, 20km×20km & 50km×50km) to test whether predictor variables change in importance. The SDMs were built by assembling 6 widely used modelling algorithms (Table 2): 3 machine learning methods, Random Forest (RF), Artificial Neural Networks (ANN) and Classification Tree Analysis (CTA); two regression methods: Generalised Additive Models (GAM) and Generalised Linear Models (GLM) and one Maximum Entropy Modelling (Maxent). I fitted the SDMs for all 150 species with the five non-collinear climatic variables (Table 5.1). As different sets of data are used for calibrating the

model, to account for within-algorithm model variation, I computed distribution models for each species using ten model repetitions, producing a total of (150 species × 6 algorithms × 5 spatial resolution ×10 replicates) 45,000 models. Evaluation of the performance of the models in terms of accuracy was based on the Area Under the curve (AUC) of the Receiver Operator Characteristic Curve. The AUC's threshold and prevalence independent nature, renders it an effective model accuracy metric (Allouche et al., 2006). I then constructed ensemble species distribution models by averaging the model predictions across the individual SDMs for each species and after excluding the models with lowest AUC values (AUC <0.60). A total of 750 ensemble SDMs were obtained (150 species x 5 grid sizes). All analysis were done in the R statistical environment version 3.5.1 (R.Core Team, 2013) using the SSDM package (Schmitt et al., 2017).

Table 5.2: Statistical methods used to fit the vascular plant species distributions models

Algorithm	abbreviation	References
Random Forest	RF	Breiman and Leo (2001)
Maximum Entropy Modelling	MAXENT	Phillips et al., (2006)
Artificial Neural Networks	ANN	Ripley and Hjort, (1996)
Classification Tree Analysis	CTA	Breiman et al., (1984)
Generalised Additive Models	GAM	Hastie and Tibshirani, (1986)
Generalised Linear Models	GLM	McCullagh and Nelder, (1989)

5.3.5 Predicting Species Richness

I predicted local species richness and composition using a stacked species distribution modelling approach (Dubuis et al., 2011) and a macroecological model. I estimated the species richness with the Spatially Explicit Species Assemblage Modelling (SESAM) framework and a Macroecological Model [MEM], (Guisan and Rahbek 2011) using the ecological assembly probability ranking rule [PRR] (see D'Amen et al. 2015). The PRR rule follows as assumption that species with the highest habitat suitability are more competitive than those with the lowest habitat suitability (D'Amen et al., 2015; Schmitt et al., 2017). In the MEM a number of species equal to the prediction of species richness is selected on the basis of decreasing probability of

presence calculated by the SDMs (Guisan and Rahbek. 2011; Del Toro et al., 2019). To set the macroecological constraints per site, the ensemble SDM models were overlaid and ranked by their habitat suitability, retaining as many species as the predicted richness of the macroecological model suggested (Schmitt et al., 2017). For observed species richness, the number of species within the 150-species pool, present in each sampling plot was taken as the observed species richness.

I constructed the presence and absence species range maps to assess effects of spatial resolution of predictor variables on estimates and spatial patterns of species richness. The present time species richness maps (Figure 5.6) were achieved as described above and across the fine to coarse spatial resolutions (2km×2km, 5km×5km, 10km×10km, 20km×20km & 50km×50km).

5.3.6 Species Richness Maps Accuracy Assessment Across Spatial Resolutions

To assess the accuracy (disagreements between the prediction and reality) of the species richness maps across the sets of different spatial resolutions, I used the observed occurrence data from the plots. The proportion of accurate richness predictions and true negatives, true positives and similarities in species richness were analysed using the species richness error, prediction success, Cohen's Kappa coefficient (Schmitt et al., 2017). I compared the five species richness prediction maps, per spatial resolution, against our observed control points.

5.3.7 Drivers of Species Richness

To identify the main determinants of species richness and explore the effects of predictor spatial resolution on the species richness, I used variable importance values (see next section for a full description) as computed during the modelling of species richness.

5.3.8 Investigating Importance of Climatic Drivers across Spatial Resolutions

The modelling of species distribution entails the operation and interaction of mechanisms at different scales: one at the response scale, the analysis /operational scale, and the study extent scale (environment spatial resolutions) (Mertes and Jetz). Here I evaluate the effects of operational spatial resolution on the SDMs variable importance across fine to coarse spatial resolution (2km×2km, 5km×5km, 10km×10km, 20km×20km, 50km×50km). Using the SDM approach described above I assessed which of the variables determine the species suitable

climate space distribution. I calculated the variable importance (VI) scores from each SDM, and variable involved in the models. These VIs reflect the relative contribution of environmental predictor variables to the model outputs and may depend on the predictor spatial resolution at which the species distributions are modelled. For the VI calculations I used the "Percentage Contribution" scores (Thuiller et al. 2009; Schmitt et al. 2017), which has been successfully used in recent similar studies (Gallardo and Aldridge, 2013; Quillfeldt et al., 2013; Aguirre-Gutiérrez et al., 2017b), as a measure of variable importance. The percentage contribution is calculated by building an SDM with the original explanatory variables and then comparing it to another built by randomising the focus variable and then investigating the correlation between those two models. Therefore, the final VI score is computed as one minus the correlation value between the two models mentioned above and standardised to percentage variable importance. The higher the percentage, the more importance the variable has on the model.

I therefore evaluated the SDM outputs in three ways: (i) variable importance scores for each variable were compared across the sets of predictor spatial resolutions, (ii) species richness estimates and distribution patterns were compared across spatial resolutions of climatic predictors, (iii) model performance was compared across the spatial resolutions, based on AUC and Kappa values (Guisan et al., 2007b). In this analysis I used the spatial resolution of predictors interacting with variable identity as a test factor and the response variables being models' variable importance scores, both for single and species richness maps, model performance and model spatial output.

5.3.9 Generalized Linear Models

To investigate how the relative importance of climatic predictor variables changes as a function of the spatial resolution of the predictors, I fitted a Generalised Linear Model (GLM) (Venables and Ripley, 2002). I converted the VI scores to a 0 to 1 range and modelled them using a binomial error structure with a logit link function which I selected following a test of both the default and the user specified complementary log-log, where the model with the lowest deviance fit was then chosen. I tested the model for overdispersion using the chi-squared method, no suggestions of over dispersion were found. The fitted GLM thus contained the VI score (of the

SDMs or Species richness predictions) as a response variable and the climatic variable identity, the spatial resolution, and their interaction as explanatory variables.

The logistic regression analysis is used to (i) examine whether the relationship between the variable importance scores interacting with climatic predictors is significant; and (ii) to establish the contributions and roles of the different spatial resolution sets of climatic predictor variables.

In order to test for pairwise significant differences between the climatic variables interacting with spatial resolution, I performed a multiple comparison analysis (post-hoc comparison test) using Tukey's Honest Significant Difference (Yandell, 2017). All statistical analyses were carried out in the R platform (R development core team, 2007), with the MASS (Venables and Ripley, 2002) and the lsmeans packages (Lenth, 2016). Fitted GLM:

*Model = glm (VIscore*0.01 ~ Videntity: scale.km., family=binomial, data=mydata)*

5.4 Results

5.4.1 Species Distribution Models Evaluation

I found all species distribution models to be effective in predicting the vascular plant species distributions, with a fairly good median AUC score > 0.7 and an interquartile range of 0.1 (Figure 5.2 and Table S5.1, Appendix). There was no effect of spatial resolution in the performance of the models, as evident from the reported consistent AUC values (Table S5.1, Appendix).

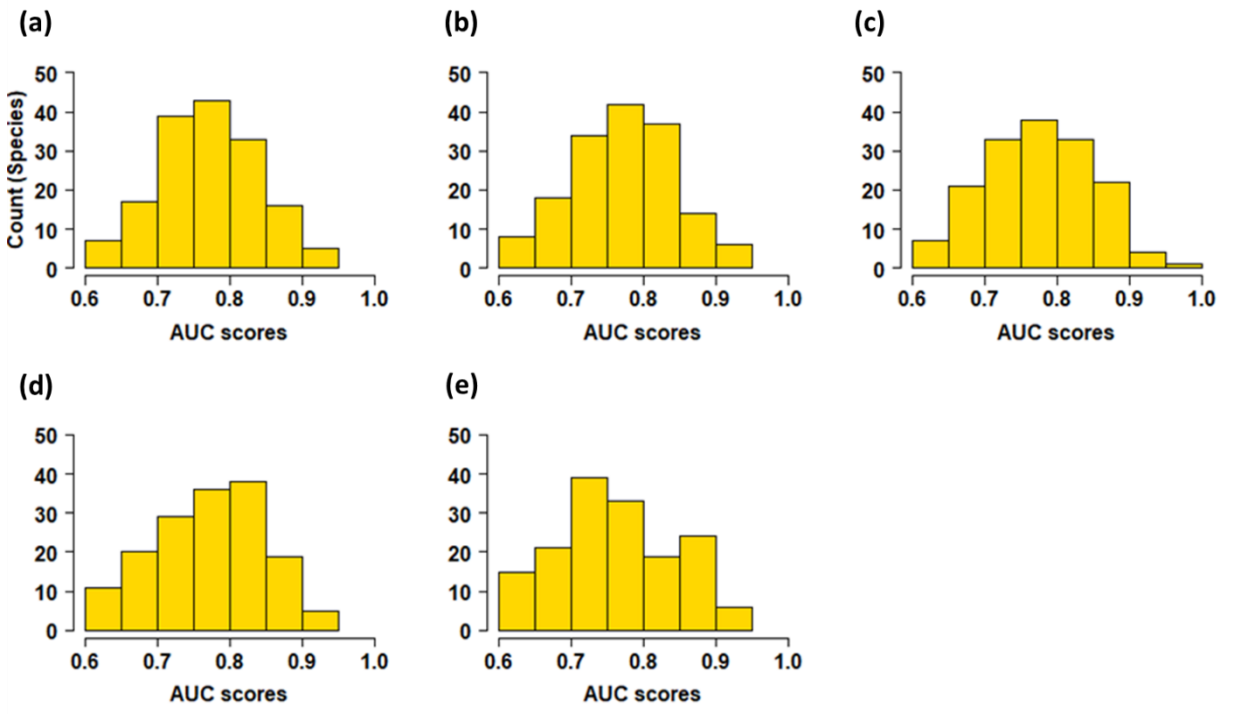


Figure 5.2: Histogram of Area Under the ROC Curve (AUC) scores showing model performance for all species (A) model performance at 2km×2km, (B) model performance at 5km×5km, (C) performance at 10km×10km, (D) performance at 20km×20km, and (E) at 50km×50km. The figure indicates that all models are effective in predicting the plant species distribution with no effect of spatial resolution in the performance of the models.

Within spatial resolutions comparisons based on Figure 5.3

Finest and fine spatial resolution (2km×2km & 5km×5km)

At the finest scale of 2km×2km a generally very good prediction accuracy of species is given, with ninety-two species models having an AUC of between 0.8-0.9, five models displaying excellent prediction accuracy AUC>0.9, fifty-six models giving good accurate predictions with AUC=0.7-0.8, and only seven models fairly predicting the species, AUC=0.6-0.7. At the fine spatial resolution of 5km×5km, a very good prediction accuracy is also achieved with the majority (ninety-three) of the models performing resulting in AUC values of between 0.8-0.9, six models excellently predicting the species at AUC>0.9, with fifty-two models giving good predictions and only 8 having fair prediction accuracy.

Intermediate spatial resolution (10km×10km & 20km×20km)

Decrease in spatial resolution from fine to coarse, does not cause any noticeable discrepancy in prediction accuracy. At both 10km×10km and 20km×20km spatial resolutions, the same number of species models give very good and good prediction AUC values as the fine spatial resolution. the 10km×10km spatial resolution sees one model achieve an excellent prediction accuracy with AUC=1.0.

Coarse spatial resolution (50km×50km)

At the coarser regional scale of 50km×50km, there are no significant differences in the model performance as compared to the fine and intermediate spatial resolutions. The pattern in performance of accuracy AUC values is similar to those in the fine models.

Across spatial resolution comparisons:

When comparing the model performance across spatial resolution, there is a clear pattern of most of the best models being achieved at AUC=0.75-0.90 across all spatial resolutions from fine to coarse. The species model performances tend not to be scale –dependent as there is similar performance of model accuracy from the fine-coarse spatial resolution (Figure 5.2). Prediction accuracy on evaluation data of the species models across different spatial resolutions is also similar as depicted by summary statistics of AUC model predictive performance (Figure 5.3)

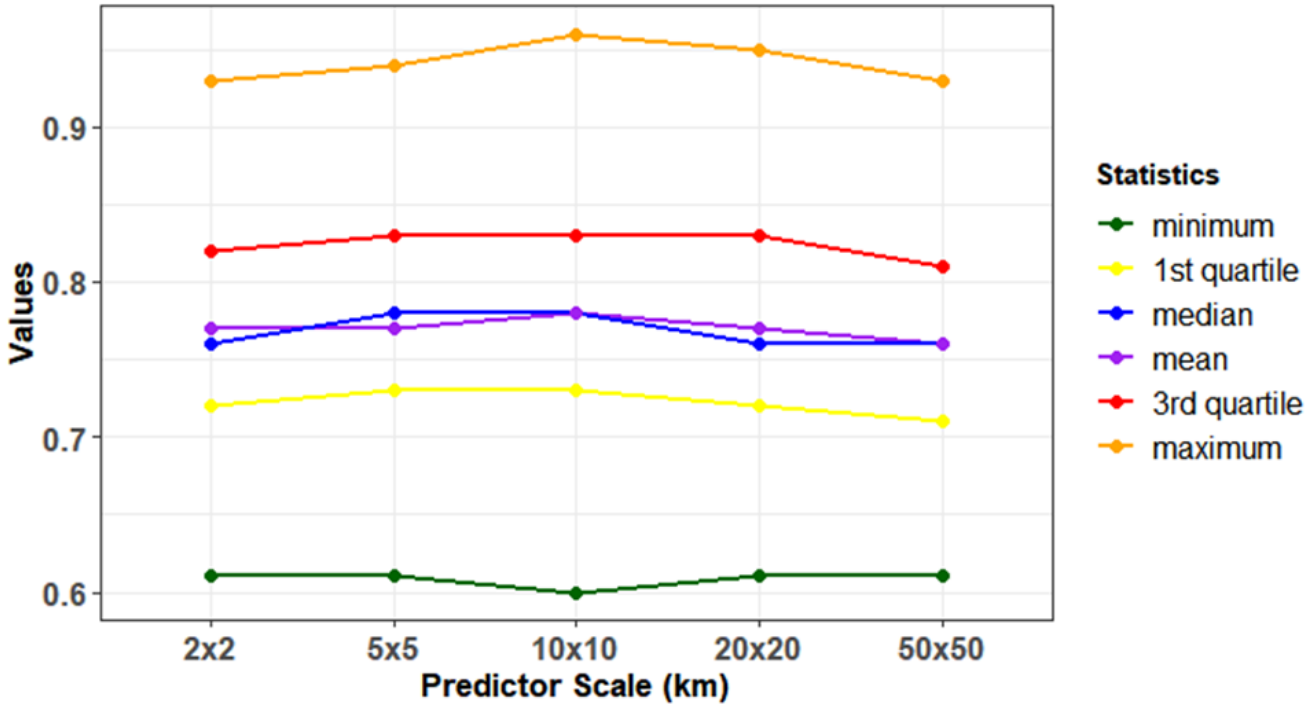


Figure 5.3: Change in the median, range and quartiles of the AUC distributions as a function of predictor spatial resolution from 2km×2km to 50km×50km

5.4.2 Main Climatic Determinants

Variations in the spatial resolutions of environmental predictors have effects on the importance of climatic variables in determining species suitable climate space. This analysis (Figure 5.4) shows PET having the largest effect in determining the species suitable climate space (distribution) of plants of the ORB at fine predictor spatial resolutions (2km×2km, 5km×5km). An aggregation of one in predictor spatial resolution (5km×5km vs 10km×10km), alters the order of the contribution of the temperature related variable to the present-day species distribution. The contribution of PET slightly reduces and mimq slightly increases at 10km×10km, with mimq accounting for the highest variability with a VI of 28%. At 20km×20km the importance contribution of PET is further reduced (Figure 5.4). However, percentage differences leading PET to lose its key determinant position at 10 and 20km^2 are negligible. At the coarse spatial resolution (50km×50km) PET reassumes its role as the strongest predictor (Figure 5.4).

5.4.3 Within Variables Effects of Spatial Resolution

Interestingly, negative interactions are portrayed between some variable identities and predictor spatial resolution. When considering the rdq, a pattern of no difference in the contribution importance is detected across all the different spatial resolutions, as the variable tends to have even importance values (Table S2: Appendix). Results from the multiple comparisons, Tukey's p-values and GLM test across spatial resolutions, show no statistically significant differences in the variable's importance in driving the species climatically determined distribution, whether on fine or coarse spatial resolution (Table 5.3; Table S3: Appendix). This pattern of no variation across spatial resolutions also holds for temperature seasonality (Table 5.3; Table S3: Appendix). Spatial resolution has therefore no significant effect on the contribution of these climatic variables to plant species distribution.

Decreases in the spatial resolution of predictor variables causing an increase in variable importance gives a mixed response. The notion is only apparent for the mtwq where the highest importance values are observed at an intermediate and coarse resolutions of 20km×20km (27%), 50km×50km (23%) and 10km×10km (23%), (Figure 5.5 & TableS2: Appendix). Significant interactions ($p<0.05$) for the effect of spatial resolution on mtwq were observed at these coarse spatial resolutions (Table 5.3). However, when considering the local spatial resolution, there is an exception to this notion as at the finest resolution of 2km×2km, the temperature variable gains more importance than at a fine spatial resolution of 5km×5km. Based on multiple comparisons, Turkey's p-value ($p>0.05$), the difference in the importance values at both the 2km×2km and 5km×5km is however insignificant (Table S2 & S3). At these fine spatial resolutions, the GLM test also displays a no significant effect ($p>0.05$) of spatial resolution to the temperature related variable (Table 5.4).

Specific climatic variables such as mimq quite clearly display less evidence of predictor spatial resolutions' influence on the variable importance. The rainfall variable performance at a 20km×20km distribution model is equivalent to that at the finest scale of 2km×2km. Even though the predictor spatial resolutions are spread apart, both produced a relative importance contribution of 22% (Figure 5.4 and Tables S2, Appendix). Multiple comparisons analysis and GLM test ($p>0.05$) show no significant difference in the importance of the variable in driving the

species climatically determined distributions, whether at the finest spatial resolution or coarse resolution (Table 5.3; Tables S3, Appendix). At the coarse 50km×50km the spatial resolution has an insignificant effect on the mimq variable importance (*p=0.254),* (Table 5.3).

Table 5.3: Model results assessing changes in the mean variable importance of climatic variables across predictor spatial resolutions. Highlighted p-values show significant effects of predictor spatial scale on the mean variable importance of climatic variables at at p<0.05. For more statistical details see the post –hoc tests, Tables S2-S3 in supplementary material Appendix S1.

Predictors	*Odds Ratios*	*C.Int(95%)*	*p*
(Intercept)	0.13	0.08 – 0.22	**<0.001**
Moisture index moist quarter:2km×2km	2.11	1.12 – 3.97	**0.020**
Mean temperature warmest quarter:2km×2km	1.69	0.89 – 3.24	0.110
Potential evapotranspiration:2km×2km	3.81	2.09 – 6.97	**<0.001**
Rainfall driest quarter:2km×2km	1.02	0.51 – 2.06	0.956
Temperature Seasonality:2km×2km	1.28	0.65 – 2.51	0.475
Moisture index moist quarter:5km×5km	2.37	1.27 – 4.42	**0.007**
Mean temperature warmest quarter:5km×5km	1.47	0.76 – 2.84	0.254
Potential evapotranspiration:5km×5km	4.31	2.37 – 7.85	**<0.001**
Rainfall driest quarter:5km×5km	1.02	0.50 – 2.06	0.958
Moisture index moist quarter:10km×10km	2.92	1.58 – 5.39	**0.001**
Mean temperature warmest quarter:10km×10km	2.29	1.22 – 4.28	**0.010**
Potential evapotranspiration:10km×10km	2.74	1.48 – 5.07	**0.001**
Rainfall driest quarter:10km×10km	0.98	0.49 – 1.99	0.964
Temperature Seasonality:10km×10km	0.92	0.45 – 1.87	0.808
Moisture index moist quarter:20km×20km	2.06	1.09 – 3.88	**0.025**
Mean temperature warmest quarter:20km×20km	2.84	1.54 – 5.26	**0.001**
Potential evapotranspiration:20km×20km	2.44	1.31 – 4.54	**0.005**

Rainfall driest quarter:20km×20km	1.30	0.67 – 2.55	0.439
Temperature Seasonality:20km×20km	1.05	0.52 – 2.11	0.892
Moisture index moist quarter:50km×50km	1.57	0.82 – 3.03	0.174
Mean temperature warmest quarter:50km×50km	2.32	1.24 – 4.33	**0.008**
Potential evapotranspiration:50km×50km	2.68	1.45 – 4.97	**0.002**
Rainfall driest quarter:50km×50km	1.86	0.98 – 3.52	0.059
Temperature Seasonality:50km×50km	1.17	0.59 – 2.33	0.648
Observations	3750		

A five - and ten-fold increase in the spatial resolution of the climatic predictor variables (10km×10km and 20km×20km) causes a significant influence in variable importance, however this was only observed in three variables; mimq, mtwq and PET (*p<0.05*; Table 5.3). A 25-fold increase to 50 km×50km exerts influence only on the importance of temperature related variables: the mtwq (*p=0.008*), and PET (*p=0.002*). The broadening of the spatial resolution from 20km×20km to regional scale of 50 km^2 does not cause any effect on mimq, or rdq and tempSea with (*p>0.05*; Table 5.3). The fine spatial resolution of 2km×2km and 5km×5km, have a statistically significant effect on PET (*p<0.001*) and a significant effect on mimq (*p=0.020* and *0.007*, respectively, Table 5.3). The results suggest that among the analysed variables, there is a significant interaction between the mean variable importance of PET only, across all spatial resolutions.

Even though the importance order of the temperature and precipitation species distribution determinants, display slightly different tendency across the spatial resolutions (Figure 5.4 and Table S5.2: Appendix), the differences in each variable's mean importance values at the fine to coarse spatial resolutions, are quite small (Tables S5.2, Appendix). Across the spatial resolutions at 5km×5km 10km×10km, 20km×20km and 50km×50km temperature seasonality maintains its position as the least importance contributor. An exception to this is depicted at the finest resolution of 2km×2km, where the temperature seasonality displays a higher importance than rainfall of the driest quarter, relative to the other spatial resolutions of the predictor variables.

Overall, the results show that importance of the climatic variables does not vary consistently with predictor spatial resolutions.

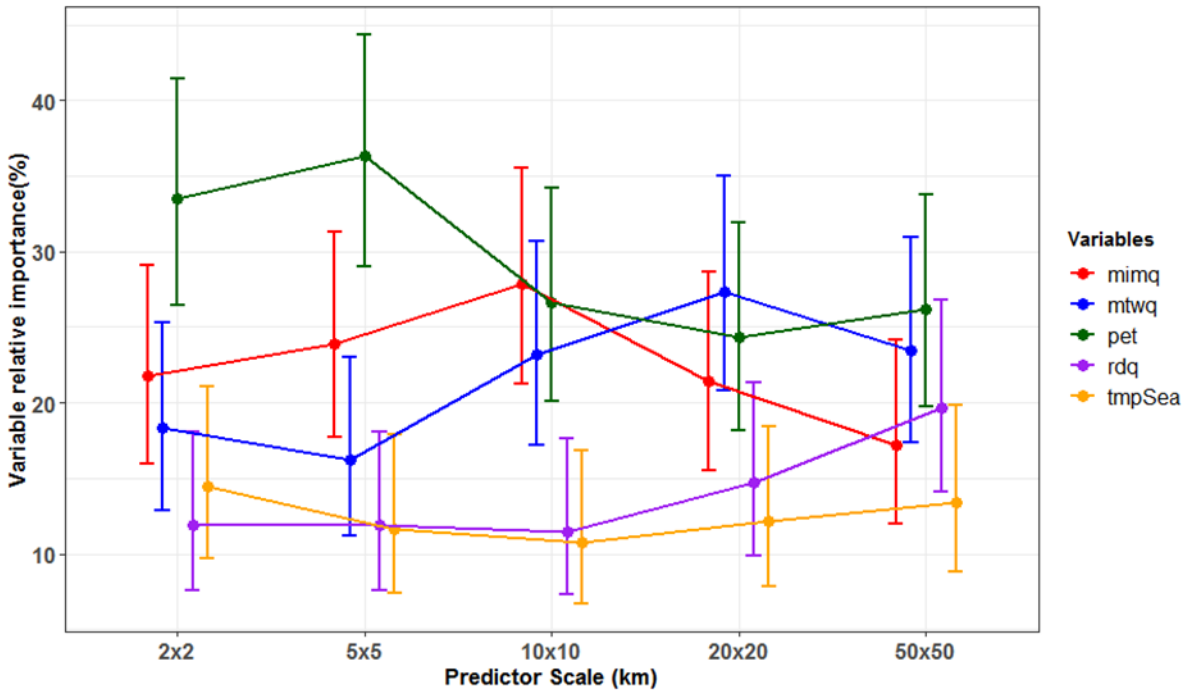


Figure 5.4: Climatic variable importance for the plant species distributions across predictor spatial resolution (2km×2km, 5km×5km, 10km×10km, 20km×20km,50km×50km). The figure depicts average effects of predictor spatial resolution on the importance of climatic variables driving species distribution (bars depict the 95% confidence interval over 150 species models). It also illustrates within and between variables, and between predictor spatial resolutions differences in the importance performance of the climatic variables driving the ORB plant species distribution. Climatic variables: moisture index moist quarter (mimq), mean temperature warmest quarter (mtwq), potential evapotranspiration (pet), rainfall driest quarter (rdq), temperature seasonality (tmpSea). For details of the generalised linear model see supplementary material Appendix S1.

5.4.4 Comparisons of Species Richness Distribution Maps Accuracy Assessment

Species richness distribution models that use different spatial resolutions of climatic predictors do not differ significantly as measured by the Kappa coefficient. Across all the species richness maps produced at different spatial resolutions, a high level of agreement with Kappa scores of 0.99 is achieved (see Table S5.5 appendix). However, corresponding levels of species presence and absence per given point against the observed occurrence data points, varied slightly across

the different spatial resolutions. The variation between the predicted and observed species richness marginally increases with the increase in the spatial resolution of predictors, where at the coarse spatial resolution of 50km×50km, the highest average of 5.56 species richness error/250km vs 2.74/4km is detected, and the lowest 2.51 species richness error/25km species richness error obtained at 5km^2 (Figure 5.5, Table S5.5).

The richness maps at the finest and coarse spatial resolutions of 2km×2km and 50km×50km, offer the highest chance of a predicted species being found in that grid square. On average, prediction success at both the local and regional spatial resolution is 19.11 and 19.26 respectively. No emerging trend is observed as the next fine spatial resolution of 5km×5km gives the lowest proportion of accurate predictions with a mean of 18.53. This analysis shows that strong predictive capacity is obtained at the coarse species richness maps (50km×50km). However, there is a very small variations in the proportions of prediction success of the models across all predictor spatial resolutions.

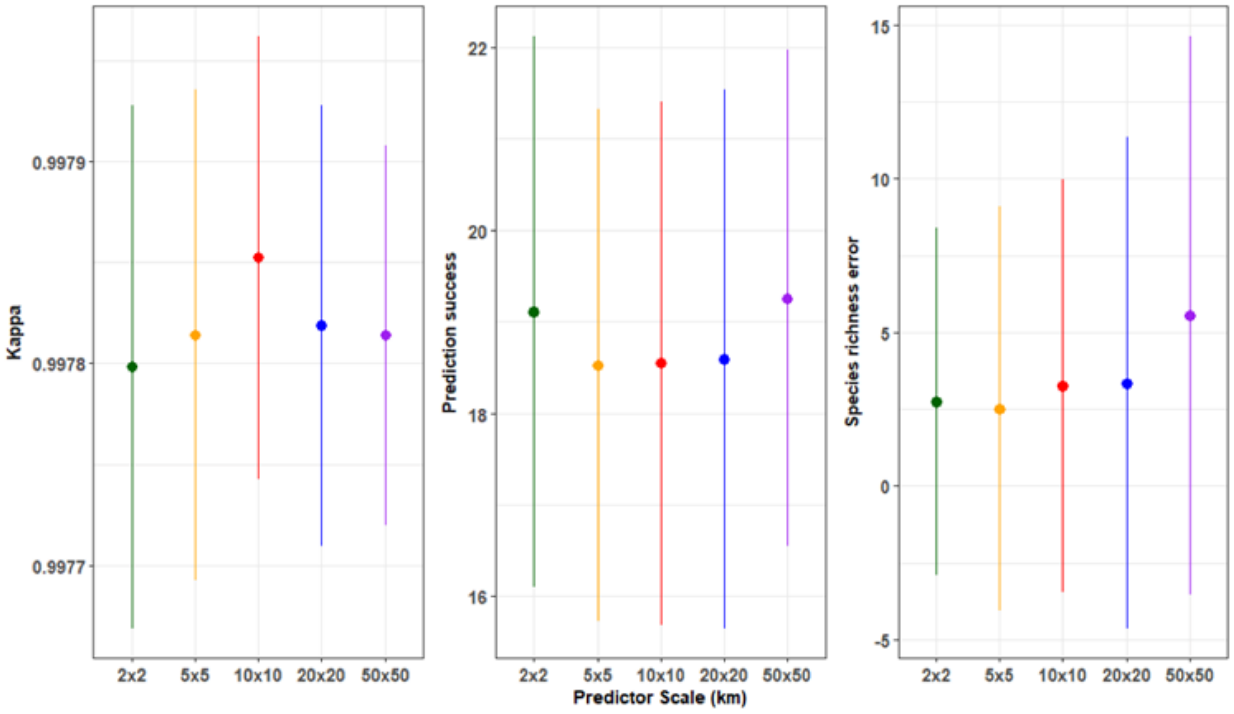


Figure 5.5: Species richness maps accuracy assessment. The figure explores the effect of predictor spatial scale and the accuracy of species richness maps based on 3 evaluation metrics; Cohen's Kappa, Prediction success, Species richness error (bars depict the 95% confidence interval).

5.4.5 Current Patterns of Species Richness across Predictor Spatial Resolution

The distribution, patterns and estimate of richness displayed no major variation with decrease of the spatial resolution of climatic predictors from local to regional scale. Within the boundaries of the case study, the maximum estimated richness of 40-60 species per km×km is in Northern Namibia, with medium (20-40 species per km×km) richness predicted in the centre of the domain, while the centre of Angola and wider Southwards areas at the bottom of the delta depict a low estimated richness of 0-20 (Figure 5.6). This pattern is observed across all species richness maps from local (2km×2km) to regional (50km×50km) scale. When considering the area coverage of richness across the projected models, we see the coarser spatial resolution (Figure 5.6c, d and e) leading to a slightly greater area predicted to contain a high richness (i.e., dark green patch increases in size 40-60 per km×km). Whereas the finer resolutions (Figure 5.6a and b) show that species richness is not equal within these high richness areas shown at a coarser resolution.

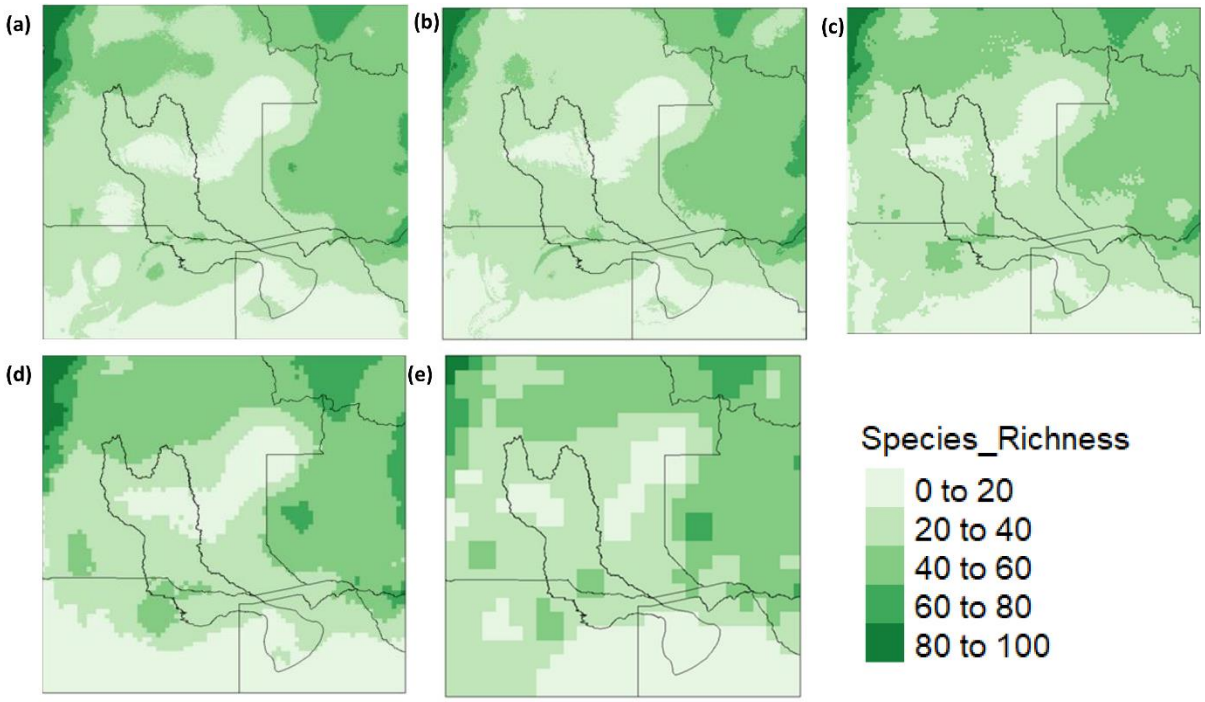


Figure 5.6: Estimate present day predictions of species richness for the study domain across predictor spatial resolutions derived from SSDM (a) species richness at a 2km×2km, (b) species richness at 5km×5km, (c) richness at 10km×10km,(d) richness at 20km×20km,(e) richness at 50km×50km.

5.5 Discussion

The understanding of how the spatial resolution of environmental predictor variables influences the species geographic occurrence is critical for studies inferring ecological niche relationships, (Verbruggen et al., 2013; Radinger et al., 2015; Manzoor et al., 2018b; Yates et al., 2018). This understanding is important for developing biodiversity monitoring tools for conservation decision making (Rodríguez et al., 2007) as well as developing management and conservation (adaptation) strategies. Moreover, accounting for any uncertainties in species distribution models is of pivotal importance, especially when building species distribution for biodiversity conservation (Vaughan and Ormerod 2003; Rodríguez et al., 2007; McInerny and Purves 2011). The results offer important insights on the relationships between changes in plant suitable climate space and environmental variables across spatial resolutions (2km×2km to 50km×50km).

5.5.1 Identification of Main Climatic Determinants of Plant Species Distributions

Some climatic variables determining species distributions were relatively inconsistent across spatial resolutions. However, PET outperformed other variables as it was progressively selected as an important driver for the plant species and richness distributions at the finest and fine spatial resolutions and the coarse resolution of 50km×50km, which is in agreement with Thuiller et al. (2003) who reported consistency in some variables selected by SDMs across spatial resolutions. It is not surprising that PET is a key driver of ecological patterns in the ORB given that an estimated 98% of total inflow to the basin is lost through evapotranspiration (Ramberg et al., 2006). The results suggest that moisture too plays and important role in determining plant distributions, as the rainfall related climatic variable; moisture index of moist quarter, presents strong predictive power at 10km×10km. This differs with findings of Revermann et al. (2016), who showed that moisture based climatic variables displayed less predictive strength over the domain of study whereas temperature related variables have strong predictive power. Plant species of the Okavango river basin are susceptible to shifts in temperature related conditions and this has implications in the vegetation patterns and diversity of the river basin (Tonkin et al., 2017). It is expected that as the climate of Southern Africa gets drier by the end of the 21st

century (Shongwe et al., 2009; Niang et al., 2014b), the basin will be dominated by drier vegetation types such as *Baikiaea burkea* and *Colophospermum mopane* woodlands.

5.5.2 Spatial Resolution Effects on the Importance of Climatic Variables

Contrary to the findings of Wan et al. (2016) whose results of a global study showed a positive dependence of variable importance on spatial resolution, this study results suggest that the response of a species to climatic variables is relatively independent of the spatial resolution of the variables in the ORB region. Spatial resolution in a relatively flat homogenous landscape like the interior sand sheet of the south western region of Southern Africa (study area) may therefore be less important than in a more heterogeneous landscape (Raes and Aguirre-Gutiérrez, 2018). Thus, landscape level homogeneity in climatic and topographic conditions (Reason et al., 2006; Weber, 2013) may also contribute to the explanation of the lower dependence of variable importance to spatial resolution in our study area. The results suggest that climatic variables that determine species distribution patterns can still be appropriately detected and estimated at coarse spatial resolutions of predictor variables. Studies with the aim of evaluating niche relations and identification of predictor variables driving species occurrence, such SDM models, can be operated at both the local (2km×2km) and regional spatial resolutions of up to 50km×50kmat least in the context of relatively flat climatically and topographically homogeneous landscapes. This is an encouraging finding for conservation practitioners, given the resource demanding processes of downscaling climate variables to fine (2km×2km) spatial resolution for ecological modelling.

5.5.3 Accuracy Assessment of Species Richness Prediction Across Spatial Resolutions

The expectation is that the levels of accuracy in species richness predictions would differ across the spatial resolution of predictors, with accuracy declining with the decrease in spatial resolution, (Connor et al., 2017). For the studied species and area, there was a high level of agreement between prediction maps based on different spatial resolutions from fine to coarse. These results are inconsistent with Seo et al. (2009), who concluded that increases in spatial resolution (1km×1km to 64km×64km) causes AUC predictive model values to decline while the

predicted geographic extent of species climatically determined distribution increased. Moreover, the results are comparable to those of Guisan et al. (2007b), who found that variation in spatial resolutions of predictor variables (between 100m-10km) had minimal impact on model performance. Therefore, the results suggest that the benefit of increasing predictor spatial resolution does not necessarily result in an increase of model accuracy.

5.5.4 Effects of Predictor Spatial Resolution on Species Richness

Measure of species richness are shaped by multiple biotic and abiotic factors, one of which may be spatial resolution (Keil et al., 2012). In this study, irrespective of the stacked species distribution models being constructed on varying resolutions of climatic predictor variables, similar distribution patterns and estimates of species richness were obtained (Figure 5.6). This implies that spatial resolution has a small effect on the estimates, pattern, and distribution of species richness in my study area. However, this does not imply that the spatial generalisation in the predictions caused by a coarse spatial resolution does not also cause a possible overestimation of species richness, as also shown by other studies (Seo et al., 2009; Franklin et al., 2013). It is therefore imperative to note that modelling species richness at coarse spatial resolutions is a trade-off between data availability and generalisation of species richness distribution patterns. Some important details, such as information associated with uncertainty of model predictions, are lost when modelling species richness patterns at coarse spatial resolutions and such limitations should be accounted for when applying SDMs for species conservation decision making.

5.6 Conclusion

This chapter's results contribute to the on-going debate on what the adequate spatial resolution of climate data is for an accurate prediction and identification of determinants of species distribution and species richness patterns. For conservation purposes, species distributions models and species richness predictions for current and future climate scenarios may be undertaken at a coarse spatial resolution in areas with relatively low climatic and topographic variation as the one shown in my study, with high statistical accuracy and from fine to coarse spatial resolutions. However, the use of SDMs across spatial resolutions will need to be tailored

to the specific location, data available and questions being addressed for effective biodiversity management and conservation. In addition, coarse spatial resolution modelling being acceptable in the case of low topographic variation needs further testing in a more heterogenous region.

6. Potential Impacts of Climate Change on Okavango River Basin Plant Species: Implications for Conservation and Management Planning

6.1 Introduction

Numerous shifts in the distribution and abundance of both flora and fauna species over the past decades have been attributed to climate change (Parmesan et al., 2003; Chen et al., 2011; Franklin et al., 2016). The effects of forest fragmentation (Opdam and Wascher 2004), and the reduction of species adaptive capabilities and opportunities (Watson et al., 2014) are set to be exacerbated by a changing climate (Bomhard et al., 2005; Midgley and Thuiller, 2011; Midgley and Bond, 2015). The documented responsiveness of species to climatic changes of a regional scale (Reichgelt et al., 2018) raise the possibility of climate change acting as a major cause of Southern African extinctions in the future (Midgely and Bond 2015). Changes to the distribution and amount of rainfall result in drying, which causes challenges to the functioning of arid tropical habitats (Zeng et al., 2000; Midgley and Thuiller, 2011), with species responding by shifting their distributional ranges (Garcia et al., 2012) leading to expansions of tropical grasslands, conversion of the savannas to grassland (Hoffmann et al., 2000; Fordham et al., 2012) and changes in the phenology and physiology of species (Scheiter and Higgins, 2009). This kind of response affects the spatial pattern of species richness, turnover (Midgley and Bond, 2015; Tshwene-Mauchaza and Aguirre-Gutiérrez, 2019), and the ecosystem services they provide such as climate regulation and forest products (Franklin et al., 2016). Increasing aridity is also one of the factors known to control the distributions of tropical woodlands and savanna grasslands (Shanahan et al., 2016).

Tropical forests are therefore susceptible to rapid climate change (Feeley et al., 2012), and for forest species to persist and avoid loss, they must adapt or migrate towards more suitable climatic conditions (Feeley et al., 2012; Carroll et al., 2015; Nicotra et al., 2015). Efforts to

assess the potential impacts of climate change and mitigate the negative effects through effective conservation planning is therefore critical.

Species Distribution Models (SDMs) are an important component of conservation planning (Guisan and Thuiller, 2005). These techniques can benefit biodiversity conservation through their linkage of science to policy and decision making processes, by conveying the potential consequences of climate change (Kupika et al., 2018; Sintayehu, 2018), land use change and degradation (Jewitt et al.; Karki et al., 2018) on biodiversity to conservation practitioners and policy makers. The predictive utility of SDMs has been recognized in identifying potential suitable sites for reintroduction of threatened species (Elith et al., 2006; Franklin, 2013; Massaro et al., 2018; Perzanowski et al., 2019) and revealed undetected new populations of modelled species (McCune, 2016; Rhoden et al., 2017). However, one of the well documented caveats of the techniques is the inadequacy of climatic variables in SDMs due to their low spatial resolution (Corney et al., 2013; Franklin et al., 2013; Bucklin et al., 2015). Understanding how projections of climate change at different spatial resolutions will influence species distributions is important in developing pragmatic policies and management strategies for biodiversity conservation in a changing climate. Failure to do so contributes to inefficient biodiversity management plans and decision making (Porfirio et al., 2014; Yates et al., 2018). In Chapter 5, I set out to address this deficiency by testing the sensitivity of predictions of SDMs to different spatial resolution of climatic predictor variables. By definition, the spatial resolution of the outputs of an SDM is determined by the resolution of its inputs, but aside from this unavoidable consequence, my findings of Chapter 5 demonstrate that in my study system with relatively homogenous conditions, the use of predictors at different spatial resolution will not intrinsically bias the contents of future species distribution models themselves. In light of these findings and given the intense resources needed to downscale climatic variables to finer scales for SDMs, modelling at coarse spatial resolutions for such purposes in areas with comparatively low topographic and climatic heterogeneity can be acceptable (Tshwene-Mauchaza and Aguirre-Gutiérrez, 2019).

The global conservation importance of Okavango River Basin (hereafter, ORB) as a Ramsar site (IUCN, 2019a), its transboundary nature, and contribution to the national income of three riparian countries, (SAP, 2011a), makes maintenance of intact biodiversity in the ORB of global, regional and local significance. Although there is wide recognition of climate change as a driver

of biodiversity loss in ORB (SAP, 2011a), systematic attempts to assess potential impacts of climate change on the terrestrial plants and predict their future shifts in location, have not yet been made.

The importance of biodiversity management for reducing the vulnerability of species to a changing climate is recognized (Prober et al., 2012b) yet approaches to facilitate comprehensive vulnerability frameworks that identify appropriate climate adaptation management actions are lacking. This is partly due to a deficiency of literature on measures for assessing and reflecting adaptive capacity, adaptation opportunity (Table S6.5 for definitions of concepts) and current management context into Climate Change Vulnerability Assessment (CCVA) approaches. For example, Wade et al. (2017a) accounted for the inclusion of adaptive capacity only. The theoretical basis for quantifying and incorporating elements of species adaptive capability and opportunity remains a challenge for researchers and practitioners.

Thus, in response to a call for CCVAs to incorporate adaptive capacity measures (Table S6.5) (Nicotra et al., 2015; Beever et al., 2016) , and adaptation opportunity (Berry et al., 2013), this chapter assesses the potential impacts of climate change on ORB plant species. In doing so I introduce and apply a novel comprehensive vulnerability assessment framework that I derived by combining different aspects of the work of Berry et al. (2006) and Berry et al. (2013) The framework , in addition to considering the key elements of species' vulnerability (i) exposure (ii) sensitivity and (iii) adaptive capacity (IPCC, 2014;WGII), therefore conceptualizes and incorporates adaptation opportunity as well as considers current management context. I also assess adaptive capability from components of dispersal and colonization abilities following Nicotra et al. (2015). I acknowledge the challenge of this endeavour and hope to prompt and/ broaden discussions between conservation practitioners and researchers on the most effective way to incorporate and account for both elements of species ability and opportunity to adapt to climate change in vulnerability assessment frameworks.

With the understanding of projected temperature and rainfall change across the fine and coarse spatial resolution models in Chapter 4, and the understanding of the effects of spatial resolution of climatic predictor variables on SDMs (Chapter 5), the next step is to project the contemporary ORB plant species distribution models achieved in Chapter 5 to future climates for the end of the

21st Century under the optimistic and baseline scenarios, RCP 4.5 and RCP8.5 respectively, and to assess implications for conservation and management planning. This is the focus of Chapter 6.

In this chapter I project future potential range shifts of a subset of conservation-relevant species in response to the anticipated climate change and assesses vulnerability of those species. I then explore the implications for conservation and management planning. Biodiversity vulnerability assessments are often deficient in providing procedures on how to assess the need for conservation actions, and how to integrate the resultant action plans into conservation planning (Oliver et al., 2012). To address this, the chapter goes on to demonstrate how effective species-specific adaptation strategies under climate change can be integrated into conservation plans. Thus, in assessing potential impacts of climate change to ORB plant species, my overarching aim for this chapter is to design and apply a framework for practitioners to assess the need for, and integration of, conservation actions into planning. This is achieved through addressing the following questions:

1. Which conservation priority ORB plant species are most vulnerable to climate change under RCP 4.5 and RCP 8.5 at the end of the 21st Century, and what are the factors contributing to their vulnerability?

2. What is the current state of the plant species conservation and management planning for climate change?

3. What are the potential implications of the projected impacts of climate change on conservation and management planning for these species?

To answer these questions, I apply the comprehensive vulnerability assessment framework I designed, conceptualized in Figure 6.1. The first step is to use SDMs to project the current ORB plant species distribution under future climates, in order to assess the sensitivity of the species to climate change. The second step is to conduct research on the species habitats and ecology to derive information on adaptive capability and adaptation opportunity (Question 1). The third step is to review the existing ORB biodiversity conservation and management plans, particularly with regards to climate change, focusing on what is currently planned/proposed for climate change adaptation, in terms of conservation, and what actions have been laid out to date (Question 2). This is to determine how effective they will be in achieving the desired conservation outcome

under climate change, with the view to making recommendations as to what changes might be needed to address the impacts of climate change, potentially resulting in a resilient ORB which currently maintains the status quo (Question 3). Using projected species potential range change distribution results achieved in question 1 and incorporating information on elements of adaptation capability and opportunity of the species, as well as current conservation interventions, I provide a robust assessment of species vulnerability to climate change. This chapter therefore brings together three critical elements in vulnerability approaches, the species distribution modelling, species habitat and ecology, and existing conservation plans, to make recommendations for how that planning might need to change in the future (Question 3).

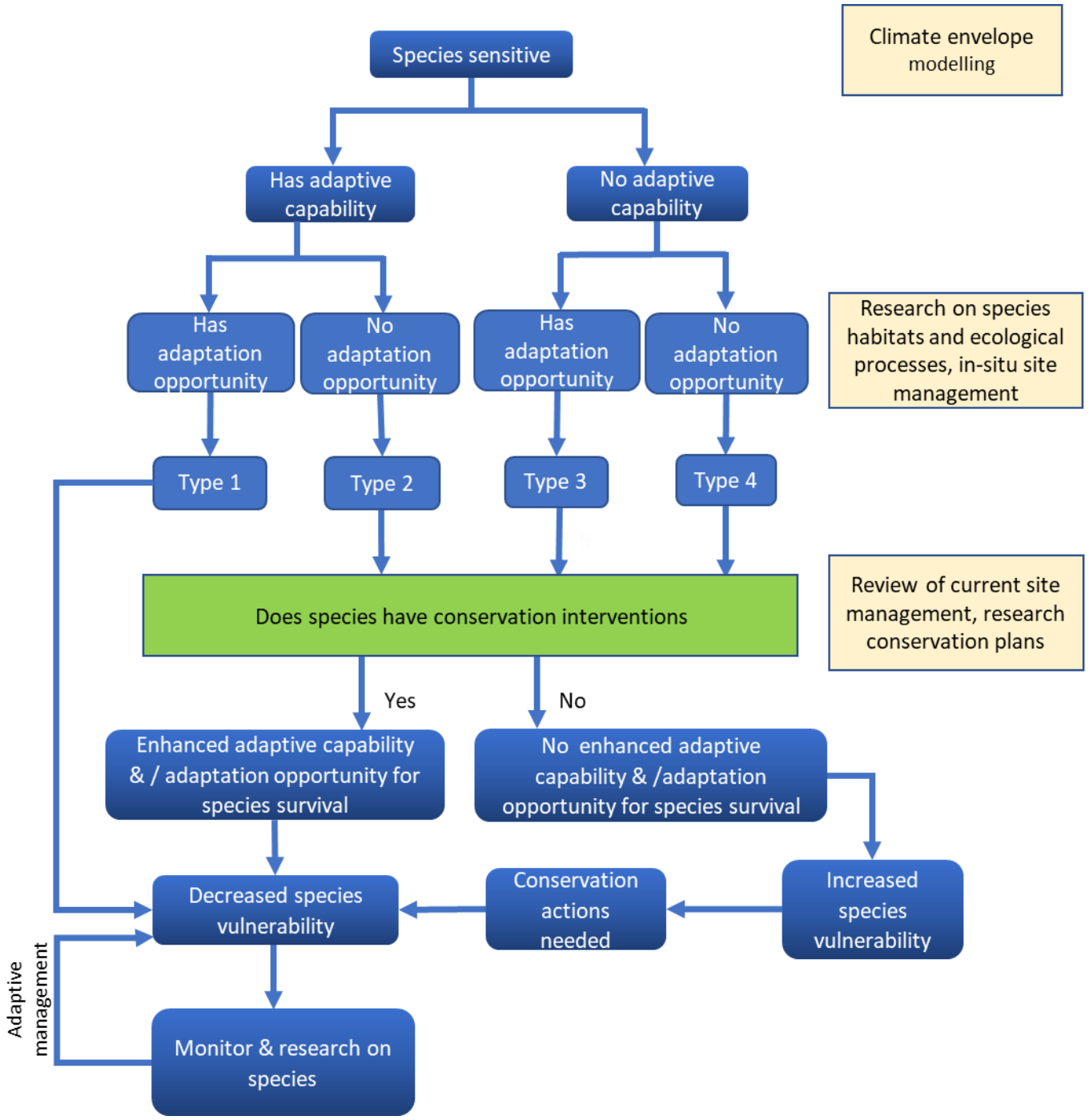


Figure 6.1: Schematic illustrating the novel framework for vulnerability assessment used in this study, building on components from Berry et al. (2006) and Berry et al. (2013).

6.2 Methods and Data

6.2.1 Data

6.2.1.1 Study region and species selection

The projection study region for this chapter is Southern Africa with focus on the ORB. Presented here is analysis of a subset of conservation relevant species based on their ecological importance, anecdotal information about exploitation and negative population trends, and in a few cases, Red List rating as revealed by the IUCN Red List (IUCN 2019). Of importance, selection criteria of the species used considered the vegetation communities of the ORB, made up of woodlands/forests, dwarf shrub-grassland, wetlands/riverine and thorn bush savanna (Revermann et al., 2016a). The selected species constitute the dominant species in each of the vegetation units (Table S6.4), they therefore can be considered representative of the flora as a whole (De Cauwer et al., 2016). Thus, the selected species represent extensive variation in habitat, ecology, life form, pollination vector and seed dispersal and colonization characteristics (Tables S6.1 & S6.2). In addition, the species hold ecological, cultural and economic values [Table S6.1 & S6.2]. Of the 12 species, *Baikiea pluriga* has a near threatened criteria status assigned by the IUCN and South African National Biodiversity Institute [SANBI] (www.SANBI.org.za), and *Pterocarpus angolensis* has a lower risk / near threatened status as it is vulnerable in Namibia and Zimbabwe due to its economic uses. The IUCN global Red List reports a decline in population trend as the tree is overexploited for its timber (IUCN, 2019b). The rest of the species have been classified as of least concern by both the SANBI and IUCN Red List; however, due to their cultural and economic importance in the region, it is critical that their vulnerability to climate change is assessed, as climate change could alter their category status.

6.2.1.2 Species occurrence data sources

I retrieved species occurrence data used in this chapter from the Global Biodiversity Information Facility database (GBIF, 2019) accessed on 10th July 2019 , merged with data from the Okavango Basin database (GIVD ID: AF-00-009, http://www.givd.info/ID/AF-00-009) (Revermann et al., 2016a). From GBIF occurrences, I eliminated species records with missing geographic information. Duplicated observational records were reduced to only one record per

grid cell, this facilitated the sourcing of unique records per species per grid cell. A total of 1707 presences were obtained from 1551 locations across the 12 IUCN Red Listed species.

6.2.1.3 Climate data

The climate data were derived from the AFRICLIM v3.0 database (https://webfiles.york.au.uk/KITE/AfriClim/), and they are therefore consistent with those used to model contemporary plant distribution. Thus, the climate projections were acquired from the AFRICLIM future projections – statistically downscaled and bias corrected projections from one CORDEX model (SMHI) forced by one CMIP5 model (EC-EARTH) [Table 6.1]. The original data therefore stems from the regional climate model RCA4 (Rossby Center regional model) forced with the global circulation models from CMIP5. Current research on the simulation of Southern Africa rainfall, uses the EC-EARTH model from CMIP5, (Pinto et al. 2018) as based on model performances, (Libanda and Nkolola, 2019) it is one of the models that has better capability in simulating features evident in the domain's climatology. The model displayed the best visual agreement with the observed climatology (Figure 4.1 and Figure 4.2). Regression line slope of the EC-EARTH model showed a closer to perfect fit with the reference (one to one) black line (Figure 4.4), supporting the overall model's better ability to simulate Southern Africa rainfall seasonal mean and general climate elements of the domains' contemporary DJF mean rainfall (4.3.1). The future climate variables used include temperature seasonality (tmpSea), mean temperature warmest quarter (mtwq), potential evapotranspiration (pet), rainfall driest quarter (rdq), and moisture index moist quarter (mimq). I chose these bioclimatic variables based on their strong link with the physiology and growth of arid tropical forest plant species (Becklin et al., 2016). The climatic variables were derived at a spatial grid size of 50km×50km.

This relatively coarse spatial resolution was chosen as being valid by the findings and conclusion of the preceding chapter, which states that the spatial resolutions of climatic predictor data have only comparatively small effects on the predictive accuracy and ability of species distribution, at least in this study system. There is therefore little variation over different spatial resolution in the predictive ability of climate in SDMs. Projections for species distributions and species richness under contemporary and future climates may be undertaken at a coarse spatial resolution in areas with relatively low climatic and topographic variation such as the one shown in the

previous Chapter 5, with comparatively high statistical accuracy. This conclusion is supported by Foden and Young, (2016) and Foden et al. (2019), who attest that finer spatial resolutions might be necessary in areas of high spatial heterogeneity and varying land surface properties. Luoto et al. (2007) also concluded that climate envelope models alone can explain species distribution and abundance at spatial resolutions of >20km. The use of coarse spatial resolution of up to 50km×50km to predict potentially suitable climate space shifts for individual species for conservation purposes has also been found to be suitable as it enables depiction of broad trends in the projected future climate space (Walmsley et al., 2007). Such resolutions have potential to reduce the danger of over interpretation of results at site level by conservation practitioners (Walmsley et al., 2007).

Two future climate change scenarios [RCP4.5 and RCP 8.5] (van Vuuren et al., 2011) based on the EC-EARTH climate model were used and applied. The EC-EARTH climate model was chosen as it most reliably simulates Southern Africa region's climatology (Chapter 4). I used two greenhouse gas emission scenarios to facilitate capturing (some of) the range of uncertainty in future projections (Berry et al., 2013). The two RCPs are chosen over the less extreme scenario of RCP 2.6 as given the current trajectory, achieving RCP 2.6 is unlikely (Schuur et al., 2013). In addition, based on the high vulnerability of Southern Africa region under climate change conditions of RCP 8.5 (Chapter 4 section 4.6), it is critical to assess potential impacts of climate change under this scenario. The same set of bioclimatic variables used for projecting current distributions were used to project future distributions.

Table 6.1: Climatic variables used to project species distributions of the vascular plant species to future climates at a coarse spatial resolution of 50km×50km (climatic data products sourced from AFRICLIM future projections – statistically downscaled and bias corrected projections from one CORDEX model (SMHI) forced by one CMIP5 model (EC-EARTH)

Variable's acronym	Description	Units
tmpSea	Temperature Seasonality	mm (standard deviation*100)
mtwq	Mean temperature warmest quarter	◦C
PET	Potential evapotranspiration	mm
rdq	Rainfall driest quarter	mm
mimq	Moisture index moist quarter	%

Climatic variables represent annual trends and seasonality.
They are derived from monthly temperature (units: ◦C) and rainfall (mm)

6.2.2 Methods

For Sensitivity (see 6.2.2.1), Adaptive Capability and Adaptation Opportunity (see 6.2.2.2) and Vulnerability (see 6.2.2.3).

6.2.2.1 Section A: Species Distribution Modelling

I built the SDMs using the biomod2 R package version 2.1.0 (Gentle et al., 1991; Maechler et al., 2019), which includes a suite of widely used niche-based modelling algorithms to offer alternative spatial projections (Thuiller et al., 2009; 2014). To reduce variability in the model predictions of the different modelling techniques, an ensemble modelling approach was used. The ensemble approach consisted of the six modelling algorithms I used to build contemporary distribution models (Chapter 5) namely, Random Forest (RF), Artificial Neural Networks (ANN), Classification Tree Analysis (CTA), Generalised Additive Models (GAM), Generalised Linear Models (GLM), and Maximum Entropy Modelling (Maxent). Default settings as recommended by Thuiller et al. (2009b) were used. The lack of true absences necessitated the use of randomly generated pseudoabsences from background data (after Barbet-Massin et al., 2012; Thuiller et al., 2016). I computed the distribution models for each species using 10 model repetitions in order to attain a robust estimate for the algorithm's performance, as well as to try and account for within-algorithm model variation when the model is calibrated using different sets of data. I trained the models on 80% of the presence data and the remaining 20% was used to

test the models, following a bootstrap approach. The ensemble approach implementation consisted of the ensemble of the ten model repetitions × six algorithms = sixty constructed models per species (12 species in total), totalling 720 models.

6.2.2.1.1 Model Performance

Evaluation criteria such as the Receiving Operating Characteristics (ROC) of the Area under the Curve (Hanley and McNeil, 1982), Kappa Statistics and the True Skill Statistics (Allouche et al., 2006) are generally used for model performance. Here I used the Area Under the Curve (AUC) to assess the model performance and create the ensemble /consensus maps, using the mean suitability score of the predictions. AUC values range between 0-1, with values below 0.5 indicating a model that is not better than random and values of 1 indicating models that have perfect accuracy (Scarnati et al., 2009). As recommended by Scarnati and colleagues, candidate models from individual modelling techniques with AUC values of >0.6 were selected for the ensemble models and the resulting ensemble models were then used to project species distributions under future climatic conditions (RCP 4.5 and RCP 8.5).

6.2.2.1.2 Assessing Species Sensitivity Based on Projected Changes in Climate Suitable Space

I built the species distribution models for the first step of the framework, which is to assess species sensitivity. To achieve this, I transformed the species ensemble models to presence / absence binary predictions in order to investigate likely changes between the current and future species suitable climate space, by means of the threshold that maximises sensitivity and specificity (Jiménez-Valverde and Lobo, 2007). This is a methodological principle to assess the species sensitivity to climate change endorsed by many studies e.g. Guisan and Thuiller (2005); Aguirre-Gutiérrez et al. (2017a). However, this approach ignores biotic interactions and population dynamics (Fordham et al. 2013), as well as processes of dispersal including lags in spatial range shifts and adaptation opportunities. The future species distribution model outputs are therefore only used to derive the sensitivity of the species, as applied at the regional scale of Southern Africa. The sensitivity is a function of the amount of change in suitable climate space;

gained climate space; lost climate space; overlap between present and future climate space (Berry et al., 2006; Cabrelli and Hughes, 2015).

The sensitivity indicators I use here should be interpreted as follows:

Current suitable climate space represents the number of 50km×50km grid cells presently occupied by the modelled species in Southern Africa; scenario is the number of grid cells modelled as suitable climate space based on the climate change scenarios plus gain (indicator A) and overlap (indicator B) is the number of grid cells occupied under the current time and scenarios. Gain: the number of grid cells not currently modelled as suitable climate space but projected to be in the future climate change scenarios (Berry et al., 2006; Thuiller et al., 2009). Loss (indicator C): number of grid cells projected to be lost as suitable climate space and indicator D: size of the projected suitable climate space [in pixels] (Berry et al., 2006; Thuiller et al., 2009).

Calculations of the sensitivity indicators A-D, following Berry et al. (2006) and Thuiller et al. (2009), are detailed in Table S6.6; in this study the class boundaries for the species sensitivity indicators in percentages are presented in Table 6.1. The outputs from the models in terms of gained climate space, overlap between present and future and lost climate space (Figs. 6.2 & 6.3) informed selection of the indicator classes.

The projected suitable climate space / species distributions change was calculated as the percentage gain minus the percentage loss in climate space. In addition to the area of suitable climate space change, the latitudinal climate space shift (north-south) was derived from change in the centroids of the binary (presence/absence) species climate space distributions (Aguirre-Gutiérrez et al., 2017a, 2017b). The difference in the latitudinal location (north/south) between the centroids of the current distribution and the future climate change scenarios was calculated for the same species. This method depicts latitudinal directional change of the suitable climate space relative to the current, in degrees latitude; values below 0 indicate suitable climate space shifts towards the south pole, while values above 0 reflect climate space shifts towards the north pole. A value of 0 shows no change in the centroid of the climate suitable space distribution, relative to the current time. The difference in the distance (in kilometres) between the centroids of the current and future distributions was also calculated. This shows the distance in shift of the

climate space in the future, relative to the present time. I carried out all analyses in R statistical environment (https://www.r-project.org) using the rgeos v0.5-1 package (Bivand et al., 2013) for calculating the distribution centroids; the distance between the centroids of species climate space distributions was carried out using the PointDistance() function in the raster v3.0-2 package, (Hijmans, 2019). I carried out the species distribution modelling analyses with the BIOMOD 2 package (Thuiller et al., 2016).

Table 6.2:The class boundaries for species sensitivity indicators (%) (From Berry et al., 2006)**.**

Score	Indicator A (Gain)	Indicator B(Overlap)	Indicator C(Loss)	Indicator D (size of new climate space)
0	$A \geq 100$	$B \geq 100$	$C \leq 0$	$D > 50$
1	$75 < A < 100$	$75 < B < 100$	$0 < C < 25$	$40 < D \leq 50$
2	$50 < A \leq 75$	$50 < B \leq 75$	$25 \leq C < 50$	$25 < D \leq 40$
3	$25 < A \leq 50$	$25 < B \leq 50$	$50 \leq C < 75$	$10 < D \leq 25$
4	$0 < A \leq 25$	$0 < B \leq 25$	$75 \leq C < 90$	$1 < D \leq 10$
5	$A \leq 0$	$B \leq 0$	$C \geq 90$	$D \leq 1$

6.2.2.2 Methods section B: Assessing Species Adaptive Capability and Adaptation Opportunity

The next stage of the Framework is to assess the adaptive capability of species. I based information to infer adaptive capabilities on species ecological processes including dispersal and colonization abilities and habitat selection (Ackerly, 2003). This follows studies such as Angert et al. (2011) where a subset of components was used in classification of adaptive capability. In assessing the potential impacts of climate change on species, one of the objectives of this chapter is to demonstrate that inclusion of adaptive capability and adaptation opportunity has an effect on vulnerability assessments.

Determining the species adaptation threat and barriers was based on literature review. Peer reviewed literature was searched using Google Scholar as it gives substantially more citing references relative the other citation databases (Lasda Bergman, 2012) with species name and adaptation parameters as search terms, the search was conducted in July 2019. The adaptation capability and opportunity parameters used were dispersal and colonisation abilities, adaptation

barrier, adaptation threat, adaptation pressures. The search terms were climate change; land use, as this can reduce habitat quality and quantity (Summerville et al., 2005); invasive species, as they can compete for habitat and resources, resulting in population declines (Gurevitch and Padilla, 2004; Didham et al., 2007). The search method was thus "Species name" AND (AdaptationParameter1 OR AdaptationParameter2 OR AdaptationParameter3); "Species name" AND (SearchTerm1 OR SearchTerm2 OR SearchTerm3).

Then the next step in the Framework is the assessment of the adaptation opportunity. This followed on the results of adaptive capability in terms of (i) whether the species suitable climate space is projected to expand or contract and (ii) whether the species has planned adaptation actions (see section 6.3). I also considered evidence of threats or barriers such as overexploitation due to unsustainable harvesting, land use change and degradation, landscape fragmentation and other natural barriers to track suitable climate space. Where a species is projected to gain some suitable climate space under either of the climate change scenarios and where there is evidence and opportunity to implement good planning, control and management practices resulting in sustainable current and future land uses, a high adaptation opportunity was assumed, the opposite resulted in low adaptation opportunity (Table 6.2).

6.2.2.2.1 Classification of Adaptive Capability and Adaptation Opportunity

I reached conclusion of a high adaptive capability where the species' potential suitable climate space is projected to expand and there is evidence of possible current and future autonomous adaption due to good dispersal and colonisation abilities, or planned adaptation. Medium adaptive capability is assumed in cases where the species has potential to gain climate space under either RCP 4.5 or RCP 8.5 climate change scenario, and where there is opportunity of actual or potential adaptation. A low adaptive capability is reached where the species is projected to lose its suitable climate space with lack of current or planned adaptation actions and management practices [Table 2 & S1] (Berry et al., 2013; Nicotra et al., 2015).

Table 6.3: Species vulnerability to climate change (SAP, 2011). This is also informed by the habitat, ecology and dispersal forms/abilities of species (Tables S6.1). Low (L), Medium (M) and High (H).

Species	Sensitivity	Adaptation threats or barriers	Adaptive capability	Adaptation opportunity	Vulnerability
Baikiaea plurijuga	H	Climate change/ variability, wood poaching, timber logging, wildfires, human population increase, firewood	L	L	H
Baphia massaiensis	H	Unsustainable harvesting of veld products, conversion to agriculture, bush encroachment, over grazing, deforestation, climate change	L	L	H
Bulbostylis hispidula	H	Conversion to arable farming, bush encroachment, over grazing, unsustainable harvesting of veld products, deforestation	L	L	H
Chamaecrista absus	L	Intensification of agricultural activities, wildlife and firewood poaching, infrastructure development	L	L	L
Commelina africana	H	Overgrazing, deforestation, anthropogenic induced climate change	L	L	H
Cyperus cf haspan	L	Increased human population, land degradation due to excavations or fertilization, reed beds conversion to grazing and agricultural land, reeds and grasses cut for domestic use, baskets and matting	L	L	H
Dichrostachys cinerea	M	Human population expansion, intensification of arable farming, causing expansion into woodlands, wood harvesting	L	L	H
Indigofera daleoides	M	Deforestation, unsustainable harvesting of veld products	L	L	H
Pterocarpus angolensis	L	Timber poaching, climate change, good dispersal capacity	H	H	L
Rhynchosia minima	L	Overgrazing, increase in arable farming	H	H	L
Rhynchosia totta	H	Range land farming, wildfires, harvesting of veld products, e.g firewood, food, construction material, medicinal plants, mining and prospecting for mineral resources, climate change	L	L	H
Tephrosia cephalantha	L	Intensification of agricultural activities, wildlife and firewood poaching, infrastructure expansion	M	M	M

6.2.2.3 Quantification and Assessment of Species Vulnerability (Incorporating Adaptive Capability and Opportunity)

The vulnerability definition applied here is the recent one from the AR5; vulnerability is "the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt" (IPCC SR1.5, 2019: pp. 1-52). In this chapter I consider vulnerability a function of sensitivity of species to climate change, adaptive capacity (IPCC 2014) and adaptation opportunity (Berry et al., 2013) and current conservation and management interventions. Quantification of sensitivity is based on scenarios of future changes of rainfall and temperature of Southern Africa which are then used to project species response to the climate change (Thuiller et al., 2009). The vulnerability assessment here combines the sensitivity metrics scores (Table S6.3) with the capacity and opportunity of the species to adapt to climate change based on their habitat and ecological assessments (Table 6.2 &Table S6.1). I therefore use three data types/information in the vulnerability assessment: climate envelope modelling, species habitat and ecology requirements, and current conservation interventions. The species distribution modelling data denotes sensitivity of the species to climate change, habitat and ecology data characterises adaptive capability and adaptation opportunity, together with existing conservation plans, give information on the species vulnerability.

This approach differs slightly from that of Wade et al. (2017a) and Ofori et al. (2017b) in that it incorporates adaptation opportunity. As species adaptive capability and adaptation opportunity have potential to alter the sensitivity score and thereby change the vulnerability ranking (Garcia et al., 2012; Berry et al., 2013), from the sensitivity indicators, two vulnerability indices are calculated:

(i) Sensitive & Vulnerable (SV); this index is used for species that cannot inhabit the projected suitable climate space, as their independent adaptation capabilities through dispersal is constrained to the boundaries of the grid cells presently occupied by the species and there are no adaptation opportunities in place (Berry et al., 2006). This index is qualitatively informed by the habitat and ecological processes information of each species, as well as information on adaptation threats and barriers (Tables S1 & Table 3) and existing conservation plans. Therefore, calculation of this index is preceded by the understanding of a species' adaptive capability and

adaptation opportunity coupled with projection of new suitable climate space. Given limited dispersal capabilities, the future climate space will not be utilised by the species. Index SV is thereby a summation of indicators A to D (Table 6.1& Table S6.3), after holding indicator A (Gain) at the highest value of 5. This methodology follows with modifications an approach used by Berry et al. (2006; 2013), in which an assessment was carried on the ability of species to utilise future climate space.

(ii) Sensitive but less Vulnerable (SLV) incorporates the species adaptive capability and adaptation opportunity (Berry et al., 2013) information. This index is applied to species with high adaptive capabilities as a result of autonomous adaptation and implementation of planned adaptation actions. The adaptive capability is considered a function of the extent of the gained future climate space. Index SLV therefore sums up indicators A to D (Table 6.1& Table S6.3), as the assumption is that the species is able to fulfil new suitable climate space, i.e. full adaptation is realised. The use of this index should therefore be based on the understanding and consideration of each species' adaptive capabilities and adaptation opportunities information.

Information on a species' adaptive capability and adaptation opportunity is critical in determining which vulnerability index to use for specific species in order to understand the level of the species' vulnerability. This is important information for conservation planners and decision makers, as it guides allocation of conservation efforts and resources.

Indices SV and SLV therefore represent extremes by which a species can potentially fulfil availability of climate space with assumptions about adaptive capability, adaptation opportunities and evidence of current conservation actions for the species. This differs from Thuiller and Guisan (2009), where consideration of the species' ability to migrate to new suitable areas of climate space is based on assumptions of no or full dispersal abilities. In recognition that in order for a species to be vulnerable it has to be sensitive, "Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt" (IPCC SR1.5, 2019: pp. 1-52), according to this definition of vulnerability, a species may be sensitive and potentially vulnerable however its capacity and opportunity to adapt reduces its vulnerability. From this understanding, I derived four types /categories of sensitivity a species can fall under as follows and captured in Figure 6.1:

Type 1: Sensitive, has adaptive capability, has adaptation opportunity

Type 2: Sensitive, has adaptive capability, zero adaptation opportunity

Type 3: Sensitive, zero adaptive capability, has adaptation opportunity

Type 4: Sensitive, zero adaptive capability, zero adaptation opportunity

Determining the level of species vulnerability is therefore based on the SV and SLV indices (vulnerability indices) by which the above four types are derived. Type 1 has a vulnerability score of 0-5, indicating that the species is sensitive but slightly vulnerable; for Type 2, a score of 6-10 shows sensitivity with medium vulnerability; for Type 3, an 11-15 score is associated with high vulnerability; while a score of 16-20 indicates a species is sensitive with extreme vulnerability (Type 4). These vulnerability scores are thus different from the sensitivity scores, as they incorporate the elements of a species' adaptive capability and adaptation opportunity.

6.2.2.4 Methods Section C: Assessing Current Conservation Interventions

My next step was to assess current conservation interventions management plans in terms of adaptation actions as they relate to the projected shifts in suitable climate space and condition of habitats. The assessment includes to what extent the current conservation actions relate to the threats posed by climate change. I looked out for evidence on the impacts the current actions will have on the vulnerability of the species. This is carried out through a review of how the current management plans recognise and lay out actions to address impacts of climate change on plant species and their habitats, if there is any evidence that the threats posed by climate change to the species are being managed in the future. For the ORB, the review is based on four significant documents for the management of this resource at both transboundary and national levels; (i) The Strategic Action Programme (SAP, 2011) for the Sustainable Development and Management of the Cubango-Okavango Basin, (ii) Angola National Action Plan (Angola NAP, 2011), (iii) Botswana National Plan (Botswana NAP, 2011), and (iv) Namibia National Plan (Namibia NAP, 2011).

6.3 Results

6.3.1 Species Distribution Model Performance and Variable Importance

The species distribution ensemble models showed good performance, with the lowest AUC values for any species at 0.94. The model sensitivity values ranged from 0.87 to 100 (Table 6.3). These values indicate a high accuracy in the models' projection of species distributions (Guisan and Thuiller, 2005; Georges and Thuiller, 2013; Bucklin et al., 2015; Thuiller et al., 2016). The climatic variables with the two highest importance values in determining the distributions varied between species (Table 6.3), with potential evapotranspiration (as observed in the species richness analysis in Chapter 5), as the key driver of the distribution for half of the studied species. *Chamaecrista absus* is the only species with two of its primary driving variables related to temperature (potential evapotranspiration and mean temperature of the warmest quarter), while *Baikiea plurijuga* is mainly driven by rainfall-related variables (moisture index of moist quarter, and rainfall of the driest quarter). For the rest of the species, the two main drivers of distribution include a combination of rainfall and temperature related variables, with a combination of moisture index of moist quarter and potential evapotranspiration being very common.

Table 6.4: Area Under the Curve (AUC) and sensitivity evaluation scores for the built species distribution ensemble models, and the importance values (ranging from 0 to 1) of each of the bioclimatic predictors for SDMs of the modelled species. The two highest climatic variables importance values for the species are highlighted.

	Baikiaea plurijuga	*Baphia massaiensis*	*Bulbostylis hispidula*	*Chamaecrista absus*	*Commelina africana*	*Cyperus cf haspan*	*Dichrostachys cinerea*	*Indigofera daleoides*	*Pterocarpus angolensis*	*Rhynchosia minima*	*Rynchosia totta*	*Tephrosia cephalantha*
Evaluation metric												
AUC	0.98	0.99	0.99	0.97	0.96	0.98	0.99	0.98	0.96	0.94	0.98	0.97
Sensitivity	98.06	100	100	96.15	87.61	100	100	100	92.14	86.60	100	100
Climatic variables Importance												
Mean temperature warmest quarter	0.02	0.12	0.02	**0.24**	0.18	**0.27**	**0.34**	0.03	0.15	**0.27**	0.13	0.03
Rainfall driest quarter	**0.44**	0.15	0.12	0.05	0.02	0.09	0.09	**0.23**	0.05	0.02	0.07	**0.29**
Temperature seasonality	0.09	0.15	0.05	0.15	**0.41**	0.12	0.04	0.06	0.15	0.17	**0.34**	0.03
Moisture index moist quarter	**0.32**	**0.19**	**0.20**	0.11	**0.36**	**0.27**	**0.23**	0.15	**0.19**	**0.17**	**0.30**	0.08
Potential evapotranspiration	0.13	**0.52**	**0.51**	**0.24**	0.08	0.11	0.17	**0.49**	**0.25**	0.04	0.04	**0.51**

6.3.2 Species Response to Projected Climate Change

To assess the species' response to probable climate change and to demonstrate the importance of applying a comprehensive vulnerability assessment that incorporates elements of species adaptive capability and adaptation opportunity and how these influences the vulnerability scores, I analyse the results to assess potential impacts of climate change to ORB, in two ways. Firstly, I do so based on the sensitivity indicator scores of the species as informed by the availability of projected suitable climate space (section 6.3.2.1). Secondly, the results are analysed based on a

vulnerability assessment that incorporates adaptive capability and adaptation opportunity of each species.

6.3.2.1 Species Sensitivity Metrics Scores Assessment

Examination of the sensitivity metrics show contractions in suitable climate space by the end of the 21st Century for half of the twelve modelled global IUCN Red List species. Under both RCP 4.5 and RCP 8.5 climate change scenarios, species *Baphia massaiensis, Baikiea plurijuga, Rynchosia totta, Bulbostylis hispidula,* and *Commelina africana* are projected to reach their bioclimatic limits, showing significant percentage losses of their current suitable climate space of between 74% to 100% (Figures 6.2&6.3). Based on the result, species with 100% loss are at risk of becoming extinct, however with no consideration of their adaptation opportunity. The pattern of spatial distribution of loss in climate suitability for the species is comparable for both climate change scenarios, with the modelled species depicting loss in the Okavango region. The magnitude and extent of the contraction in suitable climate space is (perhaps unsurprisingly) more pronounced and extreme under RCP 8.5 (Figures 6.2&6.3).

Gains of 100% in climate suitability space are also observed for five of the species, *Chamaecrista absus, Cyperus cf haspan, Pterocarpus angolensis, Rhynchosia minima* and *Tephrosia cephalantha* under both RCP 4.5 and RCP 8.5 (Figures. 6.2 & 6.3). Analysis of patterns in shift of the climate suitability space reveals similarities under both the climate change scenarios; the species show a comparable pattern of expansion with latitudinal shifts in the centroids of distribution of at least 180 km towards the north (Figure 6.4) assuming species dispersal abilities to track the new climate space. For both RCP 4.5 and RCP 8.5 scenarios, most of the species' climate suitability remains stable in the central area around the ORB region, spreading to the eastern side of Southern Africa (Figures 6.3 & 6.S2). This result indicates that the species might expand towards the northern areas and those in the central area of ORB are less vulnerable to a changing climate. It should be noted that future climate projections from which future suitable climate space depicted by the species distribution model outputs, vary in the direction and magnitude of change between models, regions and seasons (James et al., 2015) thus bringing about uncertainties in the projections. Since only one GCM-RCM combination is used in this analysis, uncertainties in the future projections should be accounted for in

interpretation of model results. Future work should expand the combination of models used to assess the stability of the results.

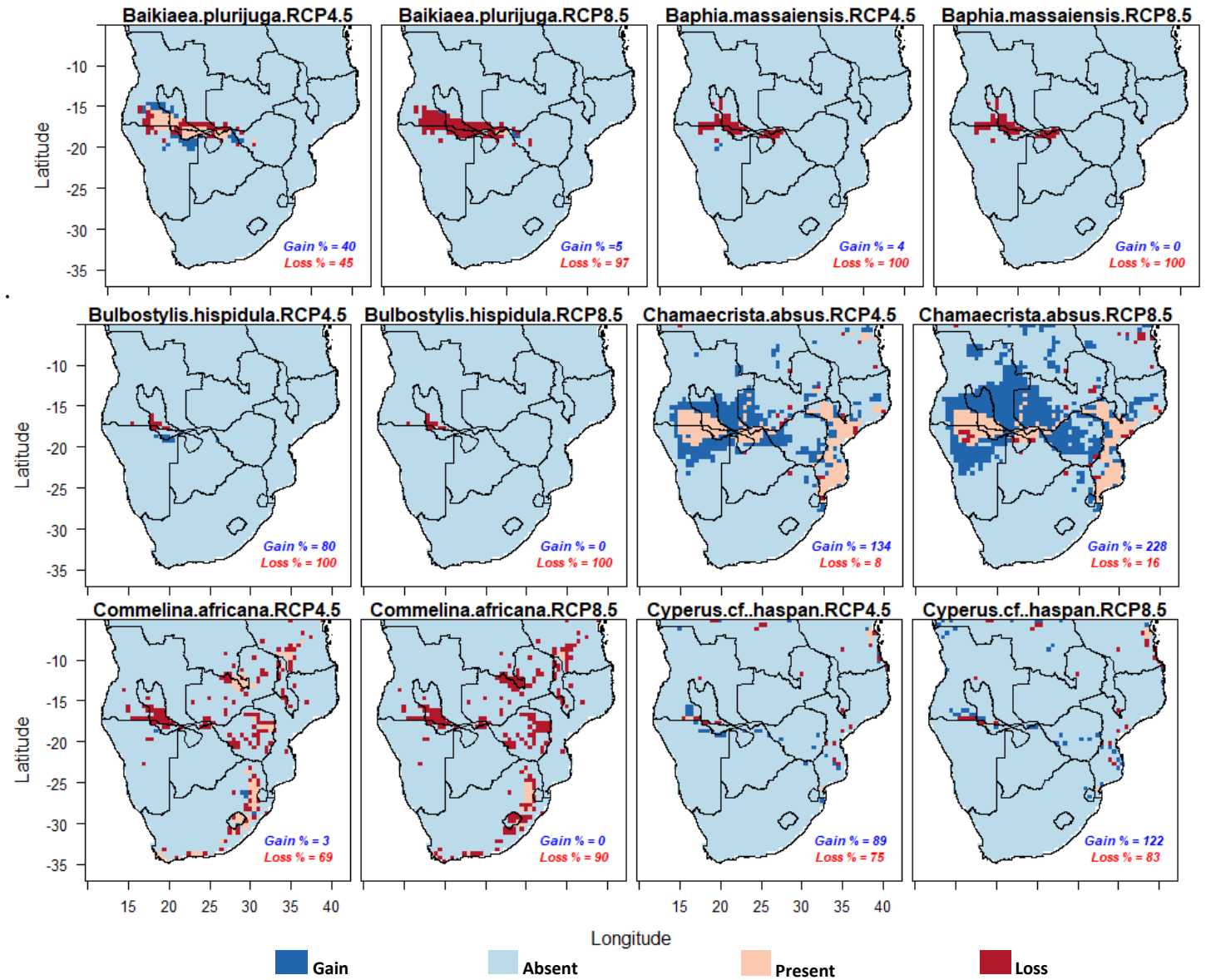


Figure 6.2: Projected change in climate suitable space for 6 out of 12 IUCN Red List species, under climate change scenarios RCP4.5 & RCP8.5 for the end of the 21st century

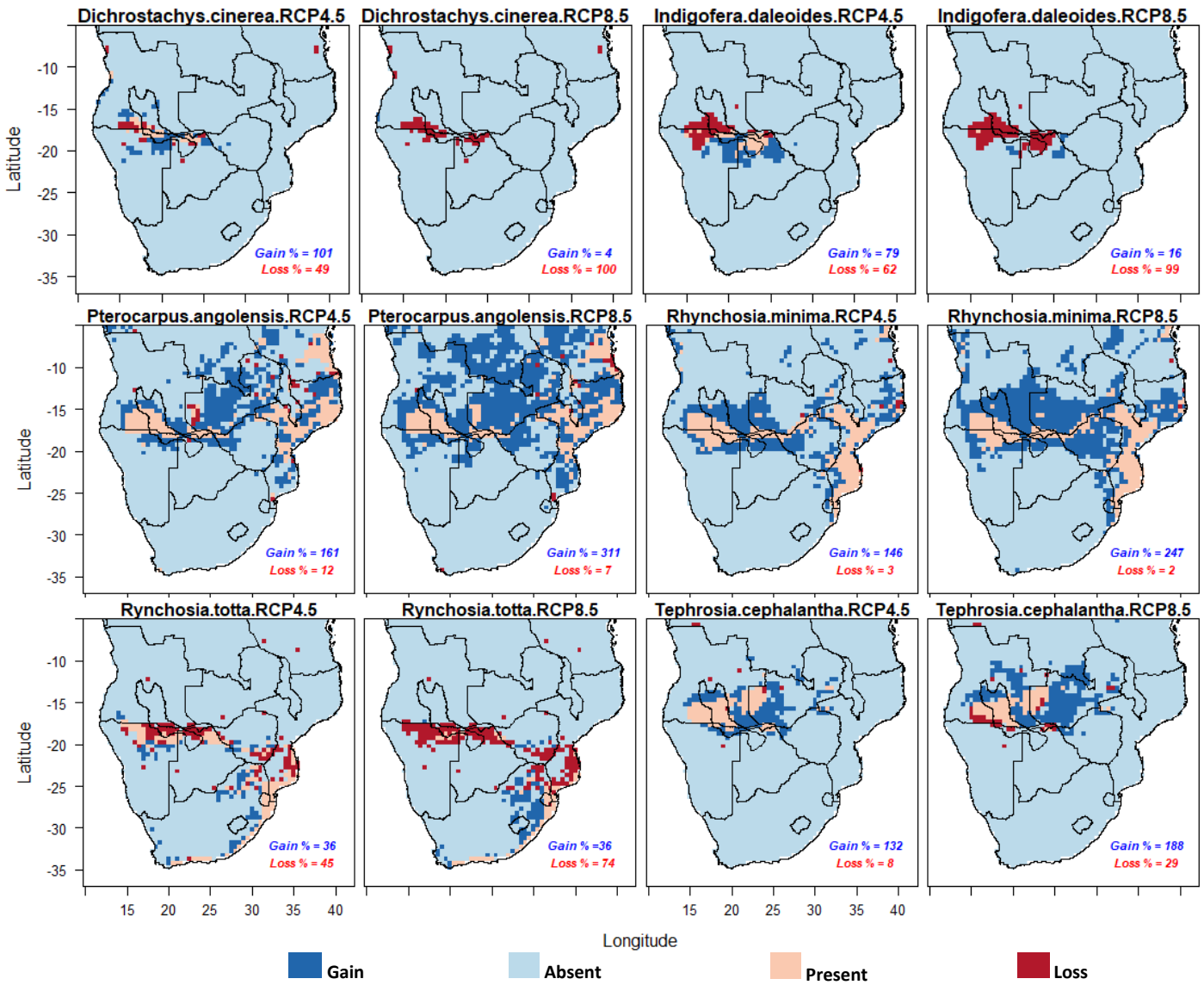


Figure 6.3: Projected change in climate suitable space for 6 out of 12 IUCN Red List species, under climate change scenarios RCP4.5 & RCP8.5 for the end of the 21st century

6.3.2.2 Species Vulnerability Assessment, Accounting for Sensitivity, Adaptive Capacity and Adaptation Opportunity

However, relative to assessment based on sensitivity metrics, examination of the full vulnerability assessment results (sensitivity metrics scores plus assessment of adaptive capability and adaptation opportunity captured in Table 6.2 & S6.1) reveals alterations to the vulnerability levels of the species to climate change. Since the modelled species are sensitive to climate change, I applied the SV index to all in order to give species vulnerability rankings. The vulnerability of the species as calculated by the SV index varies from the sensitivity assessment only (section 6.3.2.1) in that at the end of the 21st Century, under both climate change scenarios, the modelled species are projected to be vulnerable to climate change, falling under the four types of vulnerability categories, types 1-4 with scores ranging from slight (0-5), medium (6-10) to extreme (16-20) [Table 6.5]. In this index climate change sensitivity is the leading factor contributing to the species' vulnerability.

Unlike the sensitivity metrics assessment, inclusion of adaptive capability and adaptation opportunity leads to three more species being classified as extremely vulnerable. Therefore eight of the modelled species fall under type 4, extreme vulnerability under the SV index: *Baphia massaiensis, Bulbostylis hispidula, Baikiea plurijuga, Cyperus fc haspan ,Commelina africana, Dichrostachyscinerea, Indigofera daleoides, Rynchosiatotta,* with scores ranging from 15-20 (Table 6.4). The vulnerability of these species emanates from the loss of current suitable climate space, specialist habitat requirements (e.g., floodplains), narrow geographic range sizes and limited dispersal capabilities for the species to track and occupy areas of climate suitability overlap and new suitable climate areas (Table S6.1 & Table 6.2). The likely increase in vulnerability is mostly observed in the top three land cover habitats of the ORB; the *Zambezian Baikeia* woodlands, *Miombi* forests and shrub and grassland (Figure 6.4 & Table S6.4). These are habitats found towards the upper north and center of the ORB (see Revermann et al., 2016); therefore, contrary to the climate suitability assessment, the center of ORB. at least for the species modelled, is extremely vulnerable to a changing climate.

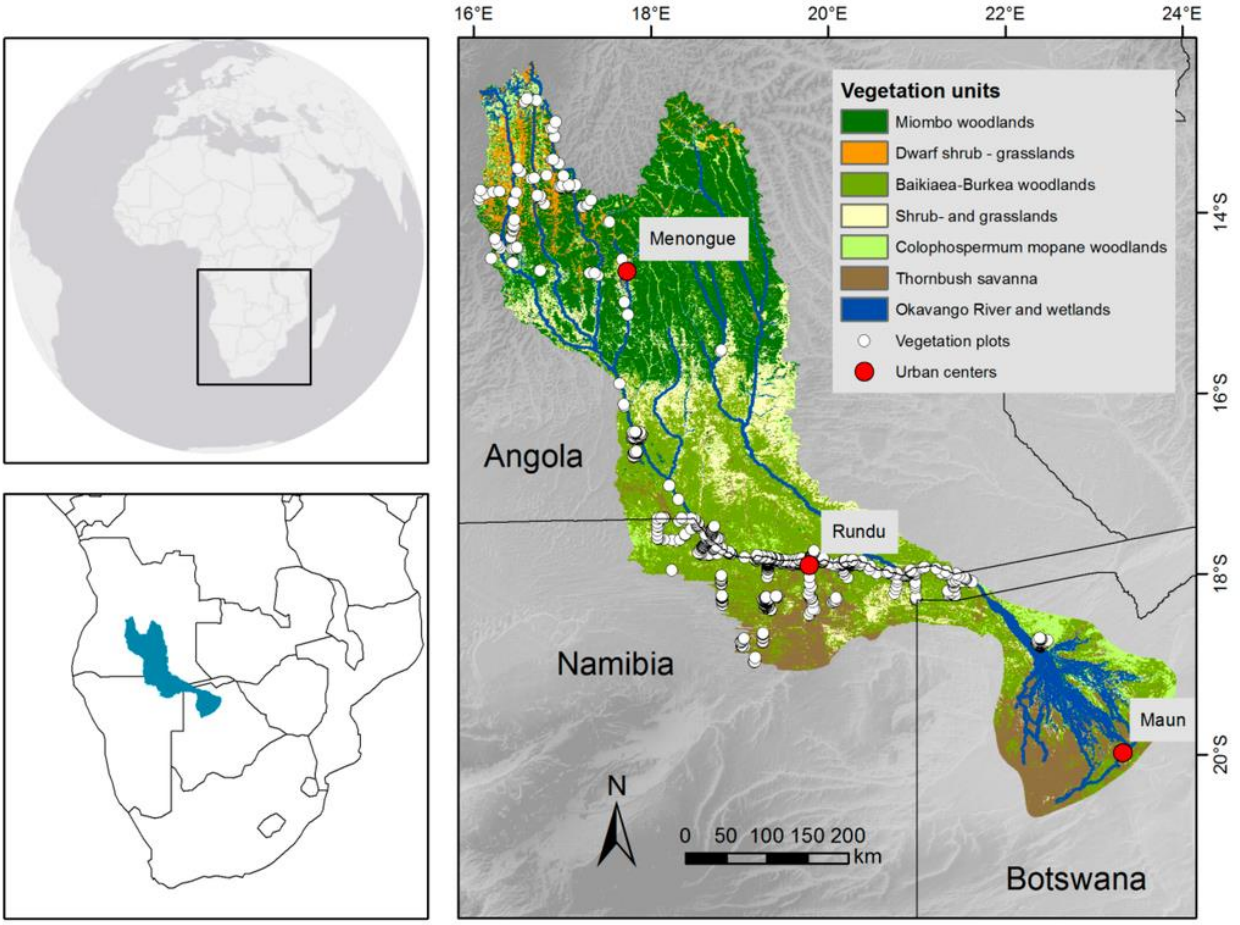


Figure 6.4: Major vegetation units of ORB, adopted from Revermann et al., (2016: p. 4)

Using the SLV index to compute vulnerability of the species with adaptive capability and adaptation opportunity (Table S6.1 & Table 6.2), the index ranking places three species under type 1, projected to be slightly vulnerable to climate change by the end of the 21 centuries; *Chamaecrista absus, Pterocarpus angolensis and Rhynchosia minima.* Species *Tephrosia cephalantha* falls under type 2, medium vulnerability (Table 6.5). These species benefit from expansion of suitable climate space and are characterized as having high dispersal capacity and opportunity to adapt, by dispersing to fill the new suitable climate space. These species therefore have potential to adapt to climate change under both scenarios, given their high adaptive capacity. Although this vulnerability index gives somewhat similar results to those obtained from the assessment based on metrics of sensitivity, the comprehensive vulnerability assessment changes the vulnerability levels of the species. Under the sensitivity metrics assessment (section

6.3.2.1), these species are projected to gain climate suitability space by 100%, denoting no vulnerability as the species have ability to fill all the new suitable climate space. However, consideration of both the species' ability and evidence of physical factors that hinder the species' adaptive capability to a changing climate, e.g., habitat loss due to land use change (adaptation opportunity), projects the species to have different vulnerability levels to climate change.

6.3.2.3 Summary of Potential Impacts of Climate Change for ORB Species

With the projected climate change increase of mean temperatures of between 3.0-4.0º C and decline in rainfall under future climate change scenarios (Chapter 4), the resilience and persistence of more than half (67%) of the modelled global IUCN Red List terrestrial plant species might be exceeded by the end of the 21st Century. Species *Baphia massaiensies, Baikiea plurijuga, Rychosia totta, Bulbostylis hispidula, Commelina africana, Cyperus cf haspan, Dichrostachys cinerea and Indigorefa daleoides,* are projected to have significant loss of potentially suitable climate space. The species are therefore potentially at risk of becoming regionally extinct. These species have similar characteristics of narrow range, low dispersal capacity and adaptation opportunity and are driven by rainfall related climatic variables. The suggestion is that within the ORB, species that fall under this category have a high likelihood of not persisting through the impacts of climate change over the next sixty years.

Vulnerability assessments in any climate change scenario also project that climate change will dramatically expand the areas of Okavango region that are climatically suitable for *Chamaecrista absus, Pterocarpus angolensis, Rhynchosia minima* and *Tephrosia cephalantha,* towards the northern area of the region.

Table 6.5: Species categorized into four vulnerability categories based on their SV index scores under diverse climate change scenarios for Southern Africa (calculations are in the online excel sheet). The numbers indicate the SV scores for each species

Vulnerability score	Baikiaea plurijuga	Baphia massaiensis	Bulbostylis hispidula	Chamaecrista absus	Commelina Africana	Cyperuscf haspan	Dichrostachys.cinerea	Indigofera. daleoides	Pterocarpus.angolensis	Rhynchosia.minima	Rhynchosia.totta	Tephrosia. cephalantha
RCP 4.5 SV												
Slightly vulnerable (0-5)												
Medium (6-10)				10					10	10		
High (11-15)	13				15		14	15			13	11
Extremely (16-20)		20	20			18						
RCP 8.5 SV												
Slightly vulnerable (0-5)												
Medium (6-10)				10					9	10		
High (11-15)											15	13
Extremely (16-20)	19	20	20		18	18	20	19				

Table 6.6: Species categorized into four vulnerability categories based on their SLV index scores under diverse climate change scenarios for Southern Africa (calculations are in the online excel sheet)

Vulnerability score	Chamaecrista absus	Pterocarpus angolensis	Rhynchosia minima	Tephrosia cephalantha
RCP 4.5 SLV				
Slightly vulnerable (0-5)	5	5	5	
Medium (6-10)				6
High (11-15)				
Extremely (16-20)				
RCP 8.5 SLV				
Slightly vulnerable (0-5)	5	4	5	
Medium (6-10)				8
High (11-15)				
Extremely (16-20)				

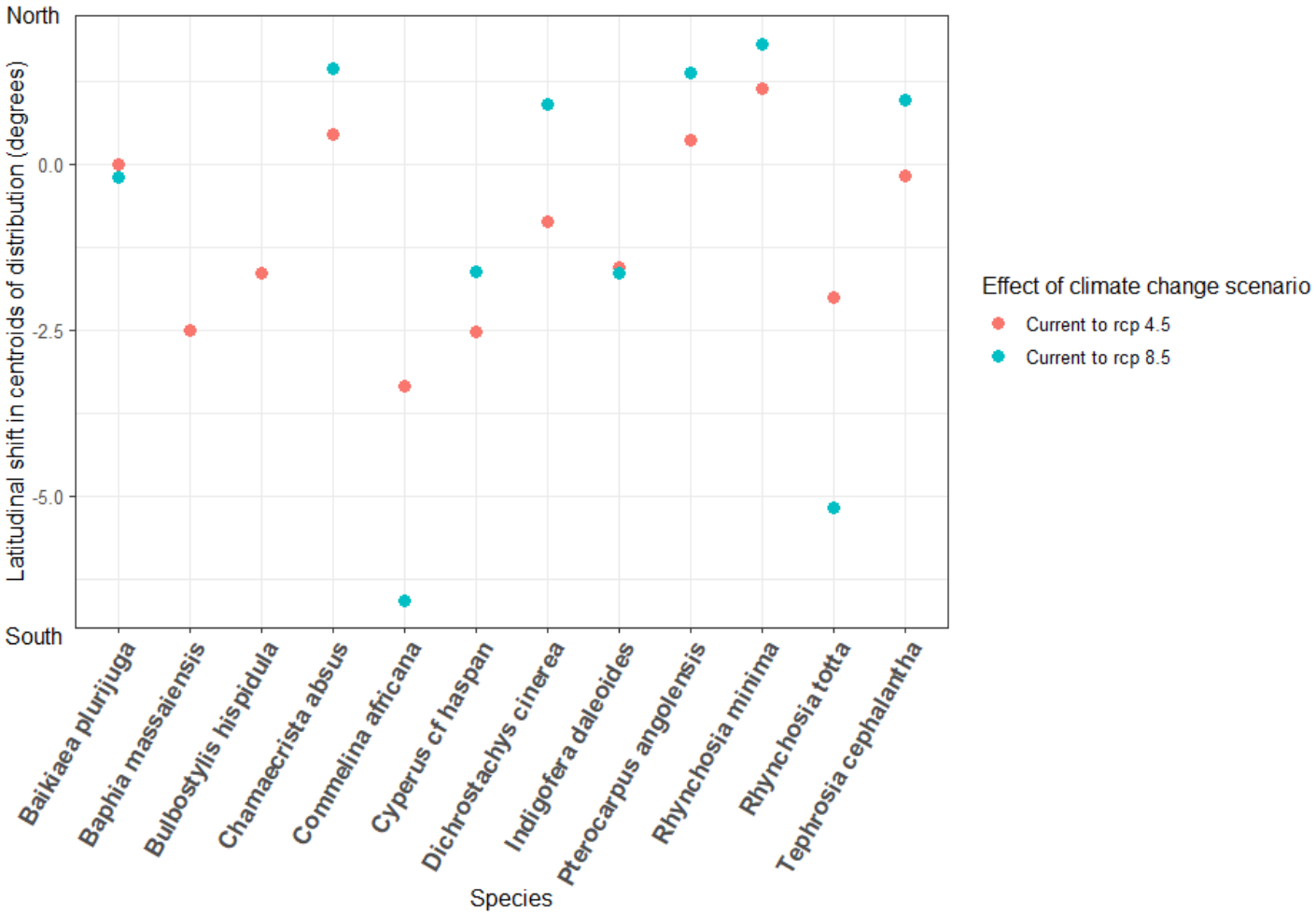


Figure 6.5: Differences in the climate space latitudinal distribution between the current projections and projections under climate change scenario RCP 4.5 and RCP 8.5 for the year 2085 respectively. This illustrates shifts towards the north and south. No shift at RCP8.5 is indicated for species *Baphia massaiensis* and *Bulbostylis hispidula* as they will lose suitable climate space in that scenario*

6.3.3 Current ORB Conservation and Management Plan Reviews

Review of the management plans documents reveal that the Okavango river basin seems not to be prepared for a changing climate, as the conservation and management plans at both national and transboundary levels only acknowledge climate change as one of the factors contributing to the environment and biodiversity problem, with lack of explicit adaptation actions to reduce its risks (Angola, Botswana, and Namibia NAPs, 2011). The information given in the SAP (2011) and NAPs does not allow for confidence that the species will adapt and be resilient to a changing climate.

The current management plans do not include an assessment of species' vulnerability to climate change in terms of their adaptation capabilities and opportunities (Berry et al., 2013; Thompson et al., 2015) nor the long-term threats of current decisions on the persistence and existence of future species. However, as confirmed by this study, comprehensive knowledge and understanding of which species are likely to be most vulnerable to climate change is critical (Midgley and Bond, 2015; Willis et al., 2015; Wade et al., 2017a).

The Strategic Action Plan, SAP (2011) and the Basin Development and Management Framework (BDMF) offer a great opportunity to enhance the resilience of the ORB at the transboundary level; however, the lack of recognition that achieving the current and future plans relies on and requires climate change adaptation actions to reduce negative impacts of climate change on species is a concern. The plans contain commitments to conserving ORB biodiversity, as well as acknowledgement of the negative effects on species from other stressors such as land use activities e.g., agriculture. The plans for managing and conserving species entail targets which have the potential to reduce species vulnerability if met. However, a concern is that they lack an explicit set of actions to meet the targets and do not consider future implications of climate change (Midgley and Bond 2015).

The vulnerability assessment carried out for the selected conservation-relevant species demonstrates different levels of species vulnerability to a changing climate, with some species having an extreme vulnerability ranking, some high and some low (section 6.3.2.3). The scale of impact of climate change on the species depends on adaptation capability and adaptation opportunity of the individual species. Section S6.1 (Targeting conservation actions for different species) sets out what would be needed for the ORB most-vulnerable species, and it lays out recommendations for enhancing their future (adaptation). In general, the ability of the species to disperse and adapt to changing climatic conditions is critical for their survival (Nicotra et al., 2015), and availability of a good network of habitats in good condition is needed for autonomous adaptation of the species (Berry et al., 2013; Ofori et al., 2017). Actions to improve and enhance the condition of habitats and connectivity (Vanderpost et al., 2005) of a protected areas network to provide for adaptation opportunity is thus important. The Kavango–Zambezi Transfrontier Conservation Area (KAZA TFCA) into which ORB falls, presents a good opportunity for improving connectivity within the protected areas network, especially those in the northern

regions. However at the time of this analysis, there is no evidence of a design of integration of landscape to allow migration and dispersal corridors (Smithers et al., 2008; Mawdsley et al., 2009; Oliver et al., 2012), and design of adaptive response to facilitate movement in response to climate change (Beier, 2012). There is a need to implement actions now that have potential to reduce other stressors on species and their habitats. The lack of adaptation actions in the NAPs and SAP that will effectively reduce vulnerability is a critical deficiency. Restoration and improvement of the protected areas network within this region is needed to enhance adaptation. Given the time lag between action and decline in vulnerability (Crooks, 2005), restoration plans and activities should be undertaken now.

There is no acknowledgement of the existing synergies between the thematic areas of the SAP policy interventions and planning for key sectors such as water resources, land use, agriculture (SAP 2011) (see the thematic areas in section 2.6); however, these have the potential to enable and enhance better species adaptation (Chong, 2014). The NAPs annex on thematic areas includes a good number of indicators (Angola, Namibia, and Botswana NAPs, 2011); however, it is weak in linking and identifying the potential impacts of climate change on these sectors/indicators and how it might affect species. For example, the thematic area 3 ("Land management"), one of the targets to achieve the thematic area objective of "reducing environmental degradation, overuse of forests and land resources…" is of repopulating forests areas along the river basin (Angola NAP, 2011:pp.22&39). This has potential to improve the habitat size and condition of the area. However, there are no actions listed on how to achieve the target. However good this target is, it is uncertain whether it will become a reality. Nor do the indicators give room for effective adaptation actions that might reduce the identified threats (Smithers et al., 2008; Mawdsley et al., 2009; Huntley, 2017). The indicators need to be improved to benefit from a resilience target: without this, it is difficult to measure achievements. In the Namibia NAP (2011) annex 1: Thematic area 3; land management, to achieve the thematic area outcome of a sustainable land use framework for the basin, identification and establishment of game corridors and river conservation zones are listed as proposed interventions. If actions for implementation can be stipulated with mention of a body responsible for implementing the actions, they have potential to enhance habitat condition and connectivity, increasing species adaptation opportunity.

The Angola NAP (2011) has no mention of monitoring and evaluation actions. In the Botswana and Namibia NAPs, there is only a column on monitoring in the NAPs' annexes, however, with no discussion of monitoring and evaluation (Botswana and Namibia NAPS 2011). The NAPs' annexes on some of the thematic areas lists descriptions of actions with no institution responsible for implementation. The plans do not entail the scale of determination needed to effectively conserve biodiversity under a changing climate. This deficiency is addressed in the following discussion section where I make recommendations on basin wide biodiversity climate change adaptation principles. Species specific management plans to integrate into the main conservation planning following vulnerability assessment are also proposed.

6.4 Discussion

Understanding how plants species respond to climate change (Hannah et al., 2005; West et al., 2009; Cross et al., 2012; Meller et al., 2014; Midgley and Bond, 2015; Pacifici et al., 2015) is critical to efforts to conserve them (Platts et al., 2014a; Willis et al., 2015; Foden and Young, 2016). In this chapter I applied a comprehensive climate change vulnerability approach that, in addition to metrics for species sensitivity, incorporated information on current conservation plans and analysis of habitat and ecological processes and theories to determine a species' capacity and opportunity to adapt to climate change. Results from the comprehensive CCVA approach suggests that simulation of changes in a suitable climate space is a necessary but first step in the assessment of species vulnerability. For this study, vulnerability results that considered and included components representing adaptive capability and adaptation opportunity varied and slightly contradicted those derived from assessment based on metrics for sensitivity only. Results for the three species that matched in both metrics highlight that adaptation capability and opportunity reflected the sensitivity. Overall, metrics assessments lacking inclusion of all elements of vulnerability may indeed give an incomplete picture of a species' vulnerability to a changing climate (Berry et al., 2013; Butt et al., 2016). My findings here support suggestions that robust vulnerability to climate change assessments should not rely solely on climate envelope models but should follow approaches that include all elements and components that affect species vulnerability (Berry et al., 2013; Wade et al., 2017); and adaptation and management

actions should be designed and integrated into conservation planning at species specific levels (Ofori et al., 2017).

6.4.1 Among-Species' Variation in Vulnerability Assessed Through the Comprehensive Vulnerability Framework.

The studied species are threatened by the projected magnitude of climate change differently according to their level of sensitivity combined with adaptive capability (range size, dispersal, and colonization abilities) and adaptation opportunity. In the ORB, the vulnerability of (8) species to climate change is exacerbated by low capacity and opportunity to adapt to a changing climate, driven by intensification of agricultural activities (Lambin et al., 2000; Zimmermann et al., 2010), population growth, land degradation and fragmentation (VanderPost et al., 2005; SAP, 2011a; Wingate et al., 2016). This supports conclusions of the IPBES/Africa (2018) that land use change is a driver of biodiversity loss, increasing species vulnerability. This creates a double-edged sword for species' ability to persist in the face of climate change.

With Southern Africa set to be drier and warmer by the end of the 21st century (Niang et al., 2014b; Gan et al., 2016), species favouring well drained deep sandy soils in arid conditions such as *Pterocarpus angolensis* (Strohbach and Peterson, 2007) are identified as less vulnerable (Type 1 & 2) to climate change. This suggests that in this study region, species inhabiting warm and dry places have relatively higher adaptive capability; this can be attributed to the species being already arid adapted, and therefore having higher tolerance to the projected climate change (Boyles et al., 2011; Fordham et al., 2013b; Hoffmann et al., 2013). As a result, the projected sensitivity to climate change for *Pterocarpus angolensis* does not exceed its safety margins for a rise in temperature (warming) and decline in rainfall (drying). This finding contradicts the notion that arid regions species exhibit high susceptibility to climate change, due to physiological limits restraining the species tolerance to high temperatures (Araújo et al., 2013; Vale et al., 2015).

6.4.2 Conservation and Management Implications

Given the review of current management plans (section 6.3.3) and analysis of the studied tropical plants' (woodlands, dwarf shrub-grassland, and thornbush savanna) response to changes in climate, evidence of future climate change resulting in substantial losses and gains (Midgley and Thuiller, 2011; Midgley and Bond, 2015) is provided. Results of index SLV, suggest that species with moderate sensitivity to climate change, high adaptive capability and adaptation opportunities have potential to adapt to climate change. The result highlights the importance of designing and implementing planned adaptation strategies (McLachlan et al., 2007; Watson et al., 2012; Williams and Dumroese, 2013) at a basin wide level, in order to reduce vulnerability for many of the species.

The results suggest that at coarse spatial resolutions northern areas might be more resilient to climate change than southern areas. This could be due to climatic buffering with the north areas depicting less warming and drying than the south (Chapter 4). The finding contradicts that of Garcia et al. (2012), where projected climate change predicted loss in species turnover for African vertebrates towards the southern regions of Namibia. From my results, areas of potential climatic refugia are identified in the north of the region. This result indicates the importance of enhancing biodiversity climate resilience in conservation areas of the north, and less so in the south. Conservation areas in the northern part of Botswana such as the Chobe National Park and KAZA TFCA should focus on the maintenance of ecological integrity (Ofori et al., 2017) and climate resilience through effective management strategies such as creation and maintenance of corridors and connectivity between current and new habitats [enhanced adaptation opportunities] (Williams et al., 2013). This will facilitate shifts of ORB species with sufficient dispersal capabilities to fill the new suitable climate space. Existence of these protected areas should provide opportunities for achieving management policy objectives in the face of a changing climate. To accommodate projected shifts in the plant species distributions, ORB conservation practitioners and managers should restore potentially climatically persistent / potential climate adapter species such as *C.absus, P.angolensis and R.minima* and *T.cephalantha,* e.g. along the north-south gradient; this has potential to increase resilience. For these species to effectively migrate and remain in their suitable climate envelope, anthropogenic dispersal barriers need to be

removed (Doerr et al., 2011). However, for those species whose distribution is mostly determined by rainfall related variables, i.e. highly sensitive to climate change, have low adaptive capabilities, and have reached their northern distribution margins, planned translocation might be the effective management strategy (Thomas et al., 2013).

Under RCP 8.5 scenario, the species vulnerability assessments suggest that the lack of planned adaptation will raise the vulnerability of the studied species to climate change. High and extreme vulnerability rankings are however not depicted for all species; there is important vulnerability variation at a species level. This suggests that not all species projected to be vulnerable will require immediate conservation concern; however, it highlights some new conservation priorities (Nicotra et al., 2015). Efforts to reduce external stressors, for example reduction of habitat degradation and fragmentation (Watson et al., 2012), should be implemented to prevent species from becoming highly vulnerable and to enhance their adaptive capabilities.

Where species are projected to expand towards the south, because of limited suitable climate space becoming available, this leads to limited adaptation options. In such cases it will be important to reduce any anthropogenic stressors and maintain the habitat. Methods to increase climatic sustainability by specific design of, among others, climate corridors (Beier, 2012) might be good adaption options. The current conservation and management plans for climate change determines the rate at which species will persist and survive under future climate change scenarios (Gillson et al., 2013; Hannah et al., 2014). Thus, climate change adaptation principles are critical for effective conservation of species under a changing climate.

6.4.2.1 Recommended Basin -Wide Biodiversity Climate Change Adaptation Principles

To reduce ORB plant species' vulnerability to climate change and enhance their resilience, design and implementation of adaptation measures is an important approach. Based on the species vulnerability assessment (section 6.2), I recommend four main adaptation principles suitable for conserving biodiversity in ORB. These principles build on the biodiversity adaptation principles generally formulated in literature e.g. (Smithers et al., 2008; Mawdsley et al., 2009). They draw on results of potential impacts of climate change presented in section 6.2 and review of the ORB current management plans (section 6.3.3).

I envision that the adaptation principles contained in the basin wide strategy would be adopted and endorsed by basin member states and implemented at the national level as part of the National Action Plans.

Principle 1: Undertake immediate conservation and management actions.

The projected scale of Southern African climate change (Chapter 4) and the potential impacts it has on ORB species (Chapter 6, section 6.2) prompts immediate action. Neither uncertainty about the extent and speed at which climate will impact biodiversity, nor the direct and indirect impacts of climate change on species and habitats should be a cause for a delay in acting. Time delays have the potential to aggravate the impacts, reduce available options for action and escalate costs of intervention (Stern et al., 2006). The time scale associated with the implementation of the adaptation actions and biodiversity response also calls for immediate action. Efforts should be focused on these actions:

- Recognize the importance of protected areas, such as the Chobe national park and KAZA TFCA. These protected areas have to be conserved by maintaining their ecological integrity, as they contain climatic envelopes conducive for some of the species in the future. They are therefore critical ecological components for the general terrestrial and freshwater ecosystems.

- Conserve existing biodiversity through *in-situ* management and monitoring (see S6.1): The abundance and richness of future biodiversity is a function of how much is conserved at the present time.

- Reduce other stresses and threats; there is a synergy between reduction of other stresses and threats to biodiversity and the ability of the biodiversity to cope with impacts of climate change. Reducing non climatic stresses such as control and monitoring of wild fires in combination with conservation efforts can enhance resilience of the high and extreme vulnerability species such as *B.massaiensis, B.hispidula, B.plurijuga, C.haspan,C.africana.*

- Assign departmental level implementation of action responsibilities.

Principle 2: Increase resilience

The projected rate and magnitude of climate change (Chapter 4) leads to some level of difficulty for species' natural adaptation to take place. Management strategies aimed at maintaining and restoring degraded biodiversity can enhance resilience and assist species to adapt to a changing climate. Options and efforts to increase the adaptive capacity and adaptation opportunities of the species and ecosystems should continue to focus on:

- Strengthening of existing protected areas networks, especially in the northern areas (based on results of the modelled species with new climate space); this facilitates wider options of conservation and sustainable use practices. It is an effective way to avoid further habitat fragmentation and isolation of terrestrial and freshwater ecosystems. In this case spatial planning efforts are of importance. Generally, to strengthen existing protected areas networks' knowledge on which direction species are likely to move is critical (Figures 6.2 & 6.3).
- Control of invasive species; alien and invasive species is one of the threats to biodiversity of the ORB (SAP, 2011b). If not monitored and controlled effectively the invasive species can cause significant degradation and loss of species.

Principle 3: Make room for change and accept change and loss

The projected shift in species distribution has potential to affect other species and habitats. As evident from the vulnerability assessment results (section 6.2), response to climate change is at the species level, causing potential changes to the structure and composition of habitats. It is thus important to understand and embrace that change is inevitable. A detailed account of the potential changes and losses to the studied conservation-relevant species is in section S6.1. Efforts should be focused on working with the projected changes by:

- Establishing species translocation and *ex-situ* conservation e.g., relocation, assisted migration, restocking, establishment of corridors; these could contribute to maintaining the adaptive capacity and opportunity of species such as *Chamaecrista absus*.
- Active response to changing conservation priorities; by regular review of conservation targets and aims. As species might expand their distribution, e.g., *Pterorcarpus*

angolensis and *Rhynchosia minima* (Figure S6.2) some contract e.g *Baikiea plurijuga* and *Rhynchosia totta* (Figure S6.4) and decline in population size, some get lost e.g., *Baphia massaiensis* and *Bulbostylis hispidula* (Figure S6.3), vegetation composition might change. The review of conservation aims will ensure resources are utilised on those species with conservation priorities.

Principle 4: Integrate actions across sectors to facilitate actual synergies:

Given the transboundary nature of the ORB, the scale of adaptation required calls for integration of key sectors such as water resources, land use, agriculture to achieve actual synergies, these sectors with harmonised efforts have the potential to enable and enhance species adaptation. There is therefore need to:

- Integrate policy and practice across the relevant economic sectors in the basin member states.
- Formulate climate change adaptation strategies in partnership with private, public and parastatal sectors.

6.4.3 Reflections on The Application of The Climate Change Vulnerability Assessment Framework

In developing and applying the rigorous CCVA, it became apparent that omission of the elements of adaptive capability and adaptation opportunity in assessments of potential impacts of climate change on species is of considerable concern. My study provides numerous theoretical and practical reasons to argue for the inclusion of these elements. From a practical viewpoint, this structured framework comprehensively facilitates the identification of the impacts of climate change on species and the required relevant adaptive management options. There are therefore no aspects of the framework that I would have approached differently.

The framework in recognizing that a species response to climate change is dependent on its adaptive capability and adaptation opportunity has enhanced my appreciation of the attributes of resistance and resilience (Prober et al., 2012) in influencing the response and outcome of species to climate change.

The only challenge I perceive in the use of the framework is that it hinges on conservation practitioners collaborating with species distribution modelers or having to acquire the relevant coding knowledge and skills for operating species distribution / climate envelope modelling software packages. However, there exists institutional/organizational and civil service capability to foster such collaboration. The species distribution modelling knowledge is needed to assess the species sensitivity to climate change. The ability to project the extent and direction of change is a critical factor for conservation and management decision making. However, I still uphold the view that the rigor and repeatability of this structured approach provides a comprehensive assessment framework and thus should be applied as is. It is worth noting that species distribution modelling software packages do not require highly developed coding capability, and they are relatively easy to learn and intuitive. The software package developers offer free online tutorials for users; with this, it would be beneficial for conservationists to invest time in learning to use and run species distribution model experiments. It is possible that in the absence of modelling capability, that the assessment of the species sensitivity to climate change can be done by expert elicitation.

Demonstrating the applicability of the framework and planning species specific adaptation actions needs was time consuming. However, for robust, effective conservation planning, adaptation actions need to be tailor-made to a species or habitat.

Periodic monitoring and reporting on species conservation status, coupled with adaptive management (Westgate et al., 2013) by conservationists is critical. Managers or conservationists will need to keep documentation on the carried-out assessment of the species or habitat vulnerability, detailing the list of species, outcome of the assessment and conservation or adaptation actions required at an individual species level. A discussion of the limitations of the assessment will also be needed.

6.5 Concluding Recommendations

Through this study I have shown that, following previous work to validate the use of coarse scale climatic data for SDM use, plant species in the ORB will respond to climate change at individualistic level, varying according to the greenhouse gas emission scenario, species habitat and ecological requirements/ processes (adaptive capability and opportunity). Using adaptive

capability measures such as dispersal capacity, species distribution size and, habitat condition, adds to the confidence in the vulnerability assessment of the species to climate change. Where information on intrinsic adaptive capability traits is not available (as is true in most cases), extrinsic traits such as habitat /range size and dispersal capabilities can therefore be used. Habitat fragmentation and barriers are likely to impede species migration in the future, thus reducing a species' adaptive opportunity, whereas maintenance of corridors and connectivity in fragmented habitats can improve adaptive capability (Nicotra et al., 2015). Thus, assessment of current management actions is one critical factor to consider in vulnerability approaches. As vulnerability assessments are to aid conservation plans, I advocate and emphasize that for CCVA to be robust, all three elements; sensitivity, adaptive capability and adaptation opportunity plus current management actions should be accounted for and factored in. I therefore recommend the application of the designed robust vulnerability assessment framework by practitioners in assessing the need for conservation efforts and integration into the main conservation planning.

The limited number of arid species modelled in this analysis calls for caution in extrapolating from these to make general statements about all arid species. The results should be used as guidelines. The study identified eight species as extremely vulnerable to climate change, with four as slightly vulnerable. Exclusion of other species within the ORB that might be extremely vulnerable to a changing climate is a possibility, especially those that have specialized habitat requirements, narrow distributions, low dispersal and adaptation opportunities, and that occur in narrow climatic conditions. Because of the species selection criteria for this chapter, some of the species with these characteristics were excluded. Assessment of the vulnerability to climate change of other species within the ORB that are not of conservation relevance is therefore recommended. There is no account of multi-model uncertainty in this chapter as only one GCM-RCM combination (one CORDEX model [SMHI] forced by one CMIP5 model [EC-EARTH] was used. The choice of the model combination was based on the EC-EARTH model's good performance in simulating climate features evident in the climatology/present day conditions of the study region (sections 4.3.2 and 6.2.1.3) and thus was used to derive the AFRICLIM climate data projections used. When applying the SDMs for conservation decision making the multi-model uncertainty, which may result in uncertainty in the projections of the plant species responses to climate change (Senay and Worner, 2019) should be taken into account. To improve confidence in the future species distribution scenarios, I recommend the use of multi-model

ensemble averaged climate projections(Daron et al., 2018) for use in SDM projections to future climates.

Summary Recommendations for Adapting for the Future

An adaptative, management approach is imperative for ORB to survive impacts of climate change. Integration of species/biodiversity adaptation management actions into conservation policies (Rands et al., 2010) is imperative. Focus should be on managing biodiversity at a basin wide level. The four main adaptation principles listed below and detailed in section 6.4.2.1 are relevant for conserving biodiversity in ORB. I recommend that the adaptation principles should be contained in the basin wide management strategy and be adopted and endorsed by basin member states and implemented at the national level as part of the National Action Plans. These adaptation principles used alongside the species-specific conservation actions in section 6.4.3 are the basis to further design a transboundary species-specific management plan. It is imperative for ORB conservation practitioners to apply the designed comprehensive vulnerability assessment framework to assess conservation needs and facilitate development of effective conservation and management plans resilient to a changing climate.

Recommended adaptation principles:

Principle 1: Undertake immediate conservation and management actions.

Principle 2: Increase resilience.

Principle 3: Make room for change and accept change and loss.

Principle 4: Integrate actions across sectors to facilitate actual synergies.

7. Conclusions

7.1 Overview of study motivation

The projected effects of global warming on key climatic variables (rainfall and temperature) related to biodiversity in Southern Africa (Kusangaya et al., 2014; Gan et al., 2016) is a concern and a pressing issue that will become increasingly important for biodiversity conservation, and the management and maintenance of ecosystem processes (IPBES Africa 2018; Rands et al., 2010). The effects of climate data spatial resolution on the projection of current and potential impacts of climate change to species distribution and richness is an important question in current ecological research (Gottschalk et al., 2011; Wan et al., 2016; Morán-Ordóñez et al., 2017; Nadeau et al., 2017). The emerging evidence that the spatial scale at which a species responds to its climatic conditions, and the spatial resolution at which the relationship is analysed, are critical and potentially confounding factors (Mertes and Jetz; Field et al., 2009; Dale and Fortin, 2014) generated my interest in carrying out this study. The issue of spatial resolution is of particular interest over Africa where there is both a lack of high resolution observed data sets against which climate models can effectively be evaluated (James et al., 2018) and a notable lack of application studies of scale-sensitive methods in the modelling and analyses of species environment relationships (Garcia et al., 2012; Midgley and Bond, 2015).

Testing the extent to which species distribution models accurately capture species-climate relationships as a function of the spatial resolution of the climatic variables in a tropical arid Southern Africa landscape is therefore a recognisable and important knowledge gap, especially given that running climate models at high resolution is a resource demanding process, in terms of computing time, disk space and analysis. Changing the resolution (i.e., grid spacing from 100 to 50 km) in a model leads to about 16 times slower running of a climate model, making it a major investment to run at high resolution. These are financial and human resources that most African based researchers and conservation practitioners lack.

Study importance

Although downscaling GCMs to higher spatial resolutions for climate change impact assessment is important, there are some practical caveats to GCM downscaling which bring about uncertainty in the downscaled climate projections (Nover et al., 2016; Vautard, 2018). One of the sources of uncertainty is, the observation datasets for creating the downscaled datasets (Daron et al., 2018). This observation datasets uncertainty emanates from the spatial density and precision of weather station data (Tabor and Williams, 2010), which has an effect on the accuracy and the spatial resolution of the baseline observation data. As a result of this, the benefit added by downscaling projected climate datasets using observation data is reduced.

Africa, including the Southern Africa region has a sparse distribution of weather stations (van de Giesen et al., 2014). This then produces a source of uncertainty when creating fine spatial resolution gridded climate observational datasets for the region. It is crucial therefore, to conduct an analysis to investigate the trade-offs between the benefit added by downscaling from GCM resolutions to higher spatial resolutions over a region with sparse weather stations. Of importance is the analysis of the appropriateness of downscaling GCM to fine spatial resolutions for studies modelling impacts assessments. This thesis in Chapter 5 sought to understand the influence of the spatial resolution of the climatic predictor variables on predicting species distributions and how the predictions might change as a function of the spatial scale of the climatic predictors used in the modelling. Conservation modelers often assume coarse scale models to be insufficient in projecting species distribution, as they are thought to be equally biologically coarse (and therefore can bias the area identified as suitable when used as SDM predictor variables) (Gottschalk et al., 2011; Seo et al., 2009), but few studies have adequately tested this assumption. This leaves conservationists faced with uncertainty in the effects of spatial and temporal scale variations in the datasets used for operating SDMs for projecting species occurrences. Questions relating to the adequate predictor spatial resolution for accurate projection (Raven, 2002; Bradter et al., 2013; Fournier et al., 2017) therefore remain partly unanswered owing to this lack of consensus. This study gives evidence-based insights that SDMs over landscapes with low topographic and climatic variation can be operated with climatic predictor data at up to 50km x 50km spatial resolution. Over such landscapes, there is therefore no need to downscale climatic variables/products to higher spatial resolutions for SDMs. The

thesis suggests that in species distribution modelling for conservation planning, assessment of the input datasets spatial resolution should be informed and guided by knowledge of the study area level topographic condition as protocol. Investigation of the effects of predictor spatial resolution is, hence, an important component to consider in the application of SDMs. Effective conservation strategies rely on the understanding and incorporation of the complete effects of the variation in the spatial resolutions of climatic predictor data in SDMs (Rodríguez et al., 2007). Despite its status as an ecoregion of global conservation priority (Botswana CBD Report, 2009), there is a deficiency in studies assessing potential impacts of climate change on the terrestrial plant species of the ORB. Provision of a comprehensive assessment of the potential impacts of climate change on plant species requires accurate distribution models. The ORB being part of a relatively homogenous climatic and topographic landscape in the interior of a continent in the subtropics thereby also presents an important case study to investigate elements of SDM framework and methodological uncertainties that might have an effect on model outputs. The significance of this thesis lies in its informing theoretical and methodological understanding of the effects of spatial resolution of climatic data in SDMs, as well as identifying the appropriate resolution for downscaling climate variables for projection of species distributions.

This chapter summarises major findings of this thesis and their significance. It gives a brief outline and discussion of original contributions to the literature and provides further research directions. The chapter ends with concluding remarks, synthesizing key messages.

7.2 Summary of the major findings

7.2.1 Effect of spatial scale of climate models in simulating observed and future temperature and rainfall over Southern Africa.

Comparisons of historical rainfall and 2-meter air temperature data from observations and models, at coarse and fine resolutions (GCM historical and future data compared to AFRICLIM historical baseline [WorldClim interpolated observations] and AFRICLIM future projections [statistically downscaled and bias corrected CORDEX projections]), over the Southern Africa domain, covering the ORB in Chapter 4, established a degree of difference in spatial distribution of climate features.

I found that even though AFRICLIM historical baseline, due to the fine spatial resolution, have more credibility in producing features of the observed climatology, the presented pattern of correlation coefficient results between the coupled coarse resolution models, show significant correlation coefficients with the observed as evident from the strongest correlations around $r=0.78$ ($p<0.05$) and the weakest around $r=0.27$ ($p<0.05$) (Chapter 4, section 4.3.3).

My evaluation of the simulated models' associated biases through an anomaly approach (Patricola and Cook, 2011), revealed that the coupled climate models (CMIP 5 models) depict wet biases in the centre of the domain within the zone of tropical convection, particularly over Zambia and the southwest Indian Ocean (Figure 4.1 & Figure 4.2h). My assessment of the spatial distribution of the wet bias showed a varied distribution, with models depicting a large wet bias over the Kalahari Desert area (Figure 2h, CNRM-CM5) and along the western coastline to Angola (Figure 4.1h, Figure 4.1r and Figure 4.2w). The evaluation showed a weakening of the mean rainfall gradient as the wetting bias intensifies. This is a key finding that calls for further research studies into the analysis of the causes of these biases, expanding on the work of Munday and Washington, (2018); this was beyond the scope of my study.

I found that in the AFRICLIM datasets, the biases are lower with a more realistic gradient across the interior of Southern Africa, this making the fine scale model capture the summer rainfall distribution with greater fidelity. This might be due to the AFRICLIM climate projections having

the advantage of being corrected for systematic biases between observed and simulated climatologies. I also found that the fine climate simulations capture the pattern features of observed temperature with skill, while the coarse coupled models show a weakness in simulating the temperature field, evident from a temperature cold bias depicted over the interior of Southern Africa. The developing question from this that was of interest to this study is, given that the model biases are a function of the scale, what effect do they have on the projection of species distribution?

My evaluation of the issue of spatial scale in climate data exposed identifiable biases between the fine and coarse scale climate models. A link between the spatial resolution of climate data and the bias in the coarse scale models has been established, this finding fills a gap in knowledge (Chapter 4).

Selection of the credible climate model to use for climate change impact studies including species distribution modelling depends in part on how the climate model replicates the historical and current conditions processes (Nazarenko et al., 2015). I found that the EC-EARTH model shows overall good performance in simulating Southern Africa rainfall seasonal mean and general climate elements of the domains' contemporary/observed DJF mean rainfall. This finding is critical to inform the selection of which climate model to derive the temperature and rainfall variables for running ensemble species distribution models (Chapters 5 & 6).

Given the differences in the characterization of the basic features of the simulated contemporary summer rainfall and temperature climates, interpretation of results of future climate impact studies relies on the understanding of projected climate change as a function of different spatial resolution of the climatic variables. In appreciation of this issue, **sub aim 1** was **to investigate the fine and coarse scale models future climate projections and their differences, in Southern Africa domain.**

7.2.1.1 Fine and coarse scale models future climate projections and their differences, in the Southern Africa domain

My evaluation of the relationship between the performances of CMIP5 and AFRICLIM models in projecting future changes in rainfall and temperature variables through comparisons of projected patterns of change, highlights that the differences in changes in future climate simulations from the GCM and AFRICLIM data for the late 21st Century is relatively minimal over ORB. Through my assessment of how strong and widespread the projected change signals are over Southern Africa from the GCM models and AFRICLIM, based on change signal measured by the (i) spatial distribution, (ii) the magnitude and pattern of change, similarities in change signal are revealed. My findings from this analysis have provided an evidence-based argument that both climate data at 200 km (from GCMs) and statistically downscaled and bias corrected CORDEX projections to fine resolutions might be equally sufficient for climate change impact assessments within Southern Africa especially over ORB.

From the findings of Chapter 4, intriguing questions emerged, such as, given that the model biases relate to scale, what effect do they have in species distribution modelling? In general, the chapter showed that contemporary climate gets more detail at different spatial resolutions, with global models being coarse and AFRICLIM being fine. However, the AFRICLIM fine resolution dataset benefits from the addition of spatial detail such as more structure reflecting the topography of the region, which is not clear in the coarse resolution dataset. I found it important to test whether this seemingly added value presents any benefit in modelling species distribution under contemporary climate envelopes obtained from fine and coarse models. This led to the **second aim** of the thesis, **to investigate the effects of spatial resolution of climatic predictor variables on plant species distributions and richness estimates in ORB.**

7.2.2 Effects of spatial resolution of climatic variables on plant species distributions and richness in ORB

Establishing the sensitivity of using coarse spatial resolution versus fine spatial resolution climatic datasets on species distribution modelling provides a useful way of establishing whether the costly laborious efforts involved in downscaling global climate model products to finer resolutions are indeed justified, at least in the context of their use for SDMs over flat terrain in the interior of subtropical regions. Through modelling terrestrial plant species in the ORB to

project their current distribution at 2km×2km, 5km×5km, 10km×10km, 20km×20km and 50km×50km spatial resolutions and using GLM and Tukey's Honest Significant Difference analysis to investigate the relationships between the variable importance scores and variable identity and their interaction with predictor spatial resolution, I found no significant effect of spatial resolution of climatic datasets in the performance of species distribution models. This is an important finding; determining the suitability of SDMs for their intended application is an essential step achieved through assessment of model performance (Guisan and Thuiller, 2005a; Barry and Elith, 2006). Model performance evaluation is also used in comparisons of different, alternative modelling algorithms (Pearson et al., 2006), it also affords modelers an opportunity to examine how varying properties of the environmental data and species occurrence data affect the accuracy of the predictive maps constructed by the models (Reese et al., 2005; Seoane et al., 2005), giving a measure of the quality of the ultimately selected model.

I found species distribution model performance not to be scale dependent, assuming the ORB to be representative of similar continental settings. Therefore, in such areas more attention should be given to the identity of the selected predictor variables for modelling the species distributions than to their spatial resolution. I also found that SDMs should be tailored to the specific location, the data available and to which questions need to be addressed for effective local biodiversity management and conservation (Chapter 5).

Although it is a commonly-stated belief that projections of species distributions require as high resolution predictor variables (Connor et al., 2017) as possible, I found that the use of predictors at different spatial resolutions may not intrinsically bias future species distribution models. In light of these findings and given the intense resources needed to downscale climatic variables to finer scales for SDMs, modelling at coarser spatial resolutions up to 50km×50km for conservation purposes in areas with comparatively low topographic and climatic variations in the interior of a continent in the subtropics can be acceptable. This is an encouraging finding for conservation practitioners. My study suggests that in SDMs for conservation planning, assessment of the input datasets' spatial resolution should be informed and guided by knowledge of the landscape level topographic conditions, as a general rule.

In addition, my study establishes that associations of predictor spatial resolution to variable importance are generally weak across spatial scales and therefore variable identity is more

important in predicting variable importance scores performance than predictor spatial dynamics. As an output, SDMs yield variable importance values for each variable involved in the models (Thuiller et al., 2009). These values reflect the relative contribution of environmental predictor variables to the model outputs. The favourable and unfavourable conditions of a species are therefore determined by the variable importance performance of the SDM. My study highlights that model importance values are more dependent on variable identity than on spatial resolution.

These valuable findings led to the **third aim** of the thesis which is **to assess potential impacts of climate change on ORB terrestrial plant species and their vulnerability and to explore the implications for conservation and management planning.**

7.2.3 Vulnerability/potential impacts of climate change to ORB terrestrial plant species

Robust assessments of potential impacts of climate change on species include the application of comprehensive vulnerability assessment approaches that incorporate elements of species adaptive capability and adaptation opportunity (Berry et al., 2013). In assessing the potential impacts of climate change on ORB plant species, I developed and applied a conceptual comprehensive vulnerability assessment framework (Chapter 6).

Through the framework I demonstrate that the use of correlative SDMs (Guisan and Thuiller 2009; 2014) in the assessment of species' vulnerability to projected climate change, is a necessary but initial step in the vulnerability assessment process. My findings highlight that assessments that omit components of species adaptive capability and adaptation opportunity may result in an incomplete picture of a species potential vulnerability, impacting on ability to implement effective and efficient management and adaptation actions (Vaughan and Ormerod 2003; Rodríguez et al., 2007; McInerny and Purves 2011). These findings support suggestions that robust vulnerability to climate change assessments should not solely rely on SDMs (also known as climate envelope models) but follow approaches that include all elements and components that affect species vulnerability (Berry et al., 2013; Gillson et al., 2013; Wade et al., 2017, 2017).

I also found that northern areas of my study region might be more resilient to climate change than southern areas. For terrestrial plant species of ORB, areas of potential refugia are therefore

identified in the north of the region. This finding is significant, as it highlights the importance of enhancing species climate resilience in conservation areas of the north, less so in the south. Therefore, conservation areas in the northern part of Botswana such as the Chobe National Park should be targeted to provide maintenance of ecological integrity (Ofori et al., 2017) and climate resilience through effective management strategies such as creation and maintenance of corridors and connectivity between current and new habitats [enhanced adaptation opportunities] (Williams and Dumroese, 2013). My finding offers invaluable information in guiding the allocation of often limited biodiversity and ecosystems conservation resources (Lindenmayer et al., 2006; Peterson et al., 2011; Rowland et al., 2011, 2019) and facilitates the design of effective management policies (Walters, 2011; Marcot et al., 2012; Naimi and Araújo, 2016). It should be noted that the future climates used to project the species distributions are derived from a single as opposed to multi-model climates, this brings uncertainties into the species distribution model outputs. For future work the stability of the results should ideally be tested on multiple model combinations. However, since the climate projections used as input datasets for the SDMs were debiased and downscaled, the SDM maps could be argued to be more reliable for indicating the potential impact of climate change. It is difficult to demonstrate this point definitely without knowing how the climate change trajectory evolves in the real world. It is recommended that the conservation decisions to be made should be in conjunction with expert ecological opinion due to the possibility of these uncertainties and the biasin species vulnerability estimates that might be introduced by under representation of species data from GBIF.

My study reveals that plant species in the ORB respond to climate change at an individualistic level, varying according to the greenhouse gas emission scenario, species habitat and ecological requirements/processes (adaptive capability and opportunity). This finding demonstrates and confirms that effective adaptation actions should thereby be guided, and tailor-made to a species-specific response to a changing climate (Tingley et al., 2014; McDonald et al., 2015).

Another important finding of my study is that the use of adaptive capability components such as dispersal capacity, species distribution size, and habitat condition adds to the confidence in the vulnerability assessment of the species. With the acknowledged scarcity of literature on measures of adaptive capability (Nicotra et al., 2015), and where sourcing of information on

intrinsic adaptive capability traits, is a challenge, e.g., evolutionary (Nicotra et al., 2010; Beever et al., 2016), extrinsic traits can be used.

This thesis' overall findings have increased evidence about the impact of spatial resolution of climate datasets on SDMs and advanced our understanding of its implications for conservation planning.

7.3 A summary of specific original contributions

The thesis provides the following key achievements:

- Evidence that coarse spatial resolution SDMs can effectively make predictions of species distributions under projections of future threats of a changing climate. Although it is imperative that the methodological approach is relevant to the study question and location, this thesis has enabled the modelling of species distributions both contemporary and future, using climatic predictor variables at a coarse spatial resolution of up 50kmx50km in the ORB, a relatively low heterogeneous topographic and climatic landscape (Tshwene-Mauchaza and Aguirre-Gutiérrez, 2019). This is a timely academic novelty when conservation practitioners need guidance on the choice of predictor spatial resolution in species distribution models for conservation purposes.

- A study analysing species richness and composition based on the spatially explicit species assemblage modelling (SESAM) framework: (a framework incorporating macroecological and species distribution models for predicting spatial and temporal patterns of species assemblies (Guisan and Rahbek, 2011) in the Southern Africa tropical forests.

- A novel approach to addressing questions on the SDM framework. Even though studies on the effects of spatial and temporal scales on SDMs have been carried out, these studies rarely aim to investigate and test for the effects of spatial resolution of climatic predictor data on the importance of these variables in determining species climate suitability space. In taking this approach, the thesis has contributed to highlighting that in SDMs, variable identity is more predictive of variable importance scores performance than predictor spatial dynamics. Determining how the spatial resolution of covariates affects a model's

variable importance is useful for providing ways to use expert or theoretical knowledge in the decision-making process of what input datasets to use in SDMs.

- A test bed to investigate intrinsic sensitivities of SDM modelling. The Southern African landscape and climatic system, in particular the qualified relatively flat homogeneous climatic and topographic landscape of the interior sand sheet of the southwestern area of the region (Reason et al., 2006; Hart, 2012; Weber, 2013; Reason, 2017) was used as a case study. Of importance is that this is a case study within African arid tropical forests, a landscape that has not been utilised before for such tests or investigative studies. The region has been declared vulnerable to climate change (IPCC, 2014) and is projected to lose a significant amount of its biodiversity to impacts of climate change (IPBES, 2018). Effective, reliable, and high performing SDMs for the arid forests of the African continent are therefore critical.

- A novel comprehensive climate change vulnerability assessment framework in response to a call for CCVAs to incorporate adaptive capability (Beever et al., 2016) and adaptation opportunity measures (Berry et al., 2006, 2013).

7.4 Further Research directions

This thesis has refined insights into the complex issue of the effects of the spatial resolution of climatic predictor data in the prediction of SDMs by modelling the distribution of terrestrial plant species of the ORB to project their current and future distribution across spatial resolutions (2km×2km, 5km×5km, 10km×10km, 20km×20km and 50km×50km). To further advance our understanding on this topic, an extension of this work would be to investigate when and how spatial resolution of predictors matters in SDMs. In addition, I specifically make the following suggestions for further research:

7.4.1 Quantification and further evaluation of models' biases

Quantification and further evaluation of the conditions associated with a strong wet bias in GCM downscaled products is needed. It is important to understand the cause of the systematic biases that are detected by the fine spatial resolution, for example over estimation of wetting in the tropical rainbelt (Chapter 4). This will among other things determine whether the disagreements

between the coarse scale and fine scale model simulation rainfall biases are due to rainfall intensity and/or spatial distribution issues. Some literature suggests that the strong wet bias could happen as a result of overestimation of the number of wet days (Ratna et al., 2014; Lewis et al., 2017). This is a call for further research.

7.4.2 Assessment of the vulnerability to climate change of other species within the ORB that are not of conservation importance

Assess the potential impacts of climate change to other species within the ORB that are not of conservation relevance. Through the vulnerability assessment I designed and applied to the global IUCN Red List species (Chapter 6), this study showed that species have the potential to be impacted by a changing climate differently, some showing low, high or extreme vulnerability. A wider assessment of ORB terrestrial plant species response to climate change would enable and guide broader conservation decision making. This would also give confidence in deriving general conclusions on arid plant species' response to future climate.

7.4.3 Extension of the application of the designed novel comprehensive vulnerability assessment framework

I recommend that the application of the comprehensive vulnerability assessment framework (Chapter 6; Figure 6.1) be extended to marine ecosystems, and other terrestrial habitats and communities. In this study I applied it to terrestrial plant species, and it proved to be a comprehensive framework for practitioners to use in assessing the need for conservation actions under a changing climate. Extension of the vulnerability assessment framework to all flora and fauna species, habitats and communities would enhance effective design of both national and transboundary strategies for conservation. It is my plan to apply this framework in my next research project to assess the vulnerability of a wider selection of ORB terrestrial plant habitats and communities.

7.4.4 Further research into ways to incorporate the concepts of adaptive capability and adaptation opportunity into vulnerability assessment frameworks

This study has highlighted that these two elements have potential to influence and alter vulnerability of species as a result affecting their vulnerability ranking to climate change. I hope the study will prompt discussions between conservation practitioners and researchers on ways to further modify the vulnerability assessment framework that incorporates and accounts for both elements of species ability and opportunity to adapt to climate change, as well as the current conservation context (Chapter 6).

7.5 Conservation and Management Policy recommendations for ORB

The plans laid out in both the SAP, (2011a) and the riparian countries' NAPs are deficient in species adaptation actions and fail to comprehensively factor in climate change. As long as these important biodiversity management documents remain vague with unclear outcomes, owing to a lack of consideration of and links to the current management actions on future impacts of climate change on species (Chapter 6), ORB runs the risk of being ineffective in achieving the outlined long-term conservation plans. In addition, achieving the goals of both multilateral environmental agreements ratified by ORB riparian countries e.g. the Convention of Biological Diversity (CBD), which states a conservation goal of protecting 60% of plant species by 2020 (Joppa et al., 2013b) and national policies, might prove a challenge.

Through this thesis I have modified and built biodiversity adaptation principles to address the identified lack of biodiversity adaptation measures in ORB. Informed by the species vulnerability assessment results (Chapter 6), and building on the biodiversity adaptation principles generally formulated in the literature (e.g., Mawdsley et al., 2009; Smithers et al., 2008; Huntley et al., 2017), four main adaptation principles are relevant for conserving biodiversity in the ORB (Chapter 6):

Principle 1**:** Undertake immediate conservation and management actions

Principle 2: Increase resilience

Principle 3: Make room for change and accept change and loss

Principle 4: Integrate actions across ORB member states

I envision that the adaptation principles contained in the basin wide strategy could be adopted and endorsed by ORB member states and implemented at the national level as part of the National Action Plan. These adaptation principles used alongside the species-specific conservation actions in Chapter 6 section 6.4.3 present valuable information to further design a transboundary species-specific management plan.

7.6 Concluding remarks

By testing the sensitivity of the prediction ability of SDMs to the spatial resolution of climatic predictor data, this thesis has contributed insights into the general debates on the adequate spatial scale of climatic data for accurate prediction of species distribution and estimates of species richness in the ORB. In landscapes with low climatic and topographic heterogeneity, reasonable conservation and management decisions can be derived from the use of climatic predictor data on a coarse spatial resolution of up to 50km×50km. I advocate that even with the lack of required resources to downscale climate datasets to fine resolutions, conservation practitioners in areas with low climatic/topographic heterogeneity can accurately project the response of species to contemporary and future climates. However, the specific location, data availability, and questions of the study should guide the selection of which spatial scale is appropriate. In assessing the potential impacts of climate change on ORB species, I designed and applied a novel comprehensive climate change vulnerability assessment framework. In doing so, I was able for the first time to identify some of ORB's most and least vulnerable terrestrial plant species and develop species-specific adaptation actions and management plan for the modelled conservation relevant species. This is valuable work that will assist in highlighting species conservation needs and targeting conservation actions for different species. I recommend the application of this novel vulnerability assessment framework by practitioners in assessing the need for conservation efforts and enabling effective adaptation responses.

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9. Appendices

Chapter 5 and 6: Supplementary Tables and Figures

TABLE S5.9.1: Summary statistics of Area under the curve (AUC) model predictive performance. This shows prediction accuracy on evaluation data of the species models across different spatial resolutions. Interquartile Range (IQR)

	AUC						
Spatial resolutions (km^2)	Min	1st Qu	Median	Mean	3rd Qu	Max	IQR
2km×2km	0.61	0.72	0.76	0.77	0.82	0.93	0.10
5km×5km	0.61	0.73	0.78	0.77	0.83	0.94	0.10
10km×10km	0.60	0.73	0.78	0.78	0.83	0.96	0.10
20km×20km	0.61	0.72	0.76	0.77	0.83	0.95	0.11
50km×50km	0.61	0.71	0.76	0.76	0.81	0.93	0.10

TABLE S5.9.2: Effects of spatial resolution on contribution of climatic variables to plant species distribution. This table shows the effect of predictor spatial resolution on the climatic variables' contribution to plant species distributions. It shows at each spatial resolution ($2km^2$,$5km^2$,$10km^2$,$20km^2$,$50km^2$), which variable is significantly more important than others. The computation was to identify the climatic variables determining plant species distribution at each predictor spatial resolution, and to investigate how the mean importance of the variable changes as the grain size changes from fine to coarse scale. Estimates (fit) are presented in mean percentages as used during the Generalised Linear Model.

Climatic Variable	**Predictor scale (km×km)**	**Estimate**	**SE**	**Lower.CL**	**Upper.CL**
mimq	2km×2km	21.82	19.77	15.93	29.14
mtwq	2km×2km	18.31	21.11	12.90	25.32
pet	2km×2km	33.53	17.30	26.44	41.45
rdq	2km×2km	11.88	25.23	7.60	18.11
tmpSea	2km×2km	14.46	23.21	9.69	21.04
mimq	5km×5km	23.87	19.15	17.72	31.33
mtwq	5km×5km	16.26	22.13	11.18	23.05
pet	5km×5km	36.32	16.98	29.03	44.31
rdq	5km×5km	11.87	25.24	7.59	18.10
tmpSea	5km×5km	11.68	25.42	7.44	17.87
mimq	10km×10km	27.87	18.21	21.29	35.57
mtwq	10km×10km	23.23	19.33	17.16	30.66
pet	10km×10km	26.59	18.48	20.14	34.22
rdq	10km×10km	11.51	25.58	7.30	17.68
tmpSea	10km×10km	10.79	26.31	6.74	16.85
mimq	20km ×20km	21.40	19.91	15.56	28.69

mtwq	20km ×20km	27.32	18.32	20.80	35.00
pet	20km×20km	24.38	19.02	18.17	31.88
rdq	20km×20km	14.71	23.05	9.89	21.32
tmpSea	20km×20km	12.19	24.96	7.84	18.46
mimq	50km×50km	17.23	21.62	11.99	24.13
mtwq	50km×50km	23.47	19.27	17.37	30.91
pet	50km×50km	26.17	18.57	19.77	33.78
rdq	50km×50km	19.70	20.53	14.09	26.84
tmpSea	50km×50km	13.43	23.95	8.84	19.87

TABLE S5.3: Changes in the importance of climatic variables across different predictor spatial resolutions. Multiple comparison analysis (adjusted Tukey's P-values are reported) the computation was to statistically investigate climatic variables within groups variations. Estimates are presented in a Least square mean as used during performing the post hoc tests. Group separations by LSmeans with compact letter are displayed. Climatic groups sharing a letter in the group column are not significantly different, at the alpha level specified (alpha=0.05). Confidence level used: 0.95. See Figure 5.4. Groups not sharing a letter are therefore not significantly different (a is significantly different from b, but not another a, b is significantly different from c, but not another b, etc).

Climatic Variable	Predictor scale (km)	LSmean	SE	lower.CL	Upper.CL	group
tmpSea	10km×10km	-2.11	0.26	-2.63	-1.60	a
rdq	10km×10km	-2.04	0.26	-2.54	-1.54	a
tmpSea	5km×5km	-2.02	0.25	-2.52	-1.52	a
rdq	5km×5km	-2.00	0.25	-2.50	-1.51	a
rdq	2km×2km	-2.00	0.25	-2.50	-1.51	a
tmpSea	20km×20km	-1.97	0.25	-2.46	-1.49	a
tmpSea	50km×50km	-1.86	0.24	-2.33	-1.39	a
tmpSea	2km×2km	-1.78	0.23	-2.23	-1.32	a
rdq	20km×20km	-1.76	0.23	-2.21	-1.31	a
mtwq	5km×5km	-1.64	0.22	-2.07	-1.21	ab
mimq	50km×50km	-1.57	0.22	-1.99	-1.15	ab
mtwq	2km×2km	-1.50	0.21	-1.91	-1.08	abc

rdq	50km×50km	-1.41	0.21	-1.81	-1.00	abc
mimq	20km×20km	-1.30	0.20	-1.69	-0.91	abc
mimq	2km×2km	-1.28	0.20	-1.66	-0.89	abc
mtwq	10km×10km	-1.20	0.19	-1.57	-0.82	abc
mtwq	50km×50km	-1.18	0.19	-1.56	-0.80	abc
mimq	5km×50km	-1.16	0.19	-1.54	-0.78	abc
pet	20km×20km	-1.13	0.19	-1.50	-0.76	abc
pet	50km×50km	-1.04	0.19	-1.40	-0.67	abc
pet	10km×10km	-1.02	0.18	-1.38	-0.65	abc
mtwq	20km×20km	-0.98	0.18	-1.34	-0.62	abc
mimq	10km×10km	-0.95	0.18	-1.31	-0.59	abc
pet	2km×2km	-0.68	0.17	-1.02	-0.35	bc
pet	5km×5km	-0.56	0.17	-0.89	-0.23	c

TABLE S5.4: Pairwise comparisons of the mean importance of climatic variables for driving plants distributions across varying predictor spatial resolutions. Multiple comparison analysis (adjusted Tukey's P-values are reported) these were computed to test for changes in the magnitude of effect for each climatic variable, across the different predictor spatial resolutions (2km×2km,5km×5km ,10km×10km, 20km×20km & 50km×50km), using the fine scale as the baseline comparison of the two-way interaction. These are pairwise comparison for two-way interaction terms, climatic variable: predictor spatial resolutions. Estimates are presented in least square means.

Climatic Variable:	**Predictor scale (km ×km)**	**Estimate**	**SE**	**z-ratio**	**p.value**
Contrast					
mimq	2km×2km vs 5km×5km	-0.12	0.27	-0.43	1.00
mimq	2km×2km vs10km×10km	0.33	0.26	1.24	1.00
mimq	2km×2km vs 20km×20km	-0.03	0.28	-0.11	1.00

mimq	2km×2km vs 50km ×50km	0.29	0.29	1.00	1.00
mtwq	2km×2km vs 5km×5km	0.16	0.30	0.53	1.00
mtwq	2km×2km vs10km ×10km	0.25	0.28	0.88	1.00
mtwq	2km×2km vs 20km×20km	0.50	0.27	1.84	0.95
mtwq	2km×2km vs 50km ×50km	-0.31	0.29	-1.10	1.00
pet	2km×2km vs 5km×5km	-0.12	0.24	-0.50	1.00
pet	2km×2km vs10km ×10km	-0.31	0.25	-1.26	1.00
pet	2km×2km vs 20km ×20km	-0.44	0.25	-1.75	0.97
pet	2km×2km vs 50km×50km	0.35	0.25	1.39	1.00
rdq	2km×2km vs 5km×5km	0.02	0.35	0.05	1.00
rdq	2km×2km vs 10km×10km	-0.06	0.35	-0.17	1.00
rdq	2km×2km vs 20km×20km	0.23	0.33	0.69	1.00
rdq	2km×2km vs 50km×50km	-0.60	0.33	-1.84	0.98
tempSea	2km×2km vs 5km×5km	0.23	0.34	0.69	1.00
tempSea	2km×2km vs 10km ×10km	-0.33	0.35	-0.96	1.00
tempSea	2km×2km vs 20km ×20km	-0.19	0.34	-0.58	1.00
tempSea	2km×2km vs 50km ×50km	0.09	0.33	0.26	1.00

TABLE S5.5: Accuracy Assessment of species richness prediction maps against observed occurrence points across the different predictor spatial resolutions. This is to assess the accuracy measurements mean scores of each species richness map and how they differ as a function of predictor spatial resolution.

Predictor Spatial resolution (km)	Species Richness Error	Prediction Success	Kappa
2km×2km	2.74	19.11	0.99
5km×5km	2.51	18.53	0.99
10km×10km	3.26	18.55	0.99
20km×20km	3.35	18.60	0.99
50km×50km	5.56	19.26	0.99

TABLE S5.6: Assessment of species richness variable importance per predictor spatial resolution. This explains the effect of predictor spatial resolution on the species richness climatic variables importance contribution performance. It shows at each spatial resolution (2km×2km,5km×5km,10km×10km,20km×20km,50km×50km), which variable is significantly more important than others at driving the species richness. The computation was to identify the climatic variables determining plant species richness at each predictor spatial resolution, and to investigate how the mean importance of the variable changes as the spatial resolution changes from fine to coarse scale. Estimates (fit) are presented in mean percentages as used during the Generalised Linear Model

Climatic variable	2km×2km	5km×5km	10km ×10km	20km×20km	50km×50km
mimq	21.56	23.79	28.02	21.05	17.64
mtwq	18.39	16.48	23.00	27.02	22.92
pet	33.63	35.93	26.63	24.28	26.27
rdq	12.13	12.09	11.55	14.82	19.47
tmpSea	14.28	11.71	10.80	12.83	13.70

Supplementary Figures

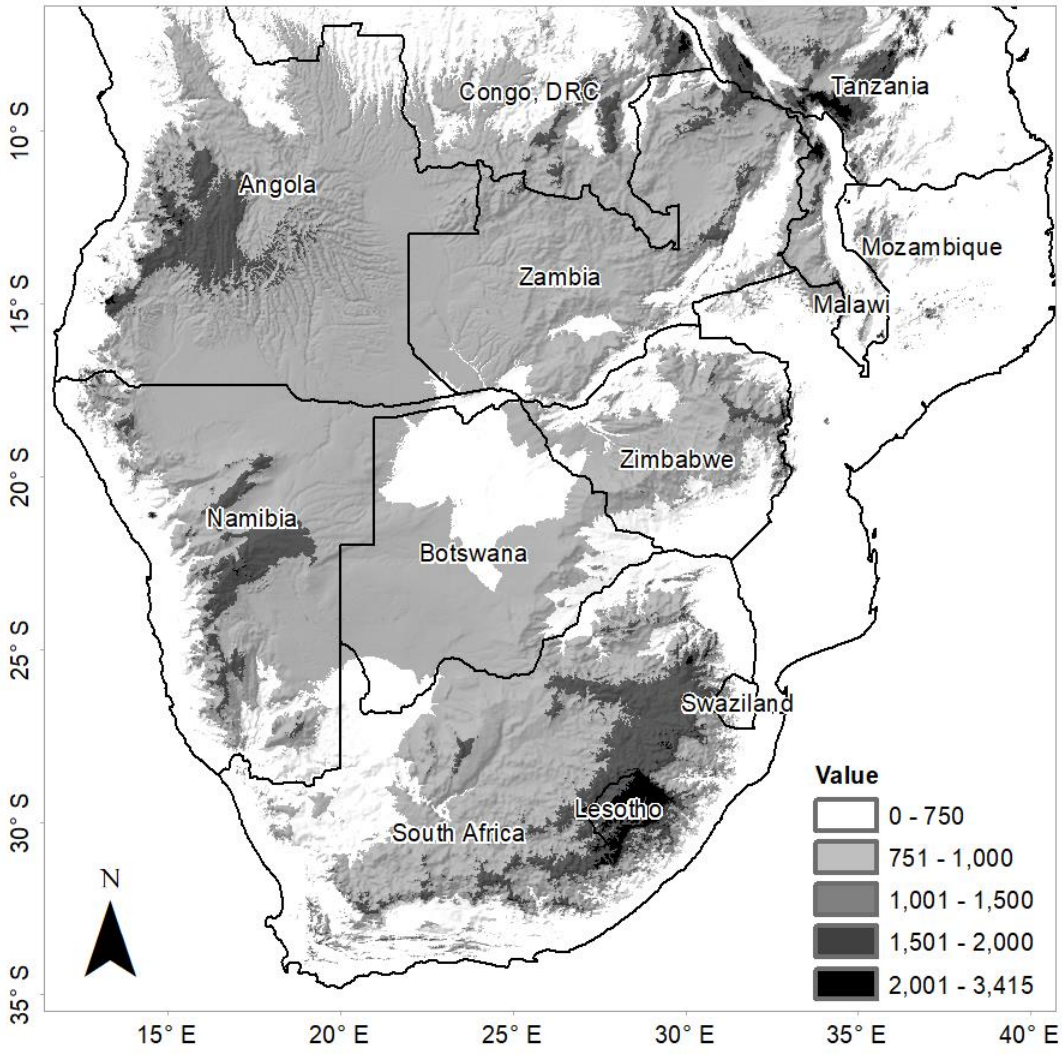


Figure S5.9.1: Elevation of Southern Africa

Chapter 6: Supplementary Tables and Figures

Table S6.1: Habitat and ecology of the study species and their threat status in Southern Africa and globally. Metrics used in climate change vulnerability assessment for each species. Presented as well is the economic and cultural uses of the species. *N/E: Not Evaluated, LC: Least concern (Barnes et al.2010;* Burrow et al.2018; Breitenbach 2001; *R Heath and A Heath, 2009*; *Hyde et al.2019; IUCN, 2019; Vera De Cauwer et al., 2016)*

	Baikiaea plurijuga	***Baphia massaiensis***	***Bulbostylis hispidula***	***Chamaecrista absus***	***Commelina africana***	***Cyperus cf haspan***
Species characteristics						
Habitat	Lowland tropical forest, Kalahari sandveld	Savanna, Shrubland	Shrubland, Wetlands (inland), Savanna, Grassland	Forest, Grassland, Savanna	Savanna, Shrubland, Grassland, Forest	Wetlands (inlands)
Ecology	Grows on deep, aeolian and fluvial Kalahari Sands	Occurs in open woodland and thicket at elevations of 42-1600 m	Grows in seasonally wet grassland and woodland, dry sandy places, on shallow soil on rocks, open dry grasslands, shrublands, and marshes adjacent to the coast. Does well in disturbed habitats	Found in grasslands, grassy hills, pastures, savannas with Bryrsonima and Curatella, also in openings in tropical deciduous forest and pine-oak forest. Roadsides, alluvium and cultivate areas	Occurs in secondary growth and disturbed localities, and as a weed on farms	Grows in flooded or moist places: sand by river margins, swamps, ditch margins in valleys, waste places, wet places, along trails, dry fields
Life /growth form	Deciduous tree	Shrub/tree up to 8 m tall	Annual/perennial Turted herb/Shrub 50-80 cm tall with slender root system	Annual / short lived perennial Plant of up to 1 m tall	Perennial herb up to 0.5m high grows very well in a wet sandy soil or during good rainfall seasons	Perennial /annual, with a short rhizome, generally growing in tuft grass-like herbaceous plant 10-60cm tall
Flowering period	November-May	October-January	May-November	February -March	November -April	September – January
Pollination vector	Insects such as bees	Insects	Insects	Insects	Insects mainly ants & bees	
Seed dispersal	Animals	Animals	Animals	Animals& humans	Animals & humans	Animals & humans
SANBI status & criteria	Near threatened	N/E	LC	LC	LC	N/A
IUCN global threat status	Near threatened	LC	LC	LC	LC	LC
Economic & cultural uses	Wood: commercial timber; fuel and charcoal The bark: medicinal purposes; source of tannins Seeds: crafts and adornments	Seeds: roasted to make coffee Branches: used as toothbrushes for cleaning teeth	Whole plant: used as broom and for making mats Leaves: used as sieve Decoction of whole plant: medicinal purposes	All parts of the plant used for medicinal purposes therefore plant harvested by pulling up the whole plant	Decoction of the root used for medicinal purposes Ash of the plant used for charm application for sterility, also used as plant fertilizer Leaves fed to livestock also human edible as vegetables	Decoction of the plant used for medicinal purposes Pith of the stems used for as lamp wicks Whole plant used for weaving mats and baskets

Table S6.1 Continuation:

	Dichrostachys cinerea	*Indigofera daleoides*	*Pterocarpus angolensis*	*Rhynchosia minima*	*Rhynchosia totta*	*Tephrosia cephalantha*
Species characteristics						
Habitat	Savanna, shrubland,forest,grasland	Forest, Grassland	Woodland/forest	Grassland, Shrubland, Savanna	Acacia thickets, wooded grassland, dambos and floodplain grasslands	Forest
Ecology	Natural forests and woodlands, bushland and thicket, agricultural areas, grasslands, riparian zones, ruderal, disturbed, scrub, shrublands, urban areas. colonize disturbed veld quickly and curbs erosion	Grows in open grasslands, in open woodlands, on sand, and also in disturbed habitat such as along roadsides. Forms a mat of growth	Grows in deciduous and Brachysteig woodland and wooded grassland. It is most common in Miombo woodland and bushveld and can be dominant on savanna. The species grows best in open, exposed area therefore often occurs as individual trees in agricultural and settled spaces. favors rocky slopes or well-drained, deep, sandy soil	Occurs in grassland, grassland with scattered trees, dambo and pan margins and woody bushland, on plain land and sandy black soil.	Occurs in grasslands, bushlands, miombo woodlands, fynbos, savanna, growing on alluvial, sandy soil, rocky outcrops or moist grounds, Rocky places, at altitudes of about 770 m above the sea level	Grows in miombo woodlands, dambo and adjacent marsh/swamp, in mixed Baikiaea forests, Isoberlinia globiflora or Brachystegia woodland, and also in woodland in Kalahari sand.
Life /growth form	Deciduous shrub or small tree up to 7m tall	perennial herb	Large deciduous tree species, growing to over 20 m in height, 50-60 cm in trunk diameter	perennial climbing or prostrate herb/plant 30 - 150cm high, up to 20mm in diameter	climber, twining or ascending perennial herb,0.2-1m long	perennial shrub
Flowering period	September to February	November - April	September (2-3weeks only)	No info	No info	No info
Pollination vector	Bats & bees	Insects	butterflies	Bees		
Seed dispersal	Animals & humans	Animals & humans	Animals & humans	Animals & humans	Animals & humans	Animals & humans
SANBI status & criteria	LC	N/E	LR-Near threatened (vulnerable in Namibia and Zimbabwe due to its economic entity	LC	LC	N/A
IUCN global threat status	LC	LC	LC (population trend decreasing, as tree is overexploited for its timber)	LC	LC	LC
Economic & cultural uses	Wood: used as fencing post, fuelwood and tool handles Roots, bark, leaves and fruits used for traditional medicinal purposes Fruits and seed for human consumption, pods eaten by game and livestock	Plant used for local medicinal purposes	Wood used for timber in carpentry, furniture manufacture and parquet floor tiles Woodcarving: construction of boats Tree including roots,used for medicinal purposes Roots used to make dye, and traditional cosmetic pomade	Medicinal purposes, food, Seeds used as poison or repellents, pre-emergence herbicide	Medicinal purposes	Used as insecticide and pesticide

N/E: Not Evaluated, LC: Least concern

Table S6.2: Scores for the species' sensitivity indicators in brackets

	Baikiaea plurijuga	*Baphia massaiensis*	*Bulbostylis hispidula*	*Chamaecrista absus*	*Commelina africana*	*Cyperuscf haspan*	*Dichrostachys cinerea*	*Indigofera daleoides*	*Pterocarpus angolensis*	*Rhynchosia minima*	*Rhynchosia totta*	*Tephrosia cephalantha*
RCP 4.5												
Indicator A (score)	40 (3)	4(4)	80(1)	134(0)	3(4)	89(1)	102(0)	79(1)	161(0)	146(0)	36(3)	133(0)
Indicator B (score)	55(2)	0(5)	0(5)	92(1)	31(3)	25(4)	51(2)	38(3)	88(1)	97(1)	55(2)	92(1)
Indicator C (score)	45(2)	100(5)	100(5)	8(1)	69(3)	75(4)	49(3)	62(3)	12(1)	3(1)	45(2)	8(1)
Indicator D (score)	2(4)	0(5)	0(5)	13(3)	2(4)	1(5)	2(4)	3(4)	16(3)	15(3)	5(4)	6(4)
RCP 8.5												
Indicator A (score)	5(4)	0(5)	0(5)	228(0)	0(5)	122(0)	4(4)	16(4)	311(0)	247(0)	36(3)	189(0)
Indicator B (score)	3(4)	0(5)	0(5)	84(1)	10(4)	17(4)	0(5)	1(4)	93(1)	99(1)	26(3)	71(2)
Indicator C (score)	97(5)	100(5)	100(5)	16(1)	90(5)	83(4)	100(5)	99(5)	7(1)	1(1)	74(3)	29(2)
Indicator D (score)	0(5)	0(5)	0(5)	17(3)	1(4)	1(5)	0(5)	0(5)	26(2)	21(3)	3(4)	7(4)

Table S6.3: Summary of adaptation actions based on the decision framework (Figure1) for species vulnerability to climate change (Oliver et al., 2015)

Species	Species vulnerability to climate change	**Sensitive area (loss)**	Adaptation actions	**Climate overlap areas**	Adaptation actions	**New suitable climate space** Area	Adaptation actions
Baikiaea plurijuga	Extreme	Centre of ORB, N.Namibia, N.Botswana	Accept loss	N.Botswana	Restore adjacent degraded habitats	N.Botswana	Focus on climate overlap
Baphia massaiensis	Extreme	ORB region	Accept loss	None projected in S.A	None	None projectd in s.A	None
Bulbostylis hispidula	Extreme	N.Namibia	Accept loss	None projected	None	None projected	None
Chamaecrista absus	slightly vuln	Central to north east region (albeit insignificant)	In-situ management, monitor and research	ORB region,KAZA TFCA, south east of Southern Africa	Restore adjacent and nearby degraded habitats	Central to northern regions	In-situ management, monitor and research
Commelina africana	Extreme	ORB region, central to south east	Focus on climate overlap	North east, south east	Restore adjacent degraded habitats	None projected	Concentrate on climate space overlap
Cyperus cf haspan	High	N.Namibia,north and eastern regions	In-situ management, monitor and research	North east	Restore adjacent and nearby degraded habitats	N.Namibia, N.Botswana (chobe national park)	In-situ management, monitor and research
Dichrostachys cinerea	extreme	ORB region, N.Botswana	Accept loss	None projected	None	None projected	None

Indigofera daleoides	extreme	Central ORB, N.Botswana (Okavango delta,Chobe national park)	In-situ management, monitor and research	None projected	None	N.Namibia, N.Botswana	In-situ management, monitor and research, restore habitat
Pterocarpus angolensis	Slightly vuln	None projected	none	ORB region, KAZA TFCA, east	In-situ management, monitor and research	Central to northern area	In-situ management, monitor and research, restore habitat
Rhynchosia minima	Slightly vuln	None projected	None	ORB region, KAZA TFCA, east	In-situ management, monitor and research	Central to northern area	In-situ management, monitor and research, restore habitat
Rhynchosia totta	High	N.Namibia, N.Botswana	Focus on areas of climate space overlap	N.Namibia, N.Botswana	In-situ management, monitor and research	South east	In-situ management, monitor and research, restore habitat
Tephrosia cephalantha	Slight	N.Namibia, N.Botswana	In-situ management, monitor and research	ORB region, KAZA TFCA (Zambia)	Restore adjacent and nearby degraded habitats	Central region	In-situ management, monitor and research, restore habitat

Table S6.4: Vegetation units of the Okavango River Basin (source: Stellmes, M., Frantz, D., Finckh, M. & Revermann, R. (2013).

Vegetation units	Percent cover over the ORB (%)	Dominant species	Value to biodiversity conservation
Woodlands on Kalahari sands/ Zambezian Baikiaea woodlands	30	*Baikiea plurijuga, Pterocarpus angolensis*	Supports endemic fauna and flora species diversity, important bird area
Miombi Forests	26	*Dichrostachys cinerea, Chamaecrista absus, Tephrosia cephalantha*	High plant diversity, high mineral composition,
Shrub-and Grassland	18	*Commelina Africana, Rhynchosia minima, Baphia massaiensis, Indigofera daleoides, Bulbostylis hispidula*	Dominance of mega herbivores,
Thorn bush savanna	13	*Acacia*, *Rhynchosia totta*	Supports concentration of various species endemic within semi-arid regions; Important area for herbivores, charismatic megafauna, supporting wildlife tourism
Wetlands	7	*Cyperus cf haspan*	Supports high diversity of plants and animals, important bird areas, protection against extreme floods and storm surges
Other woodlands	6	Colophospermum mopane	Important for mammalian diversity, dominance of megafauna

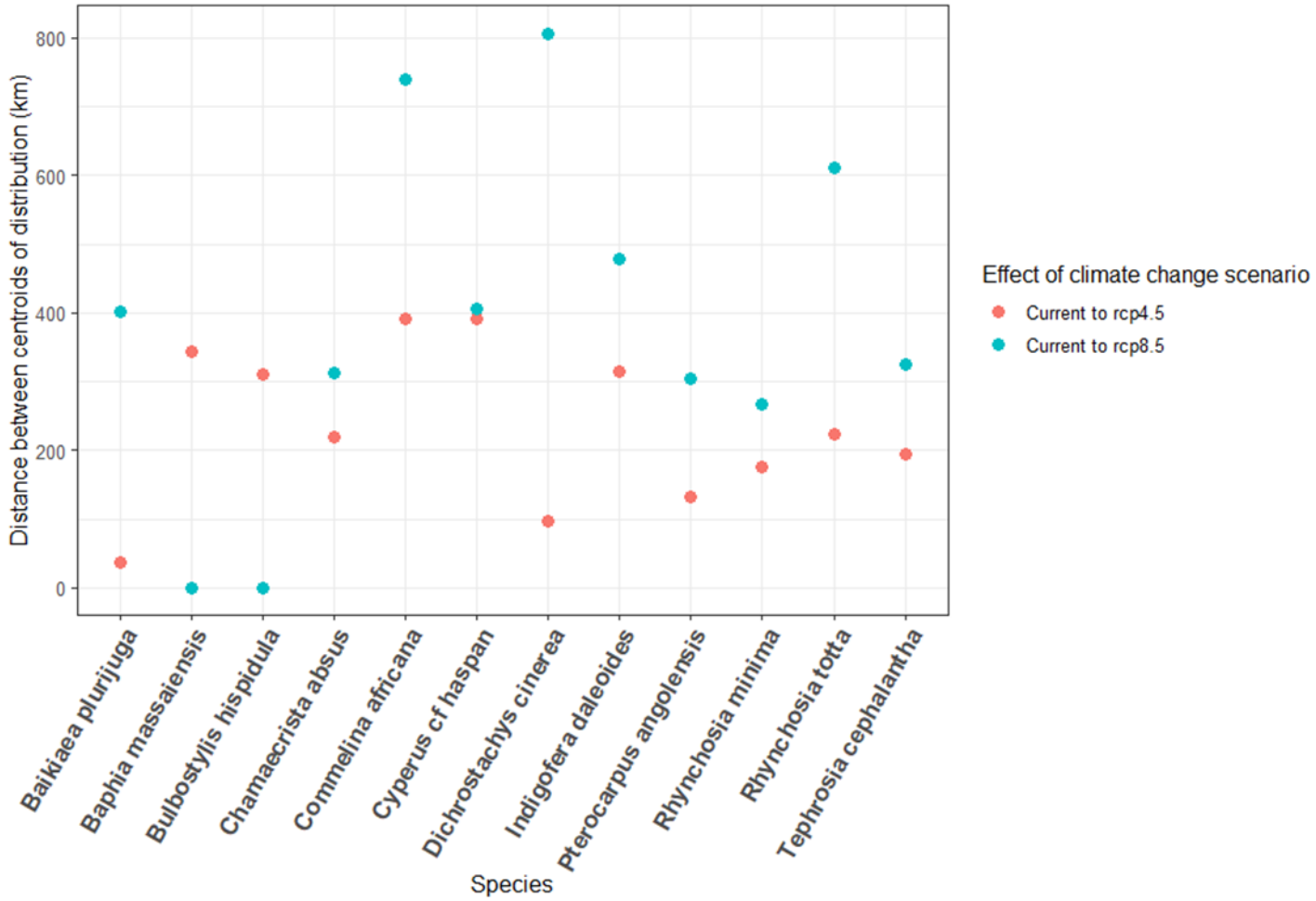


Figure S6.1: Distance between the current and future projected distribution of suitable climate space for each species under climate change scenario RCP 4.5 and RCP 8.5. Distance between the current and future RCP 8.5 for species Baphia massaiensis and bulbostylis hispidula is 0 as the species are projected to lose their suitable climate space under the scenario

Table S6.5: Definitions of concepts used in this study's vulnerability assessment (Berry et al., 2006;2013; Dawson et al., 2011; IPCC 2007)

Box 1 Definitions of concepts used in this study's vulnerability assessment (Berry et al., 2006;2013; Dawson et al., 2011; IPCC SR1.5, 2019)
vulnerability is "the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt" (IPCC SR1.5, 2019).
Exposure considers the extent by which climate change could impact on species, this depending on the rate and magnitude of projected changes in climatic conditions (temperature and rainfall) in areas and habitats occupied by the species. The exposure is derived from climate projections.
Sensitivity is a factor of exposure. It describes the degree to which the survival and persistence of species is dependent on future changes of climatic conditions, with sensitive species depicting low survival and persistence. The multiple factors determining species sensitivity e.g., microhabitat preferences and ecophysiology are thereby assessed in this chapter.
Adaptive capability refers to a species' natural resilience to climate change. It considers species ability to colonise new suitable areas under climate change, the rate at which a species is able to disperse and migrate to new areas, as well as its ability to survive and persist unfavourable climatic conditions in -situ. A variety of factors determine a species adaptive capability e.g., genetic diversity, dispersal and colonization rate, phenotypic plasticity, and life history traits. Here the adaptive capability of species is assessed through analysis of its ecology, habitat and ecological theories and processes (e,g dispersal; migration and colonization abilities and habitat preference).
Adaptation opportunity describes the physical factors that permit or hinder species' adaptive capability. It considers future changes in climate suitable areas and habitats, barriers to migration due to a lack of landscape connectivity. These form components considered in assessment of the adaptation opportunity.

Table S6.6 Descriptions and calculations of the sensitivity indicators A-D (Berry et al., 2006; Thuiller et al., 2009)

Indicator	Description and calculation
A	gain – new climate space, calculated as (scenario-overlap)/ current suitable climate space x100
B	Overlap (stable present) – number of grid cells currently modelled as suitable climate space and projected to remain as suitable climate space under future scenarios, calculated as overlap divided by current multiplied by 100; (overlap / current suitable climate space) x100.
C	loss – number of grid cells projected to be lost as suitable climate space, calculated as: (current suitable climate space-overlap)/current suitable climate space x 100
D	size of projected suitable climate space calculated as (scenario/total area of Southern Africa) x100.
A-D	The indicators A to C percentage changes in suitable climate space are calculated based on current distribution (number of grid cells modelled as suitable climate space) as the denominator. This leaves indicator D with a common denominator for inter-comparison of species. The species vulnerability assessment to climate change is conceptualized in Figure 6.1.

S6.1 Targeting Conservation Actions for Different Species Using the Framework (Figure 6.1)

In addition to the recommended basin wide climate change adaptation principles, here I use the modelled conservation relevant plant species to demonstrate how ORB conservation and management practitioners can develop species specific management plans to integrate into the main conservation planning, following vulnerability assessment. The framework utilises and applies all adaptation actions, such as *in-situ* management, landscape scale interventions and translocations or *ex-situ* conservation (Mawdsley et al., 2009). The use of GBIF data has known limitations in that it is not comprehensive and therefore some species might be under sampled (Samy et al., 2013; Beck et al., 2014) to different degrees. The effect of this possible incomplete sampling to the modelled species niche breadth might be a bias towards prediction of more vulnerability in some species (Dudík et al., 2005; Phillips et al., 2009; Lintz et al., 2013). I attempted to obtain information from the fully known ecological niche of the species under study as to minimise the effect of possible species sampling incompleteness in SDMs. To this end I obtained species presence information not only from the GBIF database but also from other large databases such as the Okavango Basin Database (Revermann et al., 2016b) [See 6.2.1.2]. However, it may still be that the estimations of species sensitivity and vulnerability in this chapter might be affected by the possible under representation of the species contemporary range. This is an intrinsic problem of the species distribution modelling approach (Araújo and Guisan, 2006; Joppa et al., 2013a; Stolar and Nielsen, 2015; Wang and Stone, 2019). In practice this means that the conservation decisions to be made should be in conjunction with expert ecological opinion, and that interpretation of model results should not be automatically prioritised over other data sources such as field surveys and literature reviews.

S6.1.1 Species with Low Vulnerability (Type 1 And 2)

Pterorcarpus angolensis

Pterorcarpus angolensis is widely distributed in the ORB and KAZA TFCA regions (Mehl et al., 2011; IUCN, 2019a), extending into central and south east areas of Southern Africa. This large deciduous tree grows in warm frost-free bushveld and woodland, favouring rocky slopes and well drained sandy soils (Breitenbach, 2001). This tree is valued across the continent for its

resistance to borer and termite; it is therefore commercially used as timber for furniture constructions (Therrell et al., 2007). The deciduous tree, being susceptible to extended periods of wet conditions (De Cauwer et al., 2016) which are projected to lessen in the future, with warmer and drier summers (Niang et al., 2014b), presents opportunities for the species to potentially colonise northern areas in the future and persist climate change. However due to its economic value, the species population trend is decreasing as a result of over exploitation (Mehl et al., 2011; IUCN, 2019a; SANBI, 2019). Loss and fragmentation of the *Baikeaia zambezi* woodland habitat required by *P.angolensis*, has been reported (DeCauwer et al., 2016), this adding to the species population lack of robustness. SANBI classified the deciduous tree as lower risk and near threatened, while IUCN maintains a least concern status. Despite historical declines in distribution due to overexploitation (Mehl et al., 2011; De Cauwer et al., 2016), the *Baikeaia zambezi* woodland, forming the largest percentage cover of ORB (Stellmes et al., 2013), is classified as not vulnerable to climate change due to its large northern expansion under climate warming (Figure 6.3) and its high adaptive capability through good dispersal abilities (Mojeremane and Lumbile, 2016).

A significant proportion of this species' current climate space is projected to remain climatically suitable by 2085 (Figures 6.2&6.3 and Figure S6.2). Therefore, maintaining current populations is important in colonizing new climate space. Even though *P.angolensis* is projected to benefit from climate change, without adaptation interventions, this deciduous tree is unlikely to persist with current unsustainable land use and management practices (Wingate et al., 2016). A priority adaptation action would be to manage threatening activities in adjacent lands through control of agricultural land expansions. Currently, the ORB woodland area is surrounded by other land cover types such as arable farming (Vanderpost et al., 2005), this reducing existing habitat. As the species is found in protected areas of Chobe national park and KAZA TFCA, improvement of habitat quality and conservation of habitat heterogeneity (Ofori et al., 2017) should also be a management focus. *In-situ* management adaptation is therefore of importance. Consideration of the existence of degraded habitats (Vanderpost et al., 2005) next to currently occupied habitats and the restoration of these habitats (Oliver et al., 2012) has potential to improve the species adaptation opportunity. Restoration of habitat quality e.g., woodland and wooded grassland through proper planning, control of timber harvesting (Caro et al., 2005) to improve adaptation opportunity in the nearby sites is important.

As the native woodland cannot be recreated through recruitment processes (Caro et al., 2005), improvement of habitat connectivity should be coupled with increase of landscape permeability by reducing and controlling land use. In addition to managing the protected areas network, creating new native woodlands through expanding other woodlands in this area such as *Colophospermum mopane (*Stellmes et al., 2013***)*** to provide corridors as a way of improving connectivity is recommended. Thus, site level efforts and targets to conserve this large tree may be attainable with planned adaptation actions. High dispersal abilities of this species mean adaptation efforts should be focused on the northern areas where the species are projected to have suitable climate space (Figure 6.3).

Chamaecrista absus:

Found in grassy savanna along roadsides, this perennial plant is a widely distributed species across Africa and other regions (Coutinho et al., 2012; Francino et al., 2015). The plant is harvested by pulling out the whole plant as all parts of this herb are used for medicinal purposes across Africa (Heath and Heath, 2009). The projected expansion of suitable climate space (Figure S6.2) and dispersal ability (Francino et al., 2015) and opportunity to adapt to climatic change, suggests that climate change will not pose direct threats to this plant. However, given its harvesting method for medicinal use within the continent, *ex situ* management of the species is crucial e.g., in botanic gardens. For this species to benefit from an increase in suitable climate space, good management practices are required to maintain the quality of the habitat of this species, such as reduction of land use change to arable farming (Mantyka-Pringle et al., 2015; Sirami et al., 2017), and control of the frequency and intensity of wild fires (Midgley and Thuiller, 2011; Adams, 2013) [Table 6.2]. Creation of connectivity between current and future habitat might be crucial to facilitate filling of new suitable climate space. Since the species is a potential adapter to climate change, it may not require immediate conservation action; however, according to Figure 6.1, monitoring actions are needed to ensure the species population remains stable over time.

Rhynchosia minima

Rhynchosia minima is used as animal feed. This perennial/ annual herb has a grassland, shrubland habitat, growing in woody bushland and sandy soils (Mercuri et al., 2018). With its predominant arid tropics and subtropics range across the region (IUCN 2019), the suggestion of

the current climate space not being threatened in the future (Figure S6.2) is not surprising. The greater intensity of drought projected for arid and semi-arid environments of Southern Africa (Duncan et al., 2012) should favour its survival and persistence. Climate change therefore offers potential to assist in conservation of the species. *In-situ* management actions such as reduction of over grazing and excessive browsing, protection of existing habitats (Mawdsley et al., 2009; Smithers et al., 2008) [Table S6.3] and monitoring of species population is therefore recommended.

Tephrosia cephalantha

Tephrosia cephalantha, a shrub with a forest habitat, occurs in Miombi woodlands (Strohbach and Strohbach, 2004; Strohbach, 2013). It is locally used as an insecticide and pesticide and has a well-defined Angola-centric focused range, expanding into Zambia (Mapaura et al., 2004; Phiri, 2005). The simulated significant gains in climate space suggest that the species will in future be more predominant in the entire KAZA TFCA region. Efforts to maintain its range, particularly in Northern Namibia and Botswana, might be attainable with planned adaptation actions.

As this species flourishes in hot dry weather conditions, which are projected to be increasing in frequency by the end of the 21st century represented by 2085, the conservation prospects of this plant are dependent on enhancement of its dispersal abilities and adaptation opportunity. This can be through management of networks, improvement of connectivity, establishment of corridors and less intensified agricultural activities (Townsend et al.; Mawdsley et al., 2009; Beier, 2012), for the species to fill new suitable climate space. Efforts to maintain its population size and establish new populations might be achievable under climate change.

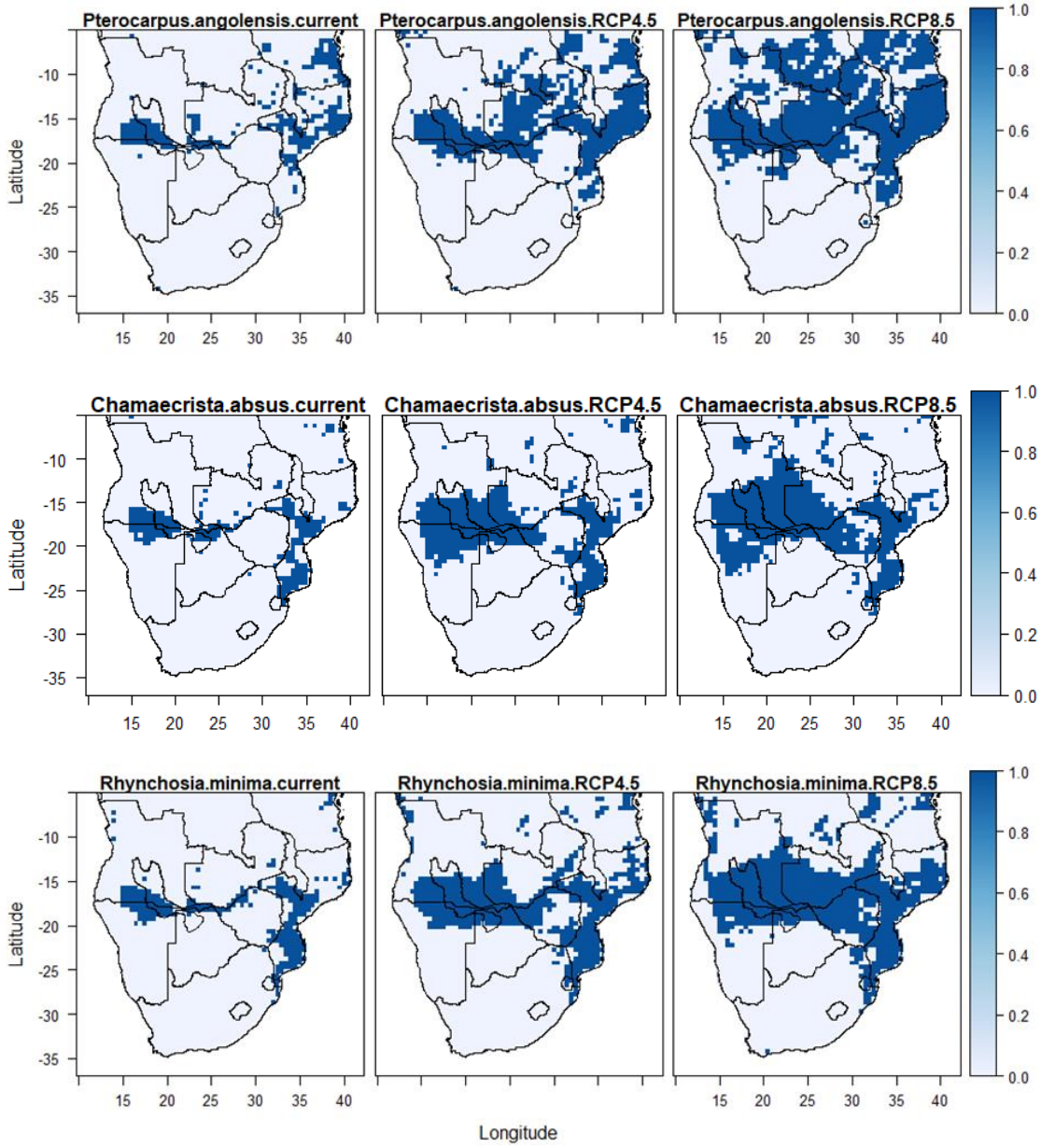


Figure S9.2: Shows current and future distributions for species with low vulnerability to climate change both under RCP4.5 & RCP 8.5 climate change scenarios for the period 2071-2100 represented by 2085.

S6.1.2 Species with high and extreme vulnerability (Type 3 and 4)

Baikiea plurijuga

Within Southern Africa, *Baikiea plurijuga* has a predominantly central distribution. The deciduous tree also occurs in southern Zambia and northern Zimbabwe, the Kavango Zambezi Transfrontier Conservation Area (KAZA TFCA), the largest trans-frontier conservation area in the world (WWF, 2012). This African teak woodland, as is commonly known, is confined to Kalahari sandveld, dominating the gusu woodland (Hyde et al., 2019). It grows on the deep, aeolian and fluvial Kalahari sands. The deciduous tree population has declined due to logging, with one hundred and three (103) occurrences across Africa, *B.plurijuga* is therefore classified as near threatened (IUCN 2019; SANBI 2019). The tree distribution is driven by rainfall related variables (Table 3). The projected increase of summer droughts due to decline in annual rainfall and increase in temperature (Niang et al., 2014b) is a clear threat to the species, as climate suitable space projections under the high emission scenario show loss for this deciduous tree by 2085 (Figure S6.3). Due to the expected contraction in population and distribution size, the species has high sensitivity and low adaptive capability and is classified as extremely vulnerable to climate change. This endangered status reflects the necessity for conservation management (Figure 6.1).

Assessment of current conservation plans (Figure 6.1) reveals that currently there is lack of evidence of regeneration and recruitment in the Okavango region for the species. With climatic conditions projected to become unsuitable, efforts to maintain and re-establish populations seem unattainable. This suggests low prospects for the viability of this valuable tree in the Okavango region. According to the decision tree (Figure 6.1), accepting loss of the populations is the recommended action (Oliver et al., 2012). However, for a species with these indicators, it is vital that fine scale habitat modelling is undertaken since there is a possibility of climatic local extirpation (Suggitt et al., 2017). With a very small area of adjacent suitable future climate space (Figure 6.2; B.plurijuga RCP8.5 & Figure 6.5), there is possibility of the species failing to persist without adaptation interventions. Of crucial importance is implementation of adaptive management, including reduction of non-climatic stressors that worsen declines and reduce adaptation opportunity (Ofori et al., 2017), such as control of timber logging by for example; increasing the life span of harvested wood products are crucial. Conservation efforts and

resources should be focused on grid cells of climate space overlap, around the northern area of Chobe National Park, where *in-situ* management and monitoring would benefit this deciduous tree, and seed banking should also be investigated to potentially preserve local genetic variants.

Baphia massaiensis

The shrub tree *Baphia massaiensis* occurs in the ORB and KAZA TFCA regions. It also occurs in the eastern parts of Southern Africa, in Tanzania, Mozambique and DR Congo. This shrub tree grows in open woodland, riverine scrub and thickets at elevations of 42-1600m, on Kalahari sands (Burrows et al., 2018). The shrub is classified as of least concern under the IUCN global threat status (IUCN 2019). However, its dramatic projected total contraction in suitable climate space (Figure 6.5), coupled with the narrow distribution of only 107 occurrences across the African continent (GBIF, 2019), and requiring riverine habitats, determined by moisture index of moist quarter and potential evapotranspiration (Table 6.3), suggests that the species could locally become extinct by the end of the 21st century represented by 2085. The species is therefore a type 4 and has been assigned an extreme vulnerability to climate change. Efforts to expand the species population size in the ORB will likely prove difficult to achieve, since further decline of this shrub tree is going to be worsened by the projected decrease in rainfall in the region, making it vulnerable to drought. Among the main non climatic adaptation threats to this shrub tree are overgrazing and preferred habitat conversion to agriculture (VanderPost et al., 2005; Wingate et al., 2016). The key adaptation action would therefore be *in-situ* management entailing control and maintenance of favourable grazing regimes in areas with high populations, effective implementation of planned adaptation strategies such as translocation. Reduction of external stressors e.g. habitat degradation, would also likely assist in maintaining the species population size in ORB and KAZA TFCA, and increase adaptation opportunity. A reassessment of the species global and regional threat status from the current least concern classification is necessary, and a more fitting conservation importance status should be considered for *B.massaiensis*.

Bulbostylis hispidula and *Commelina africana*

Bulbostylis hispidula and *Commelina africana* are perennial herbs with a predominantly central distribution within the ORB, with *B.hispidula* having a narrow distribution of only 31 observations in the continent (GBIF, 2019), taking into account the incomplete spatial sampling of the database. These herbaceous species have similar habitat and ecology of shrubland, wetlands (inlands), savanna and grassland (IUCN, 2019). They both grow in wet grasslands and sandy soils (*C.africana*) and shallow soils (*B.hispidula*). Both species do well in disturbed habitats. Their distribution is driven by temperature and rainfall related variables (Table 6.3). The localized extreme vulnerability of the species due to potential loss of significant current suitable climate space by 2085 and low adaptive capabilities and opportunity suggests a bleak outlook for the species in ORB. Under the projected drought inducing climate change of the region, efforts to regenerate and increase the species population size may become more difficult. According to Figure 6.1, the question of whether the population can be self-sustaining (Oliver et al., 2012), based on adaptive capability and opportunity, generates a negative response (Table 6.2). One of the main stressors to adaptive capability and adaptation opportunity of the species is conversion of suitable habitat to arable farming land (VanderPost et al., 2005; Winterbach et al., 2014; Wingate et al., 2016) [Table S6.3]. The possible adaptation action for this species would entail *in-situ* management. However, a change of species threat levels from least concern to near threatened or threatened may stimulate management and monitoring efforts to maintain current population size.

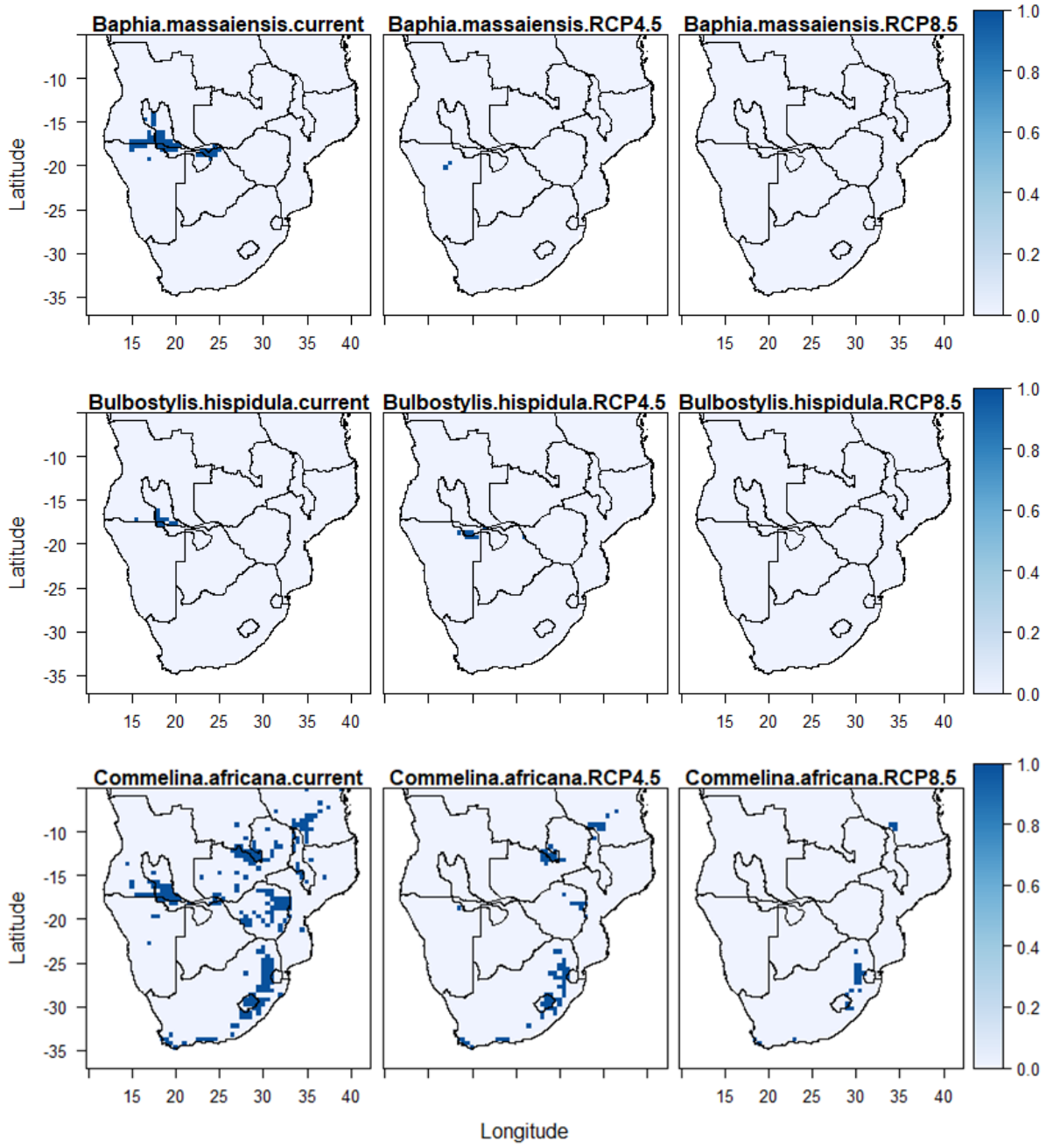


Figure S9.3: Shows current and future distributions for species with extreme vulnerability to climate change both under RCP4.5 & RCP 8.5 climate change scenarios for the period 2071-2100 represented by 2085.

Commelina africana

For this species, although vulnerable, parts of the current suitable space are considered to be in climate overlap areas (adjacent areas with suitable climate space exist). The species therefore has some potential adaptation opportunity. Some areas in South Africa and the Lesotho highlands are projected to be climatically conducive for the species by 2085 (Figure S6.3). These areas are already occupied. *In-situ* management can be the appropriate adaptation action. The herb thrives in disturbed localities and as weed on farms (Table S6.1). Conservation and management measures can include burning, cutting, grazing, to enhance the species adaptive capacity (Kolström et al., 2011) and adaptation opportunity. Effective implementation of these measures has potential to reduce declines. In addition to *in-situ* management, the species populations should be monitored (Figure 6.1) and research conducted on what is required for their long-term persistence.

Rhynchosia totta

This is a rare annual herb/plant with current distributions found in only 51 sites across the arid African tropical forest (GBIF, 2019; Moteetee et al., 2016). The herb grows in flood plain grasslands, savanna and shrublands (IUCN 2019). Given the low percentage of climate space remaining in 2085, the current narrow distribution size, and the potential loss of significant proportion of current climate space, without reductions in global emissions to levels suitable for the species, and effective adaptation plans, the species might be at risk of extinction. However, with some grid cells projected to remain as suitable climate space under the RCP 4.5 future climate scenarios, even though the species is vulnerable, it might have potential to adapt (Figure S6.4).

The distribution of this herb is determined by a moisture index of moist quarter and temperature seasonality; this coupled with its ecology of occurring on moist grounds with rocky high altitudes, it is not surprising that under the RCP 4.5 the suitable climate space is expected to increase along the Drakensberg mountains, with climate space overlap projected along the south east coast line by 2085 (Figure 6.2). The first step was to determine the ability of the species population to adapt and persist in a changing climate (Figure 6.1) (Berry et al., 2013; Oliver et al., 2012). With the narrow current distribution size and natural dispersal barrier (Drakensberg mountains), and the periphery landscapes with agricultural land, suggesting edge effects might

be a problem, it is unlikely that the present time population is robust enough to withstand a changing climate envelope, hence being assigned to type 4 (extremely vulnerable). The adaptation action recommended would be to reduce non-climatic pressures e.g., reduction of agricultural activities through policy interventions, *in-situ* management; the population must also be monitored for tracking new climate envelopes.

Consideration of whether this herb has ability to colonise new sites without intervention was critical; in the case of *R.totta* with low dispersal abilities (Moteetee et al., 2016), the answer was not promising. Next is to consider habitat restoration as a measure to improve connectivity (Hokit et al., 2010; McRae et al., 2012). Restoring wooded grassland next to currently occupied areas (Wingate et al., 2016; Vanderpost et al., 2005) might aid the expansion of the population and distribution. Adaptation actions are therefore focused on minimal climate overlap areas within a short distance from the current suitable climate space (Figures 6.2&6.3). Monitoring of potential suitable areas to ensure success is highly recommended. Revision of the least concern threat status of this perennial shrub assigned by global IUCN and SANBI may be necessary, as climate change poses a threat to the species.

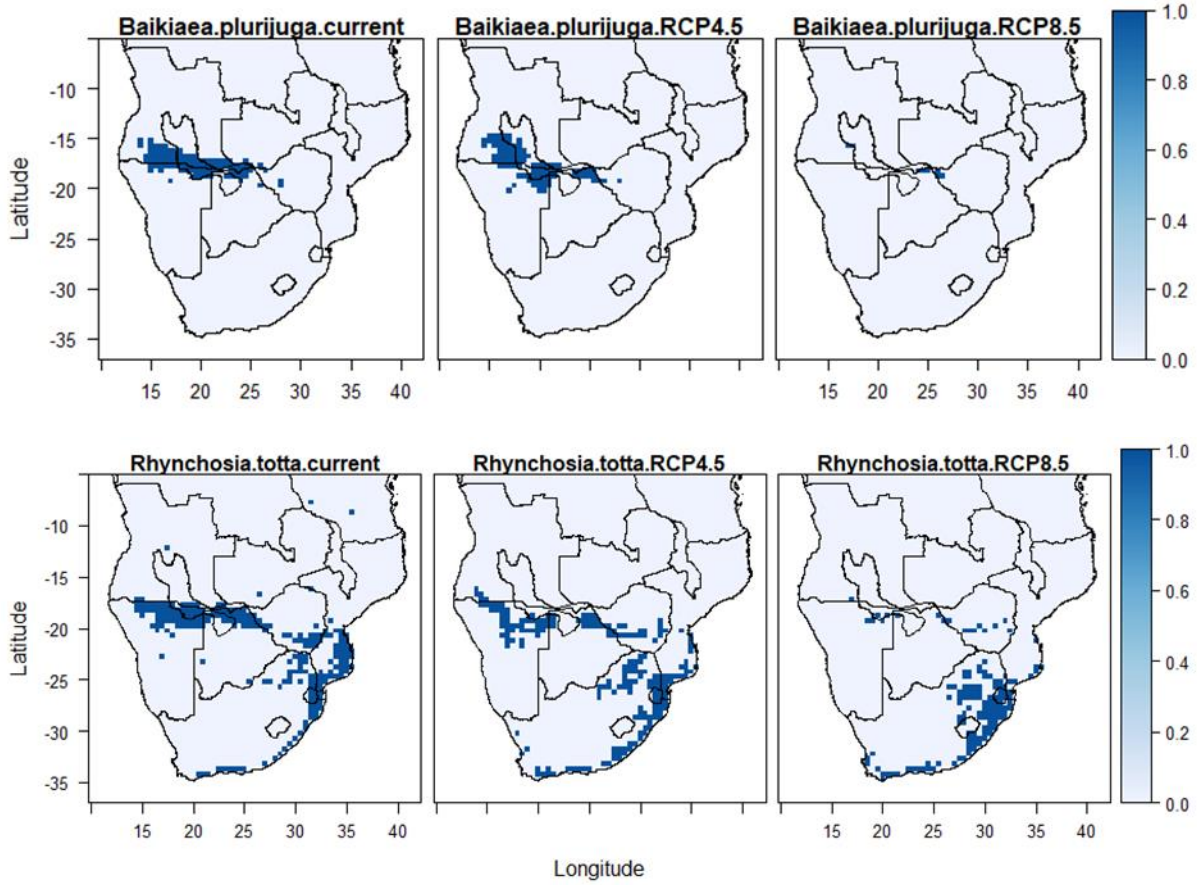


Figure S9.4: Shows current and future distributions for species with high vulnerability to climate change both under RCP4.5 & RCP 8.5 climate change scenarios for the period 2071-2100 represented by 2085.

Analysis of all the above species-specific management actions reveal synergies. Primarily, the adaptation actions required include *in-situ* management, maintenance, restoration and creation of habitats and migration corridors, management of protected areas networks and monitoring and research [Table S6.3] (Doerr et al., 2011; Dale and Fortin, 2014; Gregory et al., 2014). These have potential to facilitate effective, efficient conservation and management efforts, especially that being a river system, the ORB has natural potential for conservation and restoration as a climate corridor (Beier 2012).