

ASSESSING THE POTENTIAL IMPACT OF CLIMATE CHANGE IN THE SOUTH-EASTERN GREAT ESCARPMENT, SOUTHERN AFRICA

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Abstract

Rapid, anthropogenic climate change is a contemporary phenomenon which is threatening natural ecosystems. Mountains are globally important, housing high levels of plant and animal biodiversity, as well as being important suppliers of water with 50% of mountainous regions being essential for the provision of water to downstream inhabitants. Owing to their importance, an assessment of the historical, current and potential impacts of climate change on the south-eastern Great Escarpment encompassing South Africa and Lesotho is necessary and is the primary aim of this thesis.

In order to assess the historical and current impacts of climate change, historical rainfall records were collected from 78 sites throughout the Eastern Cape. These records were used to determine rainfall trends and trends in the frequency of daily extreme events. Climate change projections predict increasing trends in summer and annual rainfall, and a marginal increase to a slightly decreasing trend in winter rainfall, depending on if statistically downscaled or dynamically downscaled projections are examined. Extreme events are also predicted to increase in frequency. Results showed trends which generally agree with the predictions, except for extreme events for which there was insufficient data to support the projections. This has implications for farmers in the area and validates the downscaled Regional Climate Models (RCMs) to be used for the predictive analysis determining the potential future impacts of climate change on plant species' distributions in the south-eastern Great Escarpment.

In order to assess montane plant species to future climate predictions, occurrence records of 46 species were correlated to rainfall and temperature predictor variables and predictions for species richness and beta diversity were made for current and future climates. This predictive analysis used and compared two correlative species distribution modelling methods – one method used one correlating algorithm in a nuanced manner and the other method used five correlating algorithms in an ensemble. A trend of range restriction to higher elevations for the 46 species analysed was as expected from a warming climate. The nuanced, single algorithm modelling method produced less conservative models.

The predicted trend of an elevational increase in montane vegetation in this region points to Lesotho and the Drakensberg highlands as being an important refugium for montane plant taxa of the south-eastern Great Escarpment. The Maloti Drakensberg Transfrontier Conservation Area hence needs to be expanded and its mandate properly enforced to protect this region adequately.

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Chapter 1

General Introduction

What is climate change?

Climate change is the alteration of the Earth's climate through anthropogenically induced changes to the composition of the atmosphere (Karl and Trenberth, 2003; IPCC, 2007). Solar energy is received from the sun in the form of short-wavelength radiation (Karl and Trenberth, 2003; IPCC, 2007). Of this radiation, about 31% is reflected back by clouds and the Earth's surface and about 69% is absorbed by oceans and continents and then re-emitted as long-wavelength, infrared radiation (Karl and Trenberth, 2003; IPCC, 2007). This heat is then absorbed by greenhouse gases, causing a greenhouse effect on Earth which raises the global average surface temperature (Karl and Trenberth, 2003; IPCC, 2007). These gases include water vapour (H₂O), carbon dioxide (CO₂), nitrous oxide (N₂O) and methane (CH₄) (IPCC, 2007). An increasing concentration of greenhouse gases in the atmosphere has occurred since the beginning of the industrial revolution (Vitousek et al., 1997).

General impacts of climate change

Climate change is already having considerable impacts on global biodiversity. Significant species migration towards the poles has been reported, with shifts averaging 6.1km per decade for an analysis of 1700 species (Parmesan and Yohe, 2003). Spring events have advanced by 2.3 days per decade, on average (Parmesan and Yohe, 2003). A similar study by Parmesan (2006) reports average changes in species distribution range in the direction predicted from climate change. Thuiller (2007) reports climate change as a serious threat to biodiversity, though acting over a longer period of time than other threats such as habitat destruction. A review of modelled responses of biodiversity to a changing climate by Bellard et al. (2012) shows the majority of models indicate alarming biodiversity responses, the worst of which would lead to extinction rates which qualify as a sixth mass extinction. Biodiversity declines are ubiquitously reported in a global analysis by Butchart et al. (2010) and these declines are resultant of climate change pressures amongst other pressures including alien invasion and resource consumption.

Other climate change impacts on precipitation, the cryosphere, sea level, food security and human health are elucidated by the IPCC (2014). The IPCC (2014) report states that the high latitudes and the equatorial Pacific are predicted to experience increased precipitation, while sub-tropical dry regions are predicted to experience a decrease in rainfall. The report also predicts a nearly ice-free Arctic Ocean over summer by mid-century and glacier volume across the globe is predicted to

decline by between 35 and 85% for the highest emission scenario. The report predicts a sea level rise of between 8 and 16 mm/year by the end of the century for the highest emission scenario.

The IPCC (2014) predicts water scarcity to increase as temperature rises through the 21st century and wheat, maize and rice production is predicted to be negatively affected by temperature increases greater than 2°C above late 20th century levels. The IPCC (2014) predicts global climate change to exacerbate health problems that already exist and an increased risk from vector-borne diseases, such as malaria, as global temperatures rise and vectors have a larger potential area of occurrence.

Mountains

Landforms are generally considered mountains when they have sufficient elevation and sufficient prominence from the adjacent landscape – considered to be about 300 metres above the surrounding regions (Byers et al., 2013). Körner et al. (2011) also describe mountains by ruggedness, with an elevational difference of 200 meters or more between a 30 second central grid cell and eight surrounding grid cells. Mountains largely originate at plate boundaries, particularly where plate collisions occur and warp the Earth's crust (Shroder Jr. and Price, 2013). They are also formed by the bulging and eventual thinning of the Earth's crust by magma plumes which can lead to a crustal fissure through which extrusive and intrusive volcanism then shapes the landscape (Shroder Jr. and Price, 2013). The southern African great escarpment was formed in this manner.

The global importance of mountains and the threat climate change poses

Mountains are home to around 10-12% of the global population (Gardner et al., 2013). This percentage increases to 25% when including people living adjacent to mountains who are entirely or partially dependent on mountain resources including water, timber, agricultural products and minerals (Gardner et al., 2013). Mountains are seen as 'water towers' with all of Earth's major river systems gaining some or most of their water from mountains (Viviroli and Weingartner, 2008). 50% of mountainous regions are essential for the provision of water to downstream areas (Viviroli et al., 2007). Mountains have many streams, rivers and lakes and many high peaks are covered with snow and ice making them vital providers of water for local and distant communities (Gardner et al., 2013). The prevalence of rivers, lakes and streams in mountainous areas is largely linked to the impact mountains have on local air circulation – they increase precipitation amounts in windward locations through an orographic or barrier effect on air masses (Gardner et al., 2013; Vogel, 2000). This causes air masses to rise on the windward side, leading to increased condensation of water vapour and increased rainfall (Vogel, 2000).

Mountains are noted for their biological diversity which is driven by an elevation based ecosystem differentiation and many different small ecological niches because of the heterogeneous nature of the terrain (Beniston, 2003; Gardner et al., 2013). The diversity of plant life is important both economically and in terms of conservation. People have a direct relationship with mountain vegetation through the harvesting of trees and other plants (Gardner et al., 2013). Pristine mountain environments also attract tourism to a region. The plant diversity in southern Africa's mountains will be elucidated later in this chapter.

Climate change threatens to radically alter all of these fundamentally important facets of mountainous regions. A warming climate is predicted to change the hydrological cycle, with higher rates of evaporation affecting precipitation amounts and the rate of groundwater recharge (Beniston, 2003). The extent of glaciers and the amount of precipitation falling in the form of snow are predicted to decrease (e.g Haeberli and Hoelzle, 1995), with the snowline rising by about 150 m for every 1°C increase in temperature (Beniston, 2003). This has important implications for the hydrological cycle in affected areas, as well as tourism, agriculture and other key economic sectors (Beniston, 2012). Such changes to the hydrological cycle coupled with an increasing human population could lead to armed conflicts over water becoming more common.

Biological systems are also predicted to respond to a warming climate. Models and empirical data point to a trend of upslope movement for montane organisms (Beniston, 2003; Pauli et al., 2003; Gottfried et al., 2012; Pauli et al., 2012). This phenomenon will be analysed in more detail in chapter three of this thesis.

In terms of African and South African mountains, mountain plants in the Eastern Arc Mountains of east Africa and their response to a changing climate were modelled by Platts et al. (2013). The models showed distributional responses both upslope and downslope from a changing climate, and showed that where there was climate persistence, levels of endemism were greater than in regions of climatic upheaval. South African mountains, between 1960 and 2010, were found to have experienced increasing temperatures from a changing climate which corresponds with global climate change trends and potentially affects biodiversity which will be addressed in chapter three (MacKellar et al., 2014).

Southern Africa's mountains

The area of interest for this research centres on the Great Escarpment from the southern escarpment, through the Drakensberg to the Soutpansberg in the north-east. These constitute the major mountains of South Africa and Lesotho. They reach an elevation of over 3000 metres in the

Drakensberg, the dominant range of the south-eastern Great Escarpment bordering Lesotho (Attwood et al., 2011). Climate is generally characterised by a summer rainfall regime in the southern and eastern Great Escarpment, with occasional winter snowfalls (Clark et al., 2011a).

The mountains will be described in the following section of the chapter, making particular reference to the geology, predominant climate and plant diversity in the regions. All of these are pertinent properties to describe to set the scene for the rest of the thesis.



Figure 1.1: South African satellite map with research region delineated. All mountain ranges are part of the Great Escarpment.

The Great Escarpment

The dominant montane feature in South Africa's landscape is the Great Escarpment. The definition of a Great Escarpment is that it runs parallel to a coast, separating a high plateau from a coastal plain (Ollier, 1985; Partridge and Maud, 1987; Birkenhauer, 1991).

Climate

The climate over the Great Escarpment is highly varied. The southern escarpment region is described by Clark et al. (2011a) to range from humid in the east to arid in the west. The scarp region is wetter than the more arid plains inland and to the coast. The rainfall regime is summer rainfall in the main Drakensberg through to the eastern Nuweveldberge (largely convective and orographic rainfall), with all year rainfall in the rest of the Nuweveldberge and winter rainfall in the Roggeveldberge

(largely frontal and orographic rainfall). The Nuweveldberg is the most arid of the southern escarpment ranges, with the Great Winterberg-Amatoles and Stormberg the most humid (Clark et al., 2011b; Clark et al., 2014). The Roggeveldberg is the coldest range (Clark et al., 2011c).

The main Drakensberg, making up most of the eastern section of the Great Escarpment is characterised by a warm, wet, summer rainfall climate. Winters are generally dry and cool with occasional frontal snow.

The north-eastern Great Escarpment is highly seasonal with cool, arid winters and hot, wet summers. Thunderstorms and orographic rain and mist are common adjacent to the mountains (Matthews et al., 1993). Mean annual rainfall can reach 2000mm on the escarpment top (Matthews et al., 1993). There is a significant drop in rain away from the escarpment on the windward and leeward side (Matthews et al., 1993). Temperature declines in all of these ranges at higher elevations.

Geology

Geology over the southern and south-eastern escarpment is quite uniform. Beaufort Series shales and sandstones intruded by dolerite characterise the southern escarpment, with the Stormberg mountain range having Clarens Formation sandstone capped, in places, by Drakensberg basalts (Clark et al., 2011a; Johnson et al., 2006). The height of the main Drakensberg range comes from these extrusive basalt caps. In general, the hard quartzites of the Wolkberg Group and Black Reef Formation have been the creators of the escarpment top in the north-eastern escarpment region of the Wolkberg and Soutpansberg (Matthews et al., 1993).

Plant Diversity

The plant life of the Great Escarpment is highly varied and contains many species endemic to narrow sections. White (1983) described Africa's afromontane region as an archipelago-like centre of endemism. Of the 4000 species found in the afromontane area, 75% are endemic. Afromontane habitat is typified by high elevation, rolling grasslands and small patches of montane forests.

Matthews et al. (1993) analysed the north-eastern Drakensberg (in north-eastern South Africa) and noted a high number of plant families with species and full genera endemic to this north-eastern region. Liliaceae, Iridaceae, Asteraceae, Lamiaceae, Orchidaceae and Amaryllidaceae all have multiple genera endemic to the hard quartzites of the area. Dolomite rocks along this stretch of escarpment are home to numerous endemic genera in the Liliaceae, Lamiaceae, Acanthaceae and Sterculiaceae in particular. The former Transvaal escarpment region is considered a centre of

endemism by Matthews et al. (1993) with 110 endemic or near-endemic species. They state that the high number of endemics in this region is strongly influenced by geological differences between the quartzites and dolomites (containing high proportions of limestone) and the soils they produce.

The southern escarpment region incorporates the Nuweveldberg, Roggeveldberg, Sneeuberg, Winterberg-Amatola and Stormberg (see Fig. 1). The Sneeuberg were postulated, by Clark et al. (2009), to be a new centre of endemism with 46 endemic and near-endemic species. The best represented families in the range are the Asteraceae, Poaceae, Fabaceae and Scrophulariaceae with 17.4, 8.6, 4.8 and 4.5% of surveyed species respectively. The major biomes in the Sneeuberg include Grassland, Forest, Albany thicket and Nama-Karoo. The Nuweveldberge are the most arid in the southern Great Escarpment and contain 1139 taxa, of which only 0.5% are endemic (Clark et al., 2011b). The vegetation contains elements of Succulent Karoo and Grassland (Clark et al., 2011b). The Roggeveldberge comprise vegetation with Fynbos, Succulent Karoo and Nama-Karoo elements and, after fieldwork, have an expected total count of between 1500 and 2000 taxa, though more botanical work is needed for a complete list (Clark et al., 2011c). The Winterberg-Amatola range contains 1877 species, with an endemism percentage of 1.9% and, complementary to the Sneeuberg, could be classified as a new floristic centre of endemism (Clark et al., 2014). It incorporates the Grassland, Albany Thicket, Savanna, Forest, Nama-Karoo and Eastern temperate freshwater wetland biomes (Clark et al., 2014).

The Drakensberg Alpine Centre, centred over Lesotho, is the highest elevation region of southern Africa's Great Escarpment. It is particularly large at 40 000km² and supports over 2800 native taxa (Carbutt and Edwards, 2004). Of the angiosperms, which constitute 89% of the surveyed plant species, 16% are endemic (Carbutt and Edwards, 2004). Families best represented are Asteraceae, Poaceae, Fabaceae, Scrophulariaceae, Orchidaceae, Cyperaceae, Iridaceae and Asclepiadaceae (Carbutt and Edwards, 2004).

Thesis aims

Based on the importance of mountain ecosystems, both economically and in terms of biodiversity, a total analysis of the historical and potential climate change impacts in southern Africa's mountainous regions is of vital importance.

The aims of this thesis are:

- To do an analysis that examines historical rainfall records throughout the Eastern Cape's mountainous region and determines how climate change has impacted rainfall trends. The rainfall trend analysis will double as a validation of the downscaled climate models used in the predictive modelling chapter to add credibility to the results of that chapter.
- To do a predictive analysis which uses correlative species distribution modelling to predict the potential distributional response of montane plants to a changing climate. This uses dynamically downscaled Global Climate Models (GCMs) calculated by Engelbrecht et al. (2011), and two contrasting distribution modelling methodologies – an ensemble method of many algorithms and a method using a single algorithm in a nuanced manner. The performances of the two methods will be compared.

Chapter 2

Trends in historical rainfall records from the Eastern Cape Mountains – empirical evidence of local climate change and a validation of downscaled Global Climate Models

Introduction

A warming climate is predicted to change global weather patterns (IPCC, 2014). Dore (2005) synthesised global precipitation trends from empirical data and found climate change-linked shifts in rainfall regimes and amounts. Australia has experienced climate change-linked increases in rainfall in the northern, eastern and southern regions, with rainfall decreases being experienced in the west (Hughes, 2003). In India, the frequency of extreme rainfall events is decreasing in central and northern India, while it is increasing in eastern India and on the Indian peninsular (Guhathakurta, 2011). A 6.1 km average movement of species towards the poles, in a meta-analysis by Parmesan and Yohe (2003), illustrates the impacts of a changing climate on natural systems. Agricultural productivity is predicted to be adversely affected as rainfall and temperature regimes change, affecting the water balance of regions historically used for specific farming practices (Kurukulasuriya and Rosenthal, 2003).

Changes in climatic patterns are modelled using Global Climate Models (GCMs). These are models which simulate climatic changes through changes to climate forcing variables (e.g. greenhouse gases or solar activity) (McGuffie and Henderson-Sellers, 1997). GCMs simulate climate over multiple decades, are coupled atmosphere-ocean models and this means that the ocean circulation and temperature trends are coupled with the atmosphere allowing water transfer to occur (McGuffie and Henderson-Sellers, 1997).

Downscaling is a technique used to convert Global Climate Models to models making more regional, fine-scale predictions (Hewitson and Crane, 2006). There are two main downscaling methods used for southern African climate change projections: statistical downscaling and dynamic downscaling. Statistical (empirical) downscaling entails the relation of large-scale climate to local climate using historical observations (Tadross et al., 2011). It uses historical, empirical data to generate a climate relationship between the large-scale climate synoptic patterns and the local climate (Hewitson and Crane, 2006). This relationship is then used to create downscaled predictions across the GCM (Hewitson and Crane, 2006). Dynamic downscaling makes use of a regional dynamic climate model which is nested within a GCM (Tadross et al., 2011). In the case of southern Africa, the Conformal-

Cubic Atmospheric Model (CCAM) has been used as a regional climate model to determine the impact of anthropogenic forcing on regional atmospheric circulation (Engelbrecht et al., 2009; Engelbrecht et al., 2011; Engelbrecht et al., 2013). Empirical comparison and validation strengthens model-based projections. This paper therefore intends to compare empirical records to these downscaled projections for rainfall.

Predictions from southern African downscaled Regional Climate Models (RCMs)

The predictions for comparison in this chapter are for downscaled RCMs to the A2 emission scenario from the IPCC's fourth assessment report (IPCC, 2007). This scenario is a high greenhouse gas emission scenario in a world of relatively slow demographic transition, convergence in regional fertility patterns, convergence in inter-regional GDP per capita differences, energy efficiency improvements, development of renewable energy and no constraints to the use of renewable energy (IPCC, 2007). Statistically downscaled predictions suggest increased summer rainfall in the interior and eastern part of South Africa, with a decrease in winter rainfall in the Western Cape (Hewitson and Crane, 2006). Eastern South Africa, including Lesotho, is projected to experience higher annual rainfall totals (Tadross et al., 2011). The winter rainfall areas are predicted to have less total rainfall, while winter rainfall is predicted to increase marginally in the eastern half of South Africa (Tadross et al., 2011).

The dynamically downscaled projections predict rainfall decreases over the winter and summer months and in the annual rainfall total in the south-western Cape (Tadross et al., 2011; Engelbrecht et al., 2009). Conversely, south-eastern South Africa is predicted to have marginally increased annual rainfall, a rainfall increase over autumn and slight increasing trends over summer, winter and spring.

Both statistically and dynamically downscaled projections predict increasing temperatures over South Africa by mid-century, with a greater increase over the country's interior (Tadross et al., 2011).

The meteorological reasons for these changes in rainfall amounts are elucidated by Engelbrecht et al. (2009). The south-western Cape is predicted to get drier through the southward displacement of frontal rain bands because of the intensification of the subtropical high pressure belt. This intensification leads to more prominent high pressure systems over much of southern Africa, leading to a general decline in rainfall over the greater subcontinent. The weak signal for rainfall increase over south-eastern South Africa is linked to a strengthening of the Indian Ocean High in the south-western Indian Ocean. This leads to a more frequent occurrence and westward shift of the South Indian Convergence Zone (SICZ) bringing moisture over south-eastern South Africa. The SICZ is a land

based zone of air convergence which extends through south-east South Africa, bringing precipitation (Cook, 2000).

It must be noted that the changes elucidated above are to mid-century which, based on the emission scenario, has a much higher greenhouse gas concentration than is currently present. This means that empirical rainfall record trends found in this study may show early signs of change in the direction of those predicted in the downscaled models, though the magnitude of these changes may not be as strong as would be expected by mid-century.

Extreme rainfall events

Extreme rainfall events are defined in this study as all rainfall events above the 90th percentile for a particular time period. They could potentially have severe implications for agriculture, dam infrastructure such as dam walls, human livelihoods surrounding these dams and water resource management (Mason et al., 1999). They are predicted to have a higher frequency in the future in South Africa, in part because of increased convection over the eastern parts of South Africa during summer (Tadross et al., 2005; Engelbrecht et al., 2013). Concurrently, the more common formation of the SICZ should result in more extreme rainfall events occurring through convective thunderstorms (Engelbrecht et al., 2009; Engelbrecht et al., 2013). Another cause of extreme rainfall, which is not predicted to increase in frequency, is cut-off lows, although this should only impact the extreme south-west. Cut-off lows form when cold air from high latitudes is brought towards the subtropics through a meander in the jet stream (Innes, 2010). This core of air gets cut-off from the jet stream when the stream reforms (Innes, 2010). These cells would not move rapidly west with the jet stream and can bring large amounts of rainfall as they stay in one area. They are predicted to decline in frequency in response to the increased strength of the subsidence from the subtropical high pressure (Engelbrecht et al., 2013).

Comparing historical data to downscaled RCMs

Fridley (2009) notes that precise climate models are difficult to produce over mountainous terrain e.g. ground-level temperature regimes in the Great Smoky Mountains National Park in Tennessee, North Carolina vary hugely over fine scales and are only partially linked to the dominant regional synoptic weather patterns of the area. Based on these difficulties, a comparison between the historical records attained in the field and the predicted rainfall from the downscaled projections is important to determine the extent of the discrepancy between the two, also considering the coarse 15 minute spatial resolution at which the projections are being used for these models in chapter three.

Aims and hypotheses

Predictions suggest that there will be marginally increasing annual, summer and winter rainfall trends after 1980 for the Eastern Cape Mountains. Climate change predictions for extreme events suggest an increasing frequency of extreme events. The first aim of this research is to compare historical trends in summer, winter and annual rainfall in the mountains of south-eastern South Africa with future climate change rainfall projections in an attempt to validate these projections. Secondly, it aims to analyse trends in extreme rainfall events and compare them to the projected climate change trends. Implications of the rainfall trends discovered, and the implications of their predicted future trajectory on the local economy of the region and its biodiversity, will be discussed. Lastly, we aim to compare the empirical rainfall data collected to projections from dynamically downscaled RCMs for current climate (1971-2005) (Engelbrecht et al., 2011) to determine the predictive ability of the models for current climate. Accurate model predictions in comparison to empirical data allow for accurate species distribution models to be calculated for all species in chapter three.

Materials and methods

Study area

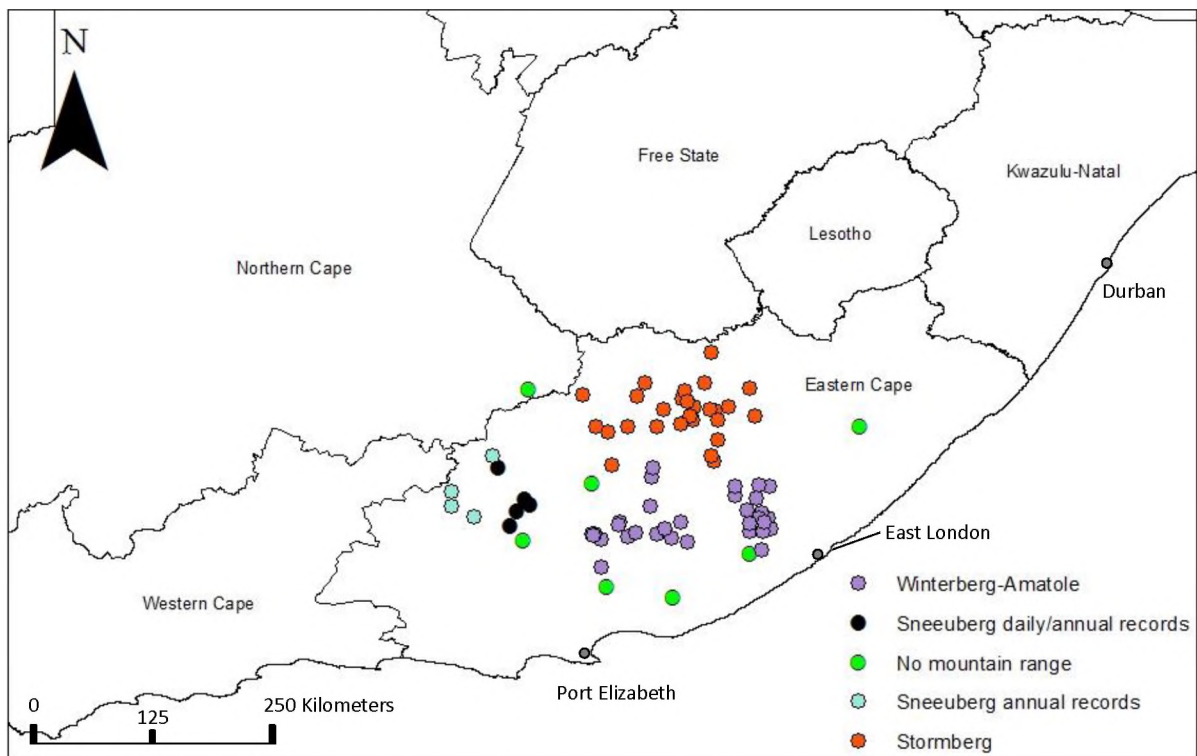


Figure 2.1: Locations from which historical rainfall records were attained.

Historical rainfall records were attained from locations centred over three southern escarpment mountain ranges in the Eastern Cape province: the Sneeuberg, Winterberg-Amatole and Stormberg. Locations in the Sneeuberg, from which daily rainfall records were collected, were used for the extreme events analysis.

The vegetation, climate and geology of the study region are described in detail in chapter one. This is an important livestock farming area, particularly for cattle, sheep (the more arid regions) and goats (Department of Agriculture Forestry and Fisheries, 2003).

Rainfall record collection

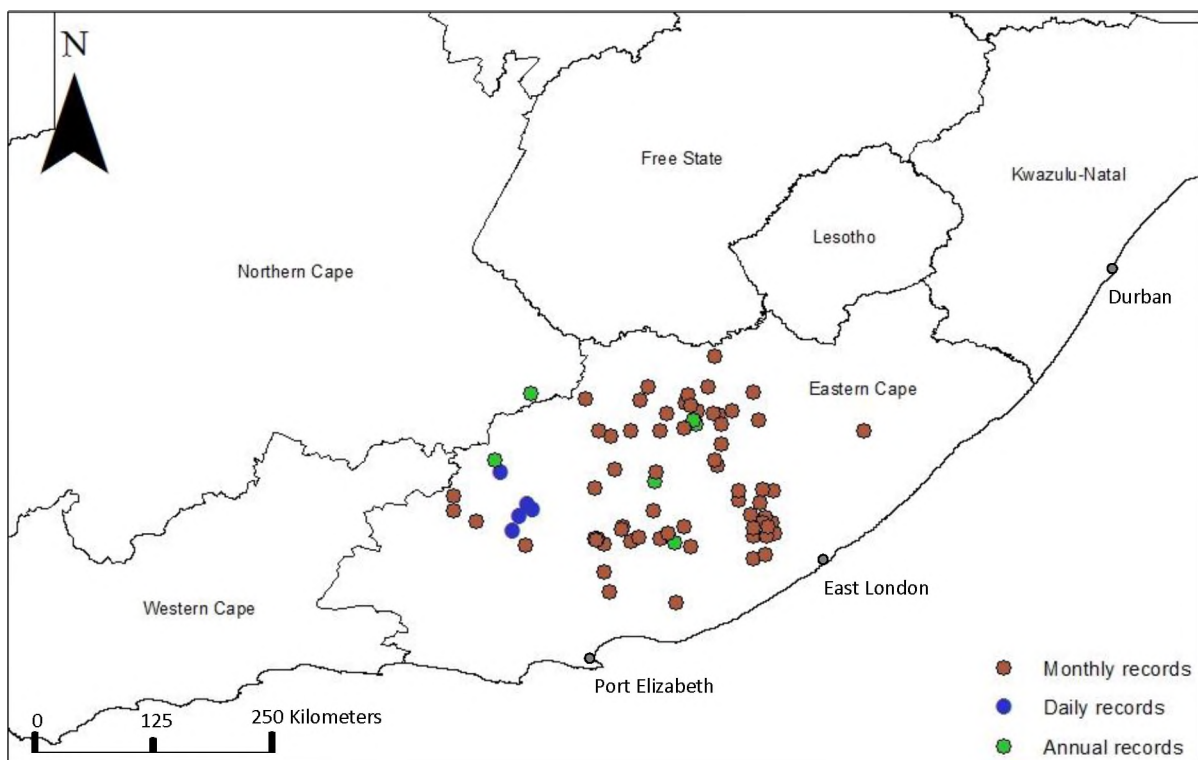


Figure 2.2: Locations from which daily, monthly and annual records were attained. Green dots show locations with only annual rainfall records. All other locations had monthly and/or daily records along with the annual records.

Rainfall records were obtained from farmers and collated from three separate field trips to the Stormberg, one to the Winterberg-Amatole/Transkei and one to the Sneeuberg. Records for further locations surrounding the three mountain ranges were acquired from the South African Weather Service. Annual rainfall was attained for every location, with monthly rainfall garnered for most locations to determine seasonal rainfall for these places (Figure 2.2). Summer rainfall included a total of December, January and February; autumn rainfall a total of March, April and May; winter rainfall a total of June, July and August; spring rainfall a total of September, October and November. A year's summer rainfall would start in December of that particular year (e.g. 1990 summer rainfall

would start in December of 1990). Farmers' records were either transcribed from digital photographs of hand-written records to Microsoft Excel spreadsheets, or were received directly in Microsoft Excel format. This was done with extreme care and double-checked after each transcription to ensure accuracy. Co-ordinates were recorded at each location.

Daily rainfall for five locations in the Sneeuberg was used to analyse the change in prevalence of extreme events for comparison with the climate change predictions. Records ranged in length from starting in 1878 to present to starting post-2000 to present (See appendix 1). Rainfall records were collected from a total of 78 locations. We analysed from locations which contained 80% of monthly data between time periods 1930 to 1979 and 1980 to 2010 which equated to 25 locations – 11 from the Winterberg, 11 from the Stormberg and 3 from the Sneeuberg. This method of location selection was done in accordance with methods from MacKellar et al. (2014).

Analyses

All analyses were completed in R version 3.1.3 (R Core Team, 2015). The year 1980 was chosen as the year at which to split data after analysis of graphs of past temperature trends in the IPCC AR5 (IPCC, 2014). The graphs show an increasing temperature trend after 1980, in contrast to a relatively stable temperature trend before then. Karl and Tenberth (2003) also note that the Earth's climate has exceeded the bounds of natural variability since about 1980. Trends through the different periods were determined using a number of statistical approaches as elucidated by MacKellar et al. (2014). The Mann-Kendall test, a non-parametric test which makes no assumptions about the underlying data distribution and is relatively insensitive to outliers, was applied to data from the different time periods. This test provides the correlation co-efficient tau, a value between -1 and 1, and the statistical significance of the trend. This was applied to seasonal and annual rainfall data for the two different time periods (1930 to 1979 and 1980 to 2010) and was graphically represented on maps with arrows for each location scaled to the size of tau which was rounded to one decimal place. A trend was considered significant with a P-value reading lower than 0.05.

The Sen's slope estimator and Loess curve were applied to the seasonal and annual time series data. The Sen's slope estimator calculates the slope of the trend by determining the median slope of all slopes between data points (MacKellar et al., 2014). The Loess curve is a peak smoothing curve for time series data (MacKellar et al., 2014). An average time series was calculated per mountain range for summer, autumn, winter, spring and annual rainfall over the time periods. This was done by determining the mean seasonal and annual rainfall amount per year over all locations within a particular mountain range. These yearly amounts were then subtracted from average seasonal and annual totals across all the years in the time period analysed. The anomaly time series produced was

then tested using the Sen's slope estimator and fitted with a Loess smoothing curve with a bandwidth of 0.25. The Sen's slope line was only added to the plots where the slope was significant.

Daily rainfall was analysed in accordance with methods used by Rahmani et al. (2015). Daily records between 1980 and 2010 were selected for four locations in the Sneeuberg. The maximum day of rainfall per year in the period 1980 to 2010 was first analysed for a significant trend using the Mann-Kendall test. The trend slope was then determined using the least squares linear regression line. The same statistical tests were performed to determine the trend on the number of rain days greater than the 90th percentile in the same time period for each of the four locations in the Sneeuberg.

Historical versus modelled rainfall comparison

A mean annual rainfall amount over the years 1971 through to 2005 was determined for 37 locations for which rainfall data were available for this period. This mean annual rainfall for each location was compared to the modelled mean annual rainfall from six dynamically downscaled RCMs modelled by Engelbrecht et al. (2011) used in chapter three. The current climate (1971-2005) models were used for the comparison to annual rainfall amount (bio 12) at the same location. The extract function in R version 3.1.3 was used to determine the modelled rainfall amount at each of the 37 locations. Scatter plots comparing recorded values and predicted values were created. The raster layers from the six models were analysed at both 15 and 9 minute spatial resolutions. The comparison with the 9 minute spatial resolution models was done because this is the original and highest resolution these models come in, while the 15 minute resolution comparison was done because this was the resolution used for the climate models in chapter three.

Results

Tau indices for 1930 to 1979

Results for precipitation trends were split into 1930 to 1979 and 1980 to 2010 time periods so that a general spatial trend pre and post 1980 could be attained. Below, the trends in rainfall are reported for each of the three mountain ranges and of the Eastern Cape interior region as a whole for the 1930 to 1979 time period (Figure 2.3).

Mountain Range 1: Stormberg

An increasing rainfall trend seems to predominate across the Stormberg (1) for seasonal and annual rainfall, with a number of locations in JJA and SON having significantly increasing rainfall (Figure 2.3).

Mountain Range 2: Sneeuberg

Trends from tau are non-significant across all seasons and locations (Figure 2.3). DJF rainfall shows a non-significant declining trend across all Sneeuberg (2) locations, while MAM, JJA, SON all have increasing trends across most locations, although again these are non-significant (Figure 2.3). Annual rainfall has a declining trend over two of the three locations (Figure 2.3).

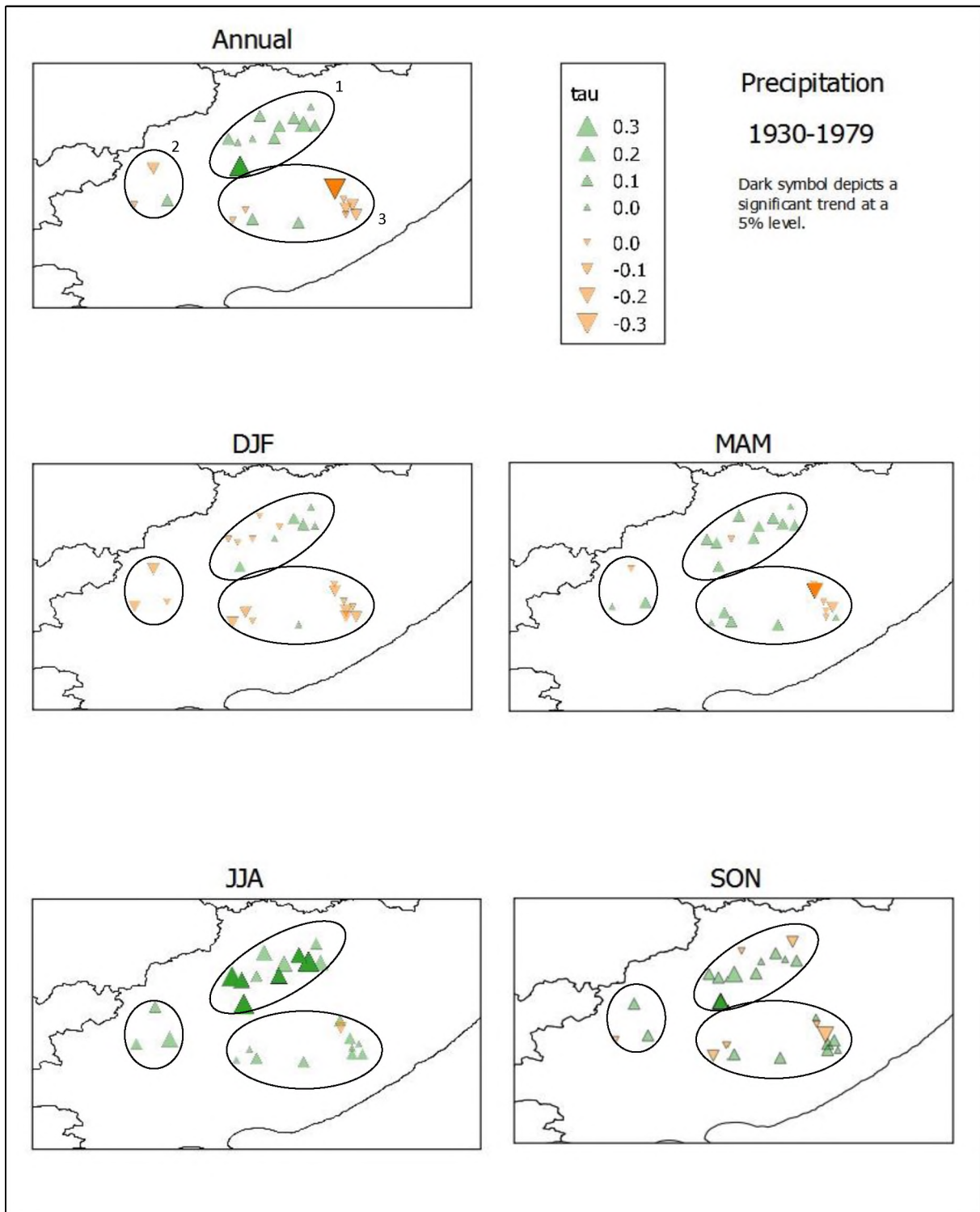


Figure 2.3: Rainfall trends over all locations between 1930 and 1979 as represented by tau from the Mann-Kendall statistical test. Arrows are scaled to the size of tau and darkened arrows denote a significant trend. DJF is summer rainfall, MAM is autumn rainfall, JJA is winter rainfall and SON is spring rainfall. Mountain ranges are delineated by ovals with 1 being the Stormberg, 2 the Sneeuberg and 3 the Winterberg-Amatole range.

Mountain Range 3: Winterberg-Amatoles

Rainfall in DJF has a non-significant decline across all locations (Figure 2.3). All other seasons have rainfall increases across most locations, although these are not significant (Figure 2.3). Annual rainfall for the Winterberg-Amatoles (3) indicates a decline across most locations (Figure 2.3).

Total trend over all locations and time periods

Across all locations and time periods there is a general marginal increase in rainfall (Figure 2.3).

Tau indices for 1980 to 2010

Below, the trends in rainfall are reported for each of the three mountain ranges and of the Eastern Cape interior region as a whole for the 1980 to 2010 time period (Figure 2.4).

Mountain Range 1: Stormberg

There are disparate trends for seasonal rainfall in the Stormberg (1) (Figure 2.4). DJF and MAM show general increases in rainfall in the Stormberg, with DJF having one significantly increasing location (Figure 2.4). JJA and SON show general decreases in rainfall in the Stormberg, although none of these is a significant decrease (Figure 2.4). Annual rainfall shows an equal number of stations with increasing and decreasing trends (Figure 2.4).

Mountain Range 2: Sneeuberg

Trends for the range differ between the seasons, with DJF and MAM, having increasing trends, while JJA and SON have decreasing trends (Figure 2.4). DJF has one significantly increasing station (Figure 2.4). Annual rainfall has more stations with increasing rainfall trends than decreasing, although these changes are marginal and non-significant (Figure 2.4).

Mountain Range 3: Winterberg-Amatoles

Annual rainfall and seasonal rainfall for DJF, MAM and JJA have increasing trends, with significantly increasing locations in both annual and MAM rainfall (Figure 2.4). SON has a decreasing rainfall trend across the region (Figure 2.4).

Total trend over all locations and time periods

There is disparity in the spatial trends between DJF and MAM, and JJA and SON, with DJF and MAM having increasing rainfall and JJA and SON decreasing (Figure 2.4). Annual rainfall is increasing across most locations, suggesting a stronger total signal for increasing rainfall than decreasing (Figure 2.4).

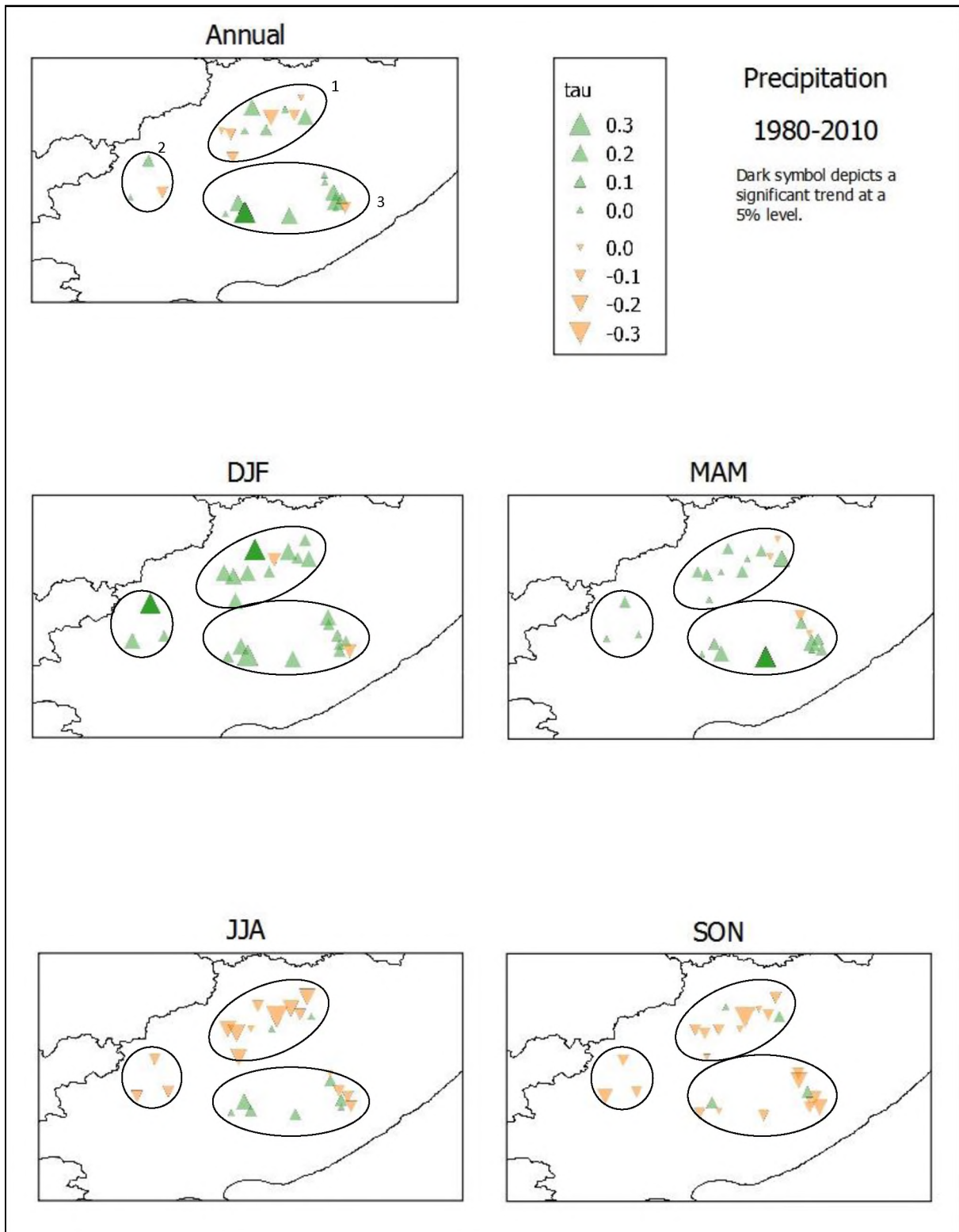


Figure 2.4: Rainfall trends over all locations between 1980 and 2010 as represented by tau from the Mann-Kendall statistical test. Arrows are scaled to the size of tau and darkened arrows denote a significant trend. DJF is summer rainfall, MAM is autumn rainfall, JJA is winter rainfall and SON is spring rainfall. Mountain ranges are delineated by ovals with 1 being the Stormberg, 2 the Sneeuberg and 3 the Winterberg-Amatole range.

Average anomaly analysis for 1930 to 1979

The Sen's slope calculated on the average anomalies over all locations in each mountain range is used to determine the significance and slope of the time series. The analyses are done on seasonal and annual rainfall (Figure 2.5). Descriptions of the prevailing trends in each mountain range and, in total across the Eastern Cape interior, are shown below.

Mountain Range 1: Stormberg

There are some marginal increases in rainfall for MAM, SON and annual rain, and declines for the rest (Figure 2.5). None of these trends is significant.

Mountain Range 2: Sneeuberg

There are some marginal declines for MAM, SON and DJF and for annual rain in the Sneeuberg between 1930 and 1979, but none of these is significant (Figure 2.5).

Mountain Range 3: Winterberg-Amatoles

JJA and DJF and annual rainfall show marginal declines in rainfall, although these are not significant. The rest have non-significant increases (Figure 2.5).

All locations and time periods

There is very little signal for any definite change in precipitation amount, with most declines and increases small and non-significant (Figure 2.5).

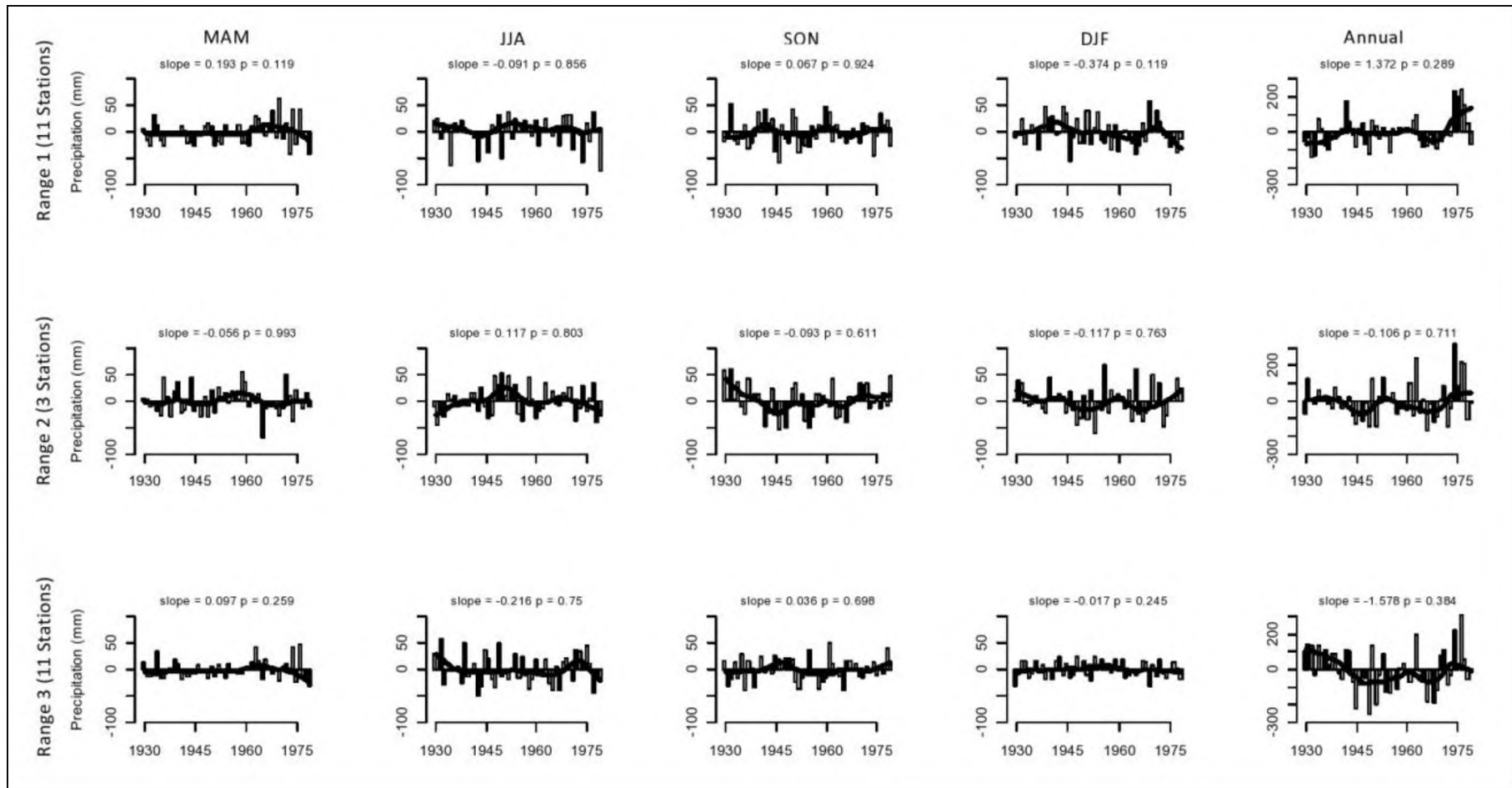


Figure 2.5: The mean time series for the three mountain ranges for the time period 1930 to 1979 for the seasons autumn (MAM), winter (JJA), spring (SON) and summer (DJF), and for annual rainfall. Bars are the yearly rainfall anomalies from a rainfall average across all stations in the mountain range and across all years in the time period. The Sen's slope line was only added for significant trends and the loess smoothing with a bandwidth of 0.25 line was added to all anomalies in the time series. The slope reading above each graph notes the slope on the Sen's slope and the significance reading, the significance of the slope.

Average anomaly analysis for 1980 to 2010

The Sen's slope calculated on the average anomalies over all locations in each mountain range is used to determine the significance and slope of the time series. The analyses are done on seasonal and annual rainfall (Figure 2.6). Descriptions of the prevailing trends in each mountain range and, in total across the Eastern Cape interior, are shown below.

Mountain Range 1: Stormberg

There are slight declines in rainfall amount for MAM, SON, DJF and annual rainfall (Figure 2.6). All of these declines are non-significant.

Mountain Range 2: Sneeuberg

There are declines in rainfall for JJA and SON. JJA rainfall has a significant decline over the time period (Figure 2.6). All rainfall increases were non-significant.

Mountain Range 3: Winterberg-Amatoles

Declines in rainfall can be seen for MAM, SON and DJF, although none of these is significant (Figure 2.6). There are increases in rainfall for JJA and annual totals (Figure 2.6).

All locations and time periods

There is minimal to no signal for any change in precipitation amount, with most rainfall increases and decreases being non-significant (Figure 2.6).

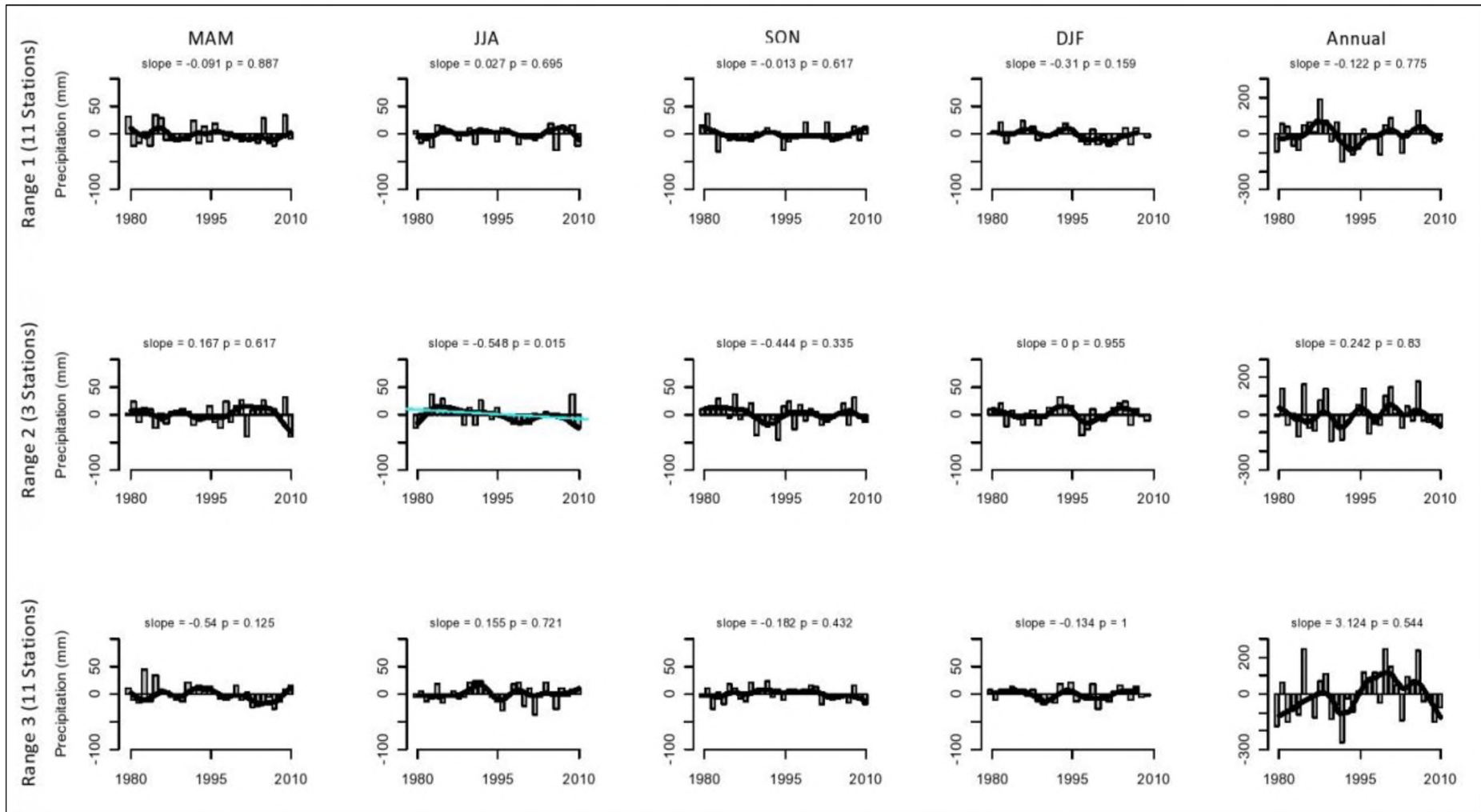


Figure 2.6: The mean time series for the three mountain ranges for the time period 1980 to 2010 for the seasons autumn (MAM), winter (JJA), spring (SON) and summer (DJF), and for annual rainfall. Bars are the yearly rainfall anomalies from a rainfall average across all stations in the mountain range and across all years in the time period. The Sen's slope line is in blue and was only added for significant trends and the loess smoothing with a bandwidth of 0.25 line was added to all anomalies in the time series. The slope reading above each graph notes the slope on the Sen's slope and the significance reading, the significance of the slope.

Maximum day of rainfall per year

The temporal trend of the maximum day of rainfall per year for each of the four locations is shown below (Figure 2.7). Oordonantie and Asante Sana have increasing trends, with an increase rate of 0.321 mm/year and 0.841 mm/year respectively, while Wheatfields has an almost flat trend and Wellwood has a slightly decreasing trend (Figure 2.7). None of these trends is significant based on the Mann-Kendall test (Figure 2.7).

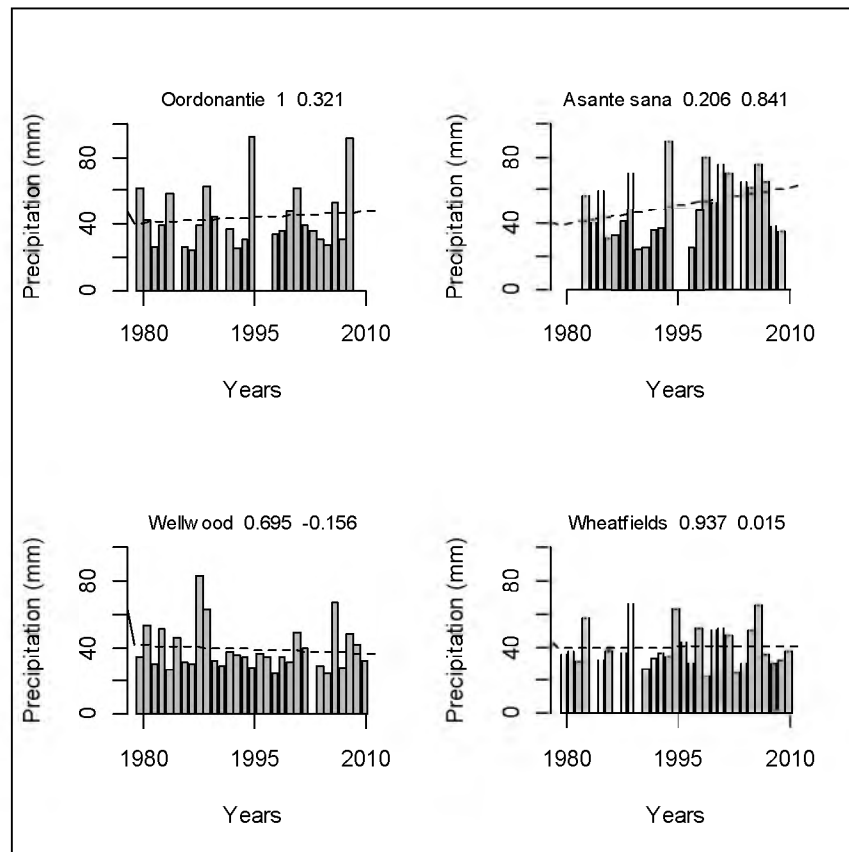


Figure 2.7: Maximum day of rainfall per year between the years 1980 and 2010 to determine a temporal trend in extreme rainfall events. Grey bars denote the size of the rainfall event, while the dotted line denotes the trend line from the linear regression test. The Mann-Kendall level of significance is the second number in the heading and the slope of the regression line is the third number in the heading.

Frequency of rainfall days greater than the 90th percentile per year

The frequency of rainfall days shows an increasing frequency of rainfall events above the 90th percentile for all locations, with Asante Sana having an increase of approximately 3 days per years over the 30 year timespan of the records (Figure 2.8). The other locations have marginal increases (Figure 2.8). None of the trends is significant according to the Mann-Kendall test at the 5% level of significance, although Asante Sana can be considered to be marginally significant with a p-value of 0.051 (Figure 2.8).

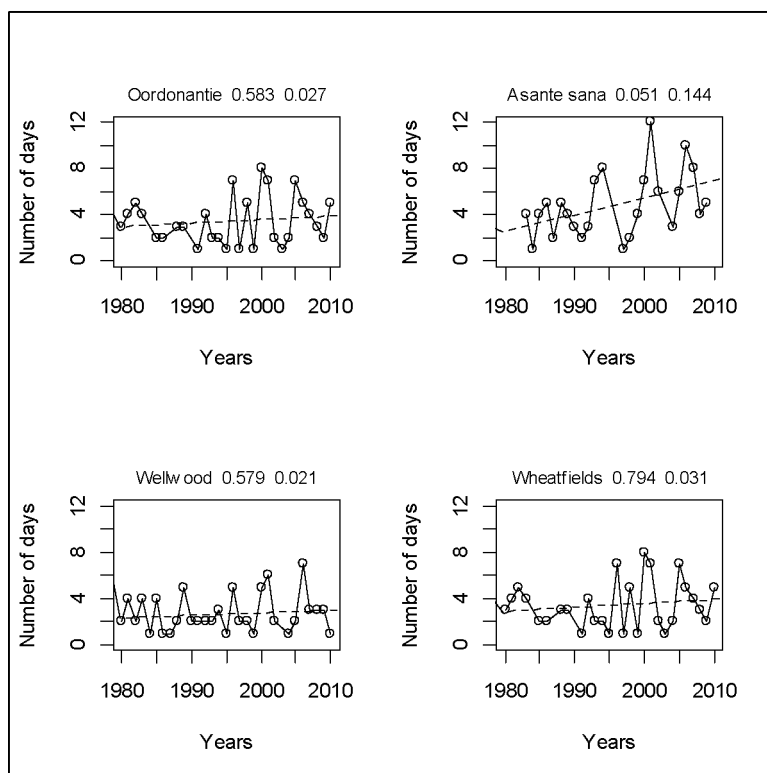


Figure 2.8: The number of rainfall days greater than the 90th percentile per year showing a temporal trend in heavy rainfall days. The dotted line is the regression line on the data giving the slope of the trend, which is given as the third number in the heading. The second number in the heading is the test for the significance of the trend using the Mann-Kendall test.

Comparison of historical data to downscaled RCMs

Predicted mean annual rainfall amounts in comparison to recorded amounts for 37 data locations show a maximum under prediction of 271.82 mm and over prediction of 355.62 mm for the 15 minute resolution climate models (Figure 2.9). The 9 minute resolution climate models have a maximum under prediction of 280.65 mm and over prediction of 347.87 mm (Figures 2.9). Deviations are very similar between the two spatial resolutions and among the six climate models. The dotted lines in Figures 2.9 and 2.10 constitute a one-to-one relationship and a climate model which perfectly predicts rainfall amount would show all data locations on this line. Locations from the Winterberg-Amatole mountain range (black dots) generally have over predicted rainfall by the climate models. In contrast, locations from the Sneeberg (blue dots) generally have under predicted rainfall, although for most locations these are not large under predictions. The Stormberg (green dots) and red dots (locations outside a mountain range) generally have predictions close to the line. Despite large maximum under and over predictions, 54.05% of projected rainfall amounts fell within 100 mm above or below the recorded historical records for the 15 minute resolution climate model projections and 51.35% for the 9 minute resolution models. This was found when

deviations between the actual and predicted rainfall were averaged across the six climate models. Over 30% of the discrepancies were less than 50 mm above or below the recorded records for both the 15 minute and 9 minute resolution. Most small discrepancies came from locations in the Stormberg and Sneeuberg.

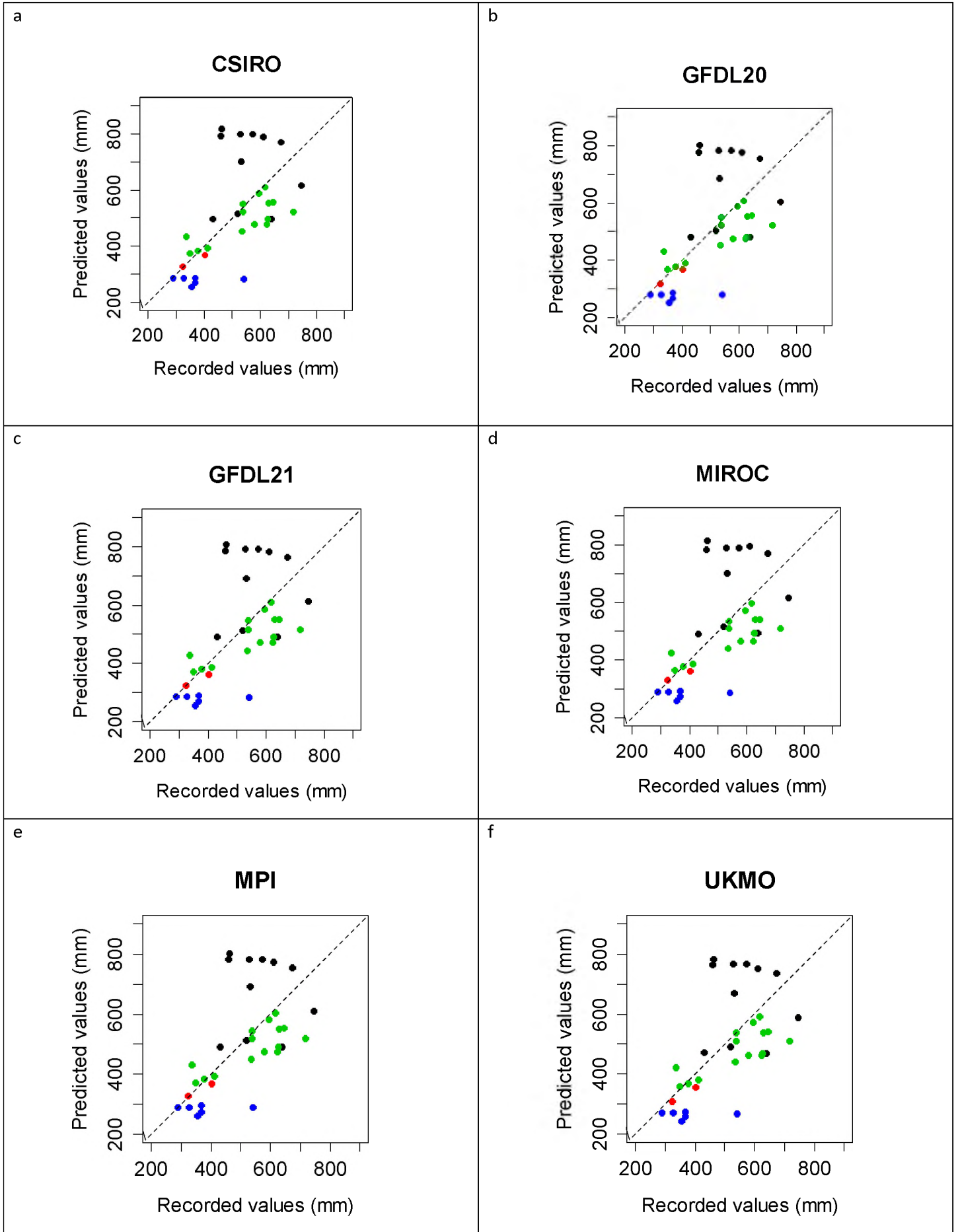


Figure 2.9: Mean annual rainfall modelled values in comparison to recorded values for a) 15 minute CSIRO b) 15 minute GFDL20, c) 15 minute GFDL21, d) 15 minute MIROC, e) 15 minute MPI and f) 15 minute UKMO. The dotted lines on the scatter plots show a one to one relationship. Black dots are data locations from the Winterberg-Amatole range; green dots are for the Stormberg range; red dots are not in a mountain range and blue dots are for the Sneeuberg range.

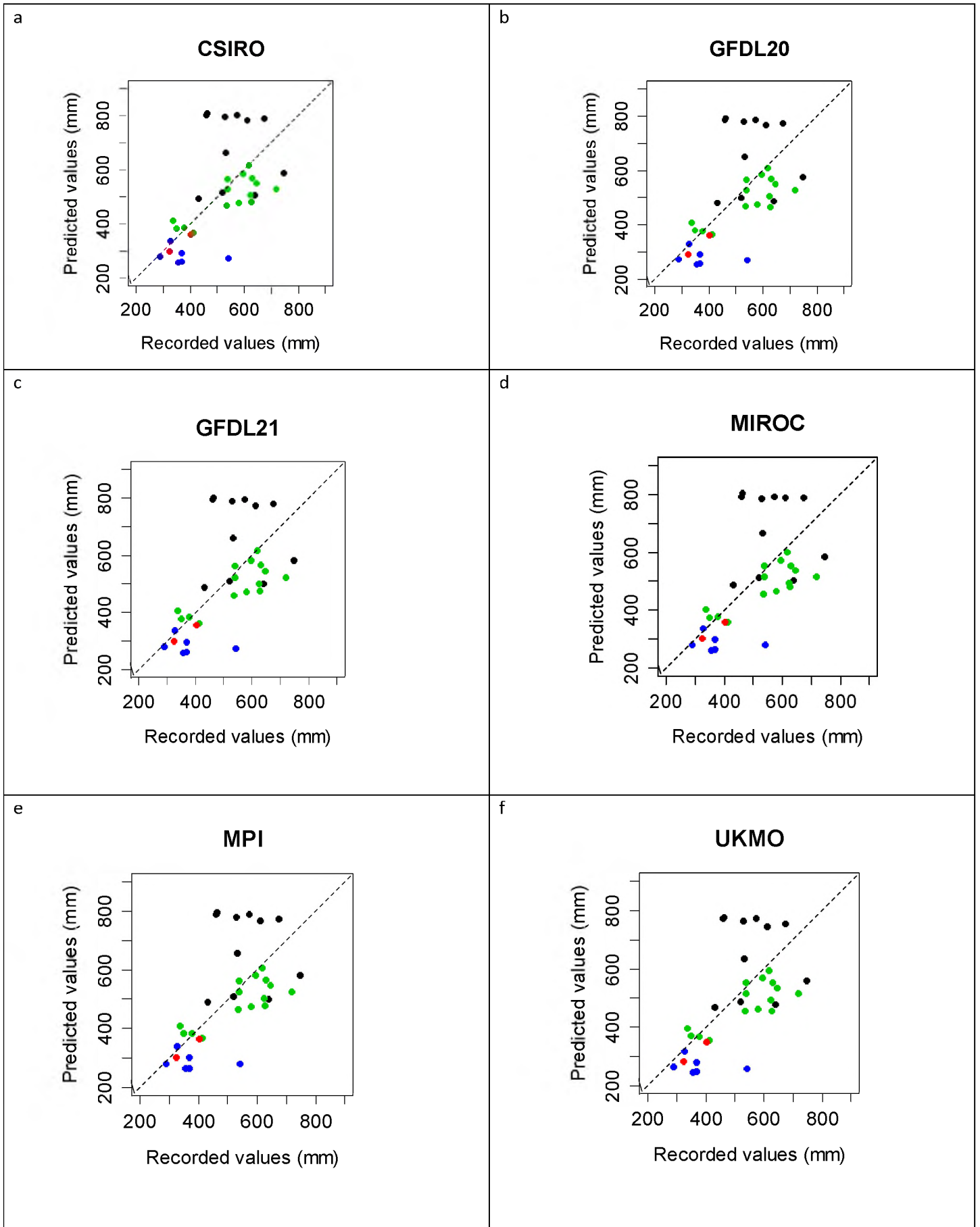


Figure 2.10: Mean annual rainfall modelled values in comparison to recorded values for a) 9 minute CSIRO b) 9 minute GFDL20, c) 9 minute GFDL21, d) 9 minute MIROC, e) 9 minute MPI and f) 9 minute UKMO. The dotted lines on the scatter plots show a one to one relationship. Black dots are data locations from the Winterberg-Amatole range; green dots are for the Stormberg range; red dots are not in a mountain range and blue dots are for the Sneeuberg range.

Discussion

Rainfall trends and model validation

The first aim of this chapter is to validate the climate change projections used in chapter three with historical data. Empirically corroborated climate change projections allow species distribution models using these projections to be made with confidence. Climate change is already changing vegetation community structures (e.g. Kelly and Goulden, 2008), so having confidence in climate change predictions is important to accurately determine the nature and extent of these changes.

South-eastern South Africa, over the historical data collected, shows a trend of marginally increasing rainfall. This increasing rainfall signal is most noticeable in the representations of tau which show increasing rainfall post 1980, particularly in DJF and MAM, but most of these increasing trends are not significant. In the pre-1980 data, tau figures show more definite increasing rainfall trends in MAM, JJA and SON than in DJF, although again most of these changes are not significant. Annual rainfall, both pre and post 1980 for all locations shows predominantly positive tau figures with some significant increases, although most are not significant. The post 1980 results are of more interest to us as these could potentially be influenced by climate change. The pre and post-1980 time series results in which average anomalies across a mountain range were analysed showed less in terms of directional changes than the tau representations. This may be because the single station responses, as seen in the tau analyses, are diluted by getting an average response for seasonal and annual rainfall across a mountain range. Climate change predictions for rainfall trends in the south-east of the country are varied and conflicting between statistically and dynamically downscaled projections. A marginal annual rainfall increase is predicted, with seasonal increases in summer and autumn rainfall, but winter rainfall predictions by some authors show slight decreases (Hewitson and Crane, 2006; Engelbrecht et al., 2009; Tadross et al., 2011). There is signal for autumn and summer increases in the tau figures for post 1980 historical data, with slight decreases occurring in winter rainfall. Climate change predictions used are to mid-century so a stronger signal is to be expected at this stage. The historical data therefore corresponds with and validates the climate change predictions.

Extreme events

Extreme events results show only one of the four stations having a strongly increasing trend, with the others having marginal or no increases. Climate change predictions predict increases in the occurrence of extreme events (Tadross et al., 2005; Engelbrecht et al., 2013). Most of the rainfall data was collected as monthly records, resulting in only four locations being analysed for the

regularity of extreme events and of these four locations only one had a definite increasing trend. There is therefore insufficient data to be able to support the climate change predictions.

Comparison between modelled data and historical data

A quantitative comparison of historical data with modelled data was used as a form of ground truthing and took a sample of 37 points across the south-eastern escarpment mountains. This comparison found over 50% of the points had predicted rainfall amounts within 100 mm above or below the recorded records for 15 and 9 minute resolution projections. It must be noted that comparisons were against model projections at 15 and 9 minute spatial resolutions in mountainous regions – coarse climate predictions over heterogeneous terrain which are noted by Fridley (2009) to be difficult to model climate in because of their heterogeneous nature. Van Niekerk and Joubert (2011) analysed current climate surfaces from the Western Cape and found that the surface interpolations improved in accuracy when topographical information such as slope gradient and aspect, elevation, hillshade and the distance to the ocean were included. These studies show the impact heterogeneous terrain has on climate and the importance of including topographical information for fine scale climate models. Despite this, for a large scale climate change response analysis as will be done in chapter three, the large scale projections used in this thesis should be accurate enough.

Implications

An increase in extreme events frequency has potential implications for agriculture, particularly if following a prolonged dry spell, and can affect soil quality and flooding prevalence which would affect crop yields and pests (Rosenzweig et al., 2001). This increase could also impact dam wall infrastructure and water resource management (Mason et al., 1999). The increased size and frequency of extreme events also has potential implications in terms of urban infrastructure and urban drainage for towns in this area and this needs to be addressed to stop urban flooding in the future (Willems et al., 2012). As stated, our data provides insufficient support for an increasing regularity of extreme events, although that is the prediction.

A marginal increase in precipitation could lead to wetter conditions in Eastern Cape livestock farming areas, although predicted increasing temperature should negate this. The Department of Agriculture Forestry and Fisheries (2003) notes the Eastern Cape as an important area of livestock farming – particularly goats, sheep (in the more arid regions) and cattle, so a rainfall increase in these areas is economically important. The extent to which this increased rainfall would be negated by increased

temperature is debatable and beyond the scope of this research, making it difficult to predict the impact these trends would have on livestock farming in the Eastern Cape.

Conclusion

This chapter had the aims of determining the impact of climate change on rainfall trends and extreme events, exploring some of the implications of these impacts and validating the climate change predictions to set the scene for chapter three. Historical rainfall trends seem to agree with the downscaled climate change predictions, with general increases across the study area particularly in annual, summer and autumn rainfall after 1980. Extreme events results provide insufficient data to support the climate change predictions. Historical records, when compared to modelled records for current climate, are similar enough for the large-scale land cover research being undertaken in chapter three. Implications of the increasing rainfall and extreme events trends are discussed and these include an impact on flooding prevalence affecting crop yields and pests, impacts on dam wall infrastructure and water resource management, as well as the importance of an increase in rainfall on economic activities, although the inability to predict how rising temperature will negate a slight increase in rainfall makes it difficult to consider direct implications of increasing rainfall in the area.

Chapter 3

Determining the potential impact of climate change on plant distribution in South Africa's mountainous regions using two correlative species distribution modelling paradigms

Introduction

Climate change impacts on plant diversity in mountainous regions

Global climate change is one of the world's foremost issues for the immediate future. The IPCC (2014), in their fifth assessment report, state that unmitigated climate change is very likely to lead to increased risk of extinction for many organisms. Thuiller (2007) describes the impact of climate change on biodiversity as serious, but it acts over a much longer period of time than other anthropogenic factors such as habitat destruction, alien invasion and nitrogen deposition. The change that has already occurred in the global climate has led to distributional and phenological changes in many well-studied terrestrial and aquatic systems (Parmesan and Yohe, 2003; Parmesan, 2006). Bellard et al. (2012) did a review of model predictions for biodiversity under a changing climate. The review shows the majority of models indicate alarming biodiversity responses, the worst of which would lead to extinction rates which qualify as a sixth mass extinction. Biodiversity declines in many areas of the world are being attributed to environmental changes including climate change, alien invasion and resource consumption (Butchart et al., 2010).

Beniston (2003) describes mountainous areas as having a highly complex topography with very sharp climatic gradients. Mountainous regions, along with the associated climate, change rapidly with elevation over a short horizontal distance which directly affects the vegetation and hydrology of these regions (Whiteman, 2000). Mountains therefore contain very distinct vegetation belts with sharp ecotones (Beniston, 2003; Hadley et al., 2013). They are home to endemic species as these species remain isolated in small, montane climatic niches high above the broad lowland climate belts (White, 1983; Beniston, 2003). Mountainous regions have acted as important refugia during periods of climate change (e.g. Schönswetter et al., 2005; Wang et al., 2013; Nägele and Hausdorf, 2015).

There is mounting evidence that high elevation areas have a higher rate of warming as shown by Pepin et al. (2015). This is attributed to the snow-albedo feedback, clouds and aerosols in the atmosphere, among other things. As snow retreats, the land surface albedo changes and temperature increases. Clouds, which form higher in the atmosphere as temperatures rise, release

latent heat above them, raising temperature at higher elevations. Aerosols from air pollution are concentrated at relatively low elevations and cause a surface dimming effect which decreases radiation to lower mountain slopes. At higher elevations, this dimming does not occur. Mountains are therefore highly susceptible to a changing climate, magnify these changes because of their physical properties and also contain biodiversity which is highly vulnerable to a rapidly changing climate.

Upslope movement of species, as the climate warms, is a widely predicted theoretical response for a species to remain in its climatic niche (MacArthur, 1972; Peters and Darling, 1985). The coolest climatic zone at the top of a mountain is also the smallest zone, therefore, as vegetation belts move upslope their possible area of occurrence declines in size, putting the persistence of the species at risk (Peters and Darling, 1985).

Numerous studies support the upslope migration hypothesis. Kelly and Goulden (2008) found a 65m elevation increase of the dominant plant species in the Santa Rosa Mountains of southern California between surveys in 1977 and 2006-2007. There have been elevation increases in the treeline in Europe (Meshinev et al., 2000; Kullman, 2001), in Norwegian mountain plants (Klanderud and Birks, 2003), in lowland birds in Costa Rica (Pounds et al., 1999), and in European mountain plants (Pauli et al., 2012). Meta-analyses also show general shifts of species to higher elevations (e.g Harsh et al., 2009; Chen et al., 2011).

Downslope responses have been noted by Platts et al. (2013) and Lenoir et al. (2010). Platts et al. (2013) determined, through a correlative climate modelling analysis in the Eastern Arc Mountains in east Africa, that many modelled plants moved downslope based on water availability and temperature seasonality. They state that in two thirds of the plants modelled, there was a downslope response in one of the mountain regions. The downslope response was particularly important in plants with a distribution limited by water availability and large seasonal temperature fluctuations. Lenoir et al. (2010) also note possible downslope responses of plants under future climates which they attribute to a realized niche which is considerably smaller than a fundamental niche. These plants are postulated to be limited by competition at the lowest elevations of their ranges and could, hypothetically, move lower. In all studies on plant elevation shifts analysed by Lenoir et al. (2010), which included 824 species, 25% of species have adjusted lower, with 65% moving higher.

Using Species Distribution Modelling to determine species diversity patterns in South Africa's mountains

A technique used to predict species distributional response to climate change is Species Distribution Modelling (SDM). SDM is a predictive modelling method consisting of either mechanistic or correlative modelling approaches (Araujo and Guisan, 2006).

Mechanistic models use direct variables/resource variables and the tested physiological response of plants to these environmental variables to create a model of potential species distribution (Robertson et al., 2003; Stephenson, 1998). Mechanistic models therefore create a distribution envelope for the fundamental niche of a species, which has been described by Hutchinson (1957) as constituting the environmental conditions within which a species can survive.

Correlative models correlate environmental predictors with the observed distributions through species occurrence records. They correlate these occurrence records with chosen predictor variables to create a spatial 'envelope' of occurrence (Pearson and Dawson, 2003). A change in these predictor variables because of a climatic change, for example, would change the spatial envelope. Correlative modelling inherently creates a model of the realized niche of the species – a niche that is often smaller than the fundamental niche (Hutchinson, 1957; Pearson and Dawson, 2003). The realized niche is where a species actually occurs, rather than where it physiologically could occur, and where the species is excluded from parts of its fundamental niche because of biotic interactions, dispersal limitation and disturbance particularly from fire (Hutchinson, 1957; Guisan and Zimmerman, 2000; Soberon and Peterson, 2005; Bond et al., 2005).

Climate has a strong controlling influence on where plants can grow (Woodward, 1987). South Africa's mountains are highly varied topographically, geologically and climatically. In many cases, as is stated by Cowling et al. (2009) and Matthews et al. (1993), such geological and topographical heterogeneity has a direct impact on plant diversity and the distributions of certain plant assemblages. It has caused speciation in the Cape Fold Mountains and has influenced the assemblages and levels of endemism in the north-eastern escarpment, with the number of endemics on dolomite less than half the number on quartzite. Körner and Larher (1988) state that high elevation plant life is constrained by direct and indirect influences of low temperatures, radiation, wind, storminess and water. Global ecosystems generally correlate well with a precipitation/heat balance in an environment (Woodward, 1987). The amount of water available in a region has a large impact on the vegetation growing there. The fact that plants in Europe have, on average, moved upslope in its major mountain ranges between 2001 and 2008, as a result of a warming climate, also

lends support to the fact the many mountain plants are directly limited and their distribution ranges are directly affected by climate (Pauli et al., 2012).

The aim of this study is to conduct a rigorous assessment to determine the climate change impacts on 46 plant species, and using the species, assess changes in species richness and beta diversity in southern Africa's mountains using single and multiple algorithm approaches. It also intends to compare model performance in terms of evaluation parameter scores between the single and multiple algorithm modelling methods.

The potential distributions modelled are based on an overarching response of these plants to temperature and rainfall which makes a correlative modelling approach to current and future climate straight-forward. An ensemble approach to modelling, which creates a model from models produced by a collection of algorithms, has been found to improve the model agreement between predicted and empirically determined range shifts (Araujo and New, 2007). Ensemble models are an idealization consisting of a large number of different copies of a system considered together (Araujo and New, 2007). If each model contains individual information, combined models are expected to produce a lower mean error than the constituent models (Araujo and New, 2007). A criticism of this technique is that it may dilute a true and good response from a good predictive model (Araujo and New, 2007). An alternative to this method is to use a single algorithm in a more nuanced manner. Biomod is an R package which can be used to create model ensembles (Thuiller et al., 2014), and many correlative models have been run with an ensemble of distribution algorithms using this package (e.g. Buckland et al., 2014; Hodd et al., 2014; Vorsino et al., 2014).

The correlative method is useful for quickly determining the response of many species and thereby gaining an understanding of general vegetation responses to a changing climate. Making detailed mechanistic models, despite being a potentially better option for climate change predictions because of their use of the fundamental niche, is not feasible for 46 species in a reasonable period of time. Predictions of future plant distribution being produced are therefore a useful approximation of the impact of climate change on an assemblage of South Africa's montane plant species. Including the response of these species to small-scale edaphic and geomorphological changes in the environment, as well as biotic interactions, is beyond the scope of this research, and is beyond the predictive ability of correlative models (Pearson and Dawson, 2003). Similarly, the responses of these species to the CO₂ increases in the atmosphere and to fire, which have been documented to affect species distributions in other, non-montane habitats (Bond and Midgley, 2000; Bond et al., 2005) are not considered based on the overarching assumption and the capabilities of these models.

Based on the largely supported upslope movement response of montane plants to climate change and the types of predictor variables being used, species richness of southern Africa's mountain vegetation is predicted to get lower in low elevation, peripheral regions and contract towards a smaller area of high richness, centred on the Lesotho highlands, in the future. This is a predicted refugium for montane taxa. Beta diversity, which shows diversity changes for the plant assemblage between current climate and future climate, should show high scores at low elevation, denoting high beta diversity, with the high elevation Lesotho region showing low beta diversity. The key assumption made in this research is that plants in South Africa's mountainous regions are ultimately limited by temperature and rainfall. Pearson and Dawson (2003) state this assumption is easier to make when modelling plant distribution at a coarse scale over a large area than at a fine-scale over a small area.

Methods

Study area



Figure 3.1: South African satellite map with research region delineated. All mountain ranges are part of the Great Escarpment.

The study area constitutes the southern to eastern great escarpment (Figure 3.1). The vegetation, climate and geology of the study region are described in detail in chapter one.

Species and data selection

An attempt was made to select an assemblage of species which is representative of mountainous vegetation of the study area in consultation with Dr. V. R. Clark (2014). The selection was done across a number of growth forms, with an approximately equal number of species per growth form. A total of 46 plant species which meet these criteria and have adequate data available from the PRECIS database (more than 20 occurrence records) were selected. Dr. Clark also supplied a second independent dataset to be used for independent evaluation for 20 of the selected species. These data were collected during his fieldwork and were used in the analysis. A minimum of 5 occurrence records per species was deemed necessary for an independent dataset to be useful.

Table 3.1: Names, growth forms, families, habitats and number of occurrence records of the 46 selected species

Species	Growth Form	Family	Habitat	Occurrence records	Independent occurrence records
<i>Ajuga ophrydis</i>	Suffrutex	Lamiaceae ¹	Grassland ¹	204	9
<i>Alchemilla woodii</i>	Suffrutex	Rosaceae ²	Mostly in disturbed areas ²	57	
<i>Aristea woodii</i>	Geophyte	Iridaceae ¹	Grassland ¹	40	
<i>Asplenium adiantum-nigrum</i> var. <i>adiantum-nigrum</i>	Fern	Aspleniaceae ³	Montane grassland at base of boulders ³	88	16
<i>Asplenium trichomanes</i> subsp. <i>quadrivalens</i>	Fern	Aspleniaceae ³	Cliffs and boulder scree in high altitude grassland ³	41	17
<i>Berkheya purpurea</i>	Herb	Asteraceae ¹	Steep, grassy mountain slopes ¹	25	
<i>Bromus speciosus</i>	Graminoid	Poaceae ²	Moist slopes on mountain grassland ²	25	
<i>Buddleja loricata</i>	Shrub	Buddlejaceae ⁴	Afromontane forest margins ⁴	34	
<i>Cheilanthes quadripinnata</i>	Fern	Sinopteridaceae ³	Ecotone between montane grassland and forest ³	121	21
<i>Cliffortia ramosissima</i>	Shrublet	Rosaceae ⁵	Dry Fynbos ⁵	46	11
<i>Crassula dependens</i>	Succulent	Crassulaceae ¹	Rocky outcrops in Karoo/Grassland ¹	100	20
<i>Crassula natalensis</i>	Succulent	Crassulaceae ¹	Mountain grassland, among rocks ¹	28	
<i>Dierama robustum</i>	Geophyte	Iridaceae ⁴	High altitude grassland ⁴	59	9
<i>Erica algida</i>	Shrublet	Ericaceae ¹	Grassy slopes ¹	42	
<i>Erica frigida</i>	Shrublet	Ericaceae ⁴	Frequent on cliffs and steep slopes ⁴	41	
<i>Euphorbia pulvinata</i>	Succulent	Euphorbiaceae ¹	Rocky grassland ¹	56	
<i>Euryops annae</i>	Shrub	Asteraceae ⁶	Various types of grass ⁶	75	17
<i>Festuca caprina</i>	Graminoid	Poaceae ²	Boulder beds and mountain cliff faces ²	92	
<i>Festuca costata</i>	Graminoid	Poaceae ²	Marsy areas in montane grassland ²	75	8
<i>Geranium wakkerstroomianum</i>	Herb	Geraniaceae ¹	Sheltered places around rocks on forest margins ¹	95	
<i>Gladiolus saundersii</i>	Geophyte	Iridaceae ¹	On rocky hillsides in mountains ¹	27	
<i>Haplocarpha nervosa</i>	Suffrutex	Asteraceae ⁷	Marshy grassland ⁷	43	
<i>Helichrysum herbaceum</i>	Suffrutex	Asteraceae ¹	Grassland ¹	115	
<i>Helichrysum sutherlandii</i>	Shrublet	Asteraceae ¹	Clumps hanging from cliffs and rocky outcrops ¹	45	
<i>Hypoxis multiceps</i>	Geophyte	Hypoxidaceae ¹	Grassland ¹	64	
<i>Indigofera burchellii</i>	Suffrutex	Fabaceae ⁸	High altitude Grassland and Karoo ⁸	22	8
<i>Kniphofia caulescens</i>	Geophyte	Asphodelaceae ¹	In marshes on damp mountainsides ¹	39	
<i>Leucosidea sericea</i>	Tree	Rosaceae ⁴	Forest margins in mountains ⁴	139	10
<i>Lobelia preslii</i>	Herb	Lobeliaceae ⁴	Mountain grassland - rocky gullies ⁴	43	
<i>Lotononis sericophylla</i>	Shrublet	Fabaceae ¹	Boulder beds and rocky streams in disturbed areas ¹	40	14
<i>Merxmuellera macowanii</i>	Graminoid	Poaceae ⁴	Streambanks in high altitude grassland ⁴	55	9
<i>Mohria nudiuscula</i>	Fern	Anemiaceae ⁹	Seasonally moist montane grassland ⁹	40	7
<i>Moraea spathulata</i>	Geophyte	Iridaceae ¹	Open grassland, among rocks ¹	109	9
<i>Pelargonium zonale</i>	Herb	Geraniaceae ¹⁰	Forest margins and stony slopes in EC/SWC ¹⁰	80	
<i>Polygala gymnoclada</i>	Herb	Polygalaceae ¹¹	Grassland ¹¹	48	
<i>Polygala rhinostigma</i>	Herb	Polygalaceae ¹	Mountain grassland ¹	27	
<i>Polystichum monticola</i>	Fern	Aspidiaceae ⁴	Against rocks in stream gullies ⁴	59	14
<i>Protea subvestita</i>	Tree	Proteaceae ⁴	Boulder beds and gullies protected from fire ⁴	67	
<i>Schoenoxiphium lanceum</i>	Graminoid	Cyperaceae ⁵	Fynbos ⁵	20	12
<i>Senecio asperulus</i>	Suffrutex	Asteraceae ¹³	Grassland and Karoo ¹³	105	19
<i>Senecio barbatus</i>	Suffrutex	Asteraceae ¹	Grassland swamps ¹	32	
<i>Senecio rhomboideus</i>	Suffrutex	Asteraceae ¹	Grasslands, on rocky outcrops ¹	31	
<i>Tetrachne dregei</i>	Graminoid	Poaceae ¹²	High altitude open grassland ¹²	102	6
<i>Zaluzianskya glareosa</i>	Herb	Scrophulariaceae ²	Boulder beds/around rock sheets ²	20	
<i>Zaluzianskya ovata</i>	Herb	Scrophulariaceae ¹	Partly shaded cliff faces and bare slopes ¹	37	6
<i>Zaluzianskya spathacea</i>	Herb	Scrophulariaceae ²	Damp grass slopes ²	38	

1 - Pooley, 2005

2 - Hilliard and Burtt, 1987

3 - Crouch et al., 2011

4 - Pooley, 2003

5 - Pers. comm. Clark, 2015 8 - Foden and Potter, 2005a

6 - Notten, 2009

7 - Hyde et al., 2015a

9 - Hyde et al., 2015b

10 - Lawrence, 2002

11 - Foden and Potter, 2005b

12 - Hoare, n.d.

13 - Foden and Potter, 2011

Individual occurrence points from all species were removed in R version 3.1.3 (R core team, 2015) if they were in the ocean, had (0,0) co-ordinates, were an obvious outlier far from the mountainous region of South Africa or were duplicates in a quarter degree grid cell. This was done with the help of the biogeo package in R (Robertson, 2015, unpublished). Database occurrence records were at a 15 minute resolution.

Predictor variables

The climate change predictions were done using dynamically downscaled projections for southern Africa from the globally modelled Global Climate Models (GCMs) (Engelbrecht et al., 2011). These projections use known southern African meteorological phenomena and incorporate this into a forecast to get a more precise prediction. The method uses the conformal-cubic atmospheric model which has been shown by Engelbrecht et al. (2009) to be able to correctly model current conditions and forecast for the short-term, and to garner plausible climate change predictions. The GCMs included for downscaling are the Geophysical Fluid Dynamics Laboratory Coupled Model, version 2.0 (GFDL-CM2.0); the GFDL-CM2.1; the Max Planck Institute for Meteorology ECHAM5/MPI-Ocean coupled climate model; the United Kingdom Met Office, Hadley Centre coupled model, version 3 (UKMO-HadCM3); the Model for Interdisciplinary Research on Climate, medium resolution (MIROC3.2-medres) and the CSIRO Mark3.5 (Department of Environmental Affairs, 2013).

The 19 bioclimatic predictor variables were produced with rainfall and temperature data using the dismo package in R (Hijmans et al., 2015). The data for current climate are an average between 1971 and 2005.

The distribution changes were modelled to mid-century (an average climate of 2040-2080), to the A2 climate change scenario which is a relatively high greenhouse gas emission scenario from the IPCC's 4th assessment report (AR4) (Department of Environmental Affairs, 2013). No other scenario predictions were readily available.

Temperature is predicted to rise by 2 to 3.5°C over southern Africa in this scenario (Department of Environmental Affairs, 2013). Rainfall is predicted to rise in parts of the central and eastern interior of South Africa by mid-century, with the western areas of the country, in particular, drying substantially (Department of Environmental Affairs, 2013). The eastern coastal region, moving to the north-eastern escarpment and lowveld are also predicted to get substantially drier (Department of Environmental Affairs, 2013).

Modelling algorithms

Two modelling methods were used: One method used an ensemble of algorithms in Biomod (Thuiller et al., 2014) and the other used only the MaxEnt correlating algorithm (Phillips et al., 2006).

Biomod is an R package which can be used to create model ensembles using multiple modelling algorithms (Thuiller et al., 2014). MaxEnt is a user-friendly, popular, correlative distribution modelling package (Phillips et al., 2006; Merow et al., 2013). The ensemble method made use of five algorithms which were shown by Elith et al. (2006) to perform well in a comparative study, these include: Maximum Entropy (MaxEnt), Generalised Additive Models (GAM), Boosted Regression Trees (BRT or GBM in biomod2), Multiple Additive Regression Splines (MARS) and Generalised Linear Models (GLM).

GAM, GLM and MARS are regression algorithms – they fit functions to the relationship between species occurrence and the value of a predictor variable which then acts as a predictor for future occurrence of a species based on how the algorithm has modelled the response of the species in the current climate conditions (Elith et al., 2006). GLMs fit parametric functions – usually a combination of linear, quadratic and cubic functions – while GAMs fit a non-parametric, non-linear function which allows them to model more complex ecological responses (Elith et al., 2006). The MARS algorithm uses short pieces to fit linear functions, rather than smooth functions, to also model complex responses (Elith et al., 2006).

Two machine learning algorithms were also listed by Elith et al. (2006) as good performers and were included in the ensemble model. BRT is a boosted tree algorithm which fits decision trees to occurrence records and their relationship with an environmental predictor – the predictor is classified into homogeneous rectangles and species occurrences are fit to that decision tree (Elith et al., 2008). The decision tree is then iteratively edited in a process of boosting which ultimately creates the best possible relationship between the occurrences and a predictor (Elith et al., 2008). MaxEnt is a maximum entropy algorithm which finds a predicted distribution of maximum entropy (as close to uniform as is possible) within the constraints of the relationship between occurrence records and predictor variables (Phillips et al., 2006; Elith et al., 2011).

Background and pseudo-absence creation

MaxEnt is a presence-background algorithm (Phillips et al., 2006), and it therefore does not need absence records; only a background. MaxEnt automatically assumes that a species is likely to be anywhere in the background surrounding the occurrence records, so a specific background or mask

is used to delimit the region within which a species or group of species could possibly occur based on their ecological requirements (Merow et al., 2013).

Biomod2 (Thuiller et al., 2014) ensemble runs require absences, but pseudo-absences are used if real absences are not available. Pseudo-absences are inferred absences when no real absences are available. They are often selected from a database as all other occurrence records from every other species within the modelled species' genus, or they are randomly selected from the background. Model quality and performance are strongly influenced by the method of pseudo-absence selection (Chefaoui and Lobo, 2008; Barbet-Massin et al., 2012, Van Der Wal et al., 2009). Chefaoui and Lobo (2008) and Barbet-Massin et al. (2012) recommend pseudo-absence selection that is neither too far nor too close to the presence points and that is environmentally stratified i.e. randomly selecting pseudo-absences from within a pre-determined environmental space which acts as a background beyond which occurrence is highly unlikely. This supported best-practice in the literature was followed in our methodology.

Koppen-Geiger climate zones are particularly appropriate for background creation in this research because these zones classify the Earth's surface into areas based on vegetation, climate and temperature (Koppen, 1936). Webber et al. (2011) used this method of background classification in a similar modelling study. Koppen climate zones were therefore used to delimit the background for the MaxEnt model runs. This was done by overlaying occurrence records with the climate zones and selecting the zones which overlap with the occurrences. A problem with this is that it creates the possibility of a different background for each species which would slow down the model calibration process. One background using all the occurrences for all 46 modelled species was therefore created. Pseudo-absences for the Biomod model runs were created in R version 3.1.3 by selecting all records in the delimited background that did not represent presences for each species.

Seven initial climatic predictor variables considered were selected and included: Bio 5 – the maximum temperature of the warmest month; Bio 6 – the minimum temperature of the coldest month; Bio 12 – annual Precipitation; Bio 16 – precipitation of the wettest quarter; Bio 17 – precipitation of the driest quarter; Bio 18 – precipitation of the warmest quarter, Bio 19 – precipitation of the coldest quarter. Values for the seven predictor variables associated with the occurrence records were extracted for each species for these predictors. Pearson correlations were calculated for all pairs of variables for all species (Hodd et al., 2014; Ihlw et al., 2014). Only one of any two highly correlated variables (>0.8 or <-0.8) was selected. For the MaxEnt models, predictor variables were selected for each species based on the correlation analysis. In biomod2, bio19 was removed for all species as this variable was highly correlated with most of the remaining predictors.

Ensemble models

MaxEnt

Araujo et al. (2005) found that using only models which perform well in an ensemble improves total model performance. R version 3.1.3 was therefore used to select models for current and future climates out of the cross-validation runs for each species with a test AUC score higher than 0.8 which, according to Beaumont et al. (2009), constitutes a fair to good model. These selected cross-validations were then combined in a model showing the mean predicted distribution for each of the six downscaled RCMs to create final current and future distribution models for each species for each RCM. The mean of these final six models for each RCM was then found to get an ensemble model across all six downscaled RCMs for each species. The mean was taken in accordance with Marmion et al. (2009) and their recommendations for ensemble creation. They describe the ability of the average function to have a 'cleaning' effect on predictions, wherein isolated prediction occurrences and instances of distribution overestimation may be removed by this 'cleaning' effect.

Models were run in MaxEnt Version 3.3.3k as is shown below (Figure 3.2a). *Random seed* was selected for each cross-validation. *Clamping* was selected for all runs, as well as *fade by clamping*, which was used to limit the prediction of occurrence in novel climates which cannot be predicted with a high degree of confidence. Clamping stops prediction of occurrence in future climate outside the climatic envelope trained in current climate and is recommended by Elith et al. (2010) for predicting species distributions. A *bias file* was added, which accounted for sampling effort per grid cell in the PRECIS database, by converting the number of specimens per 15 minute pixel of all plant species in the PRECIS database to a raster. MaxEnt assumes constant sampling effort across the study area when running the model so, in a region with biased sampling effort, a bias file needs to be added (Merow et al., 2013). The output format was set at *logistic*, the *regularization multiplier* was set to one, 10 000 background points was set as the *maximum number of background points*. A *Multivariate Environmental Similarity Surface (MESS)* analysis was done when projecting the trained model to current and future climate and this analysis shows regions of the map area in which data for projected environmental predictors fall outside the range of trained data. The *convergence threshold* was kept at 0.00001, *maximum iterations* and *default prevalence* were kept at 500 and 0.5 respectively.

Minimum training presence, 10th percentile presence, 5th percentile presence and 2nd percentile presence were all tested as possible probability thresholds converting probability maps to maps representing presence and absence. The 2nd percentile presence was chosen for the threshold as it

had the most accurate predictive capability based on an overlay with a subset of seven species using independent occurrence data.

Species distribution models showing the current and future probability of occurrence per modelled species in southern Africa were initially produced. Binary outputs for current climate and future climate to full and no dispersal were produced. These showed a predicted area of presence and a predicted area of absence. The full dispersal binary refers to the total predicted presence area in the future as the species is assumed to disperse to its full potential area of occurrence (Peterson et al., 2002). The no dispersal binary predicts a future area of occurrence in which no dispersal is assumed to occur and therefore the species is not predicted to be present outside the presence region of the current climate binary map (Peterson et al., 2002). For the no dispersal case, the species is assumed not to move into new areas which have become climatically suitable.

Biomod

R version 3.1.3 was used to run biomod2 to create ensemble models for each species using the five different modelling algorithms specified above (Figure 3.2b). Each correlating algorithm was cross-validated five times for the ensembles. 100 random pseudo-absences were selected from within the masked background. Clamping masks were included for both current and future model runs as is recommended by Elith et al. (2010).

Models were run to both current (1971-2005) and future climate (2040-2080). Presences and pseudo-absences were trained to masked current climate predictor variables, excluding bio 18 and bio 19, and were projected to unmasked raster layers for both current and future climate. This was done for each of the six RCMs. A total of 25 models were considered for the ensemble for each RCM and all of those 25 with an AUC greater 0.8 were selected. Mean final ensemble models took a mean of the six models for each RCM and included current and future probability of occurrence predictions and current and future presence/absence predictions for each species. Future presence/absence maps were produced for full dispersal and no dispersal scenarios.

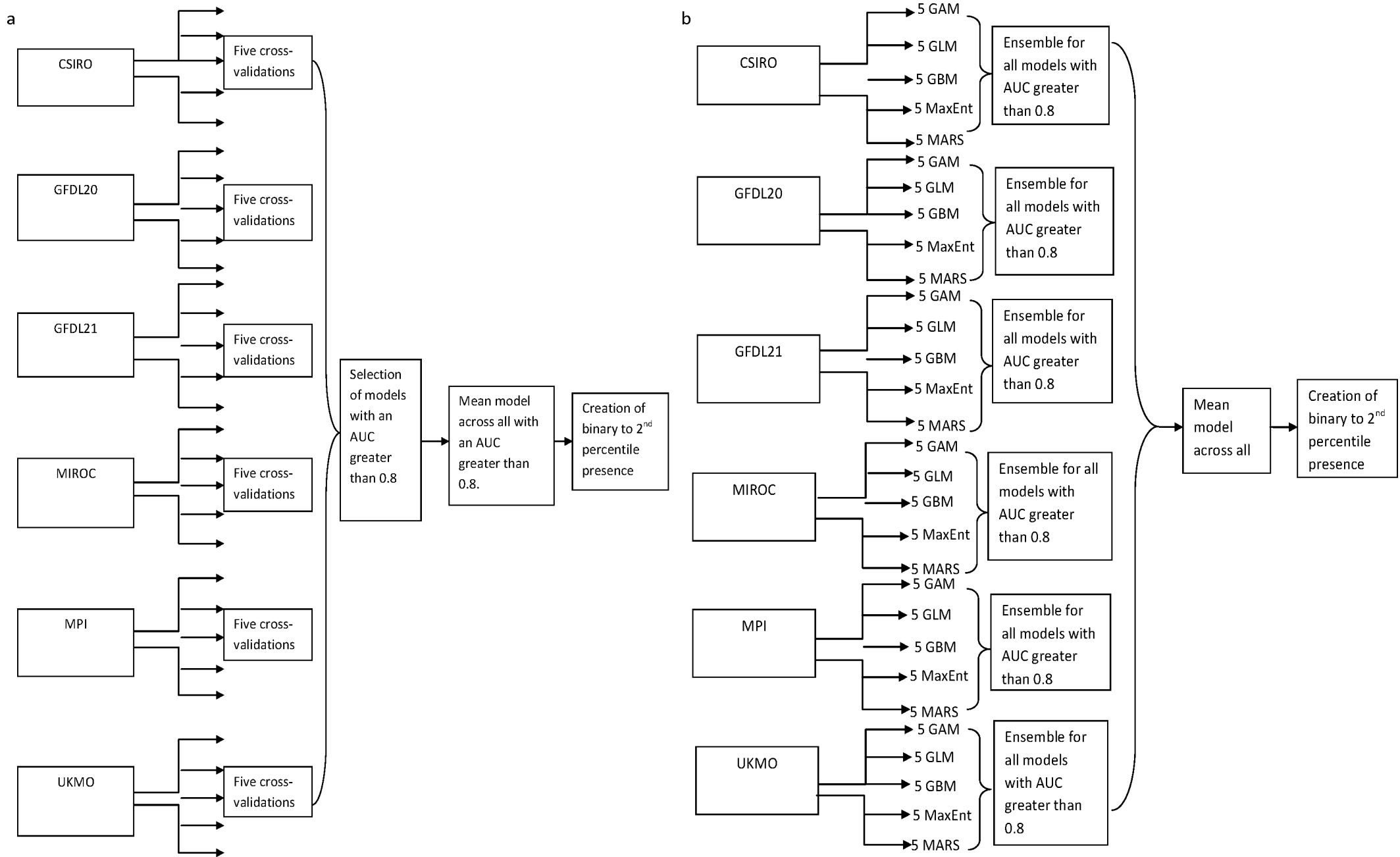


Figure 3.2: Final ensemble creation method for a) MaxEnt and b) Biomod for each of the 46 species done to current and future climate. The models were created from six different downscaled climate models and an ensemble was created from the results of all six.

Model evaluation

Two approaches to model evaluation were used: a cross-validation and an independent dataset evaluation. A five-fold cross-validation was performed on models for all species produced using the Biomod and Maxent algorithms. For a subset of 20 of the species, a model evaluation using independent records was performed. For both evaluation approaches the Area Under the Receiver Operating Curve (AUC), True Skill Statistic (TSS), Sensitivity and Specificity were calculated on models calibrated with variables representing the current climate (R version 3.1.3).

The AUC evaluation is a metric which is independent of threshold and plots sensitivity as a function of commission error across all thresholds (Lobo et al., 2008). The area under this curve provides a single number measure across all thresholds (Lobo et al., 2008). It is a metric which is based on the closeness of the prediction around a set of occurrence records – a high probability of occurrence tightly predicted around the occurrence records should give a higher AUC score. AUC scores can be misleading as they are prone to giving a higher evaluation to a model which is overfit around occurrences (Lobo et al., 2008). A score closer to 1 is an indication of better performance.

The True Skill Statistic (TSS) is recommended by Allouche et al. (2006) as a method of predicting model performance for binary predictions. It is determined by finding the Sensitivity and Specificity of the model. Allouche et al. (2006) denote sensitivity as being how good a model is at predicting occurrence – for a set of occurrence records, there will be very few false negatives in a sensitive model. A specific model predicts very few false positives and is more conservative in its prediction – it predicts a smaller area of occurrence in an attempt to minimise false positives. The TSS incorporates the two in the formula $\text{Sensitivity} + \text{Specificity} - 1$. For all metrics, numbers closer to 1 denote better performance.

An ensemble model for each species for the MaxEnt approach was generated by considering only those models calibrated with variables from the six different climate models (and 5 cross-validations) with AUC scores of greater than or equal to 0.8. The AUC score for the ensemble model for each species was calculated by taking the mean of AUC values for those models included in the ensemble. Cross-validated TSS, Sensitivity and Specificity evaluation scores were determined in R by taking a random subset of 20% of the dependent occurrence data each of five times to calculate the three indices on the final ensemble binary models for each species. A mean of the five scores from each cross-validation for each species was determined.

A total of 150 AUC, TSS, Sensitivity and Specificity scores were considered for each species from the final biomod ensembles. These were the scores across all component models which resulted in the

final ensemble. Any model runs with AUC scores lower than 0.8 were discarded and a mean final AUC, TSS, Sensitivity and Specificity score was then determined for each species.

For each species for the independent evaluations for Biomod and Maxent, AUC scores were calculated on the ensemble models using the PresenceAbsence package (v. 1.1.9) in R (Freeman, 2012). The pseudo-absences were randomly selected to fall within the mask and equal the maximum number of presences for the independent occurrence datasets which was 21.

The independent TSS, Sensitivity and Specificity scores were calculated on the final binary ensemble model for current climate for both MaxEnt and Biomod results. Pseudo-absences were selected in the same manner as for the AUC scores. TSS, Sensitivity and Specificity were then calculated based on false positive predictions and false negative predictions from the binary distribution models.

Extrapolating to future vegetation dynamics

Species Richness

Species richness for current climate and future climate was attained for both the Biomod and MaxEnt results using R version 3.1.3. The binary ensemble models for each species produced, were added up to get the number species occurring per gridcell in both current and future climate. The future climate binary maps used were for both full and no dispersal of the species.

Beta Diversity

Beta diversity was determined using R version 3.1.3 for both the Biomod and MaxEnt results, with the R package betapart being used for this analysis (Baselga et al., 2013). Beta diversity was determined from current climate to future climate using the final ensemble binary maps for current climate and a full and no dispersal future, as were used for the species richness analysis. The beta diversity outputs included three metrics β_{sor} , β_{sim} and β_{sne} . β_{sor} represents total compositional variation between the species assemblages (total beta diversity metric)– it includes both species turnover and nestedness patterns (Bishop et al., 2015). β_{sim} refers to change from species turnover – how a species assemblage has changed with outside species moving in to replace formerly established species in an area (Bishop et al., 2015). β_{sne} is the nestedness-resultant dissimilarity index – it is the difference between β_{sor} and β_{sim} and refers to assemblage nestedness in its compositional change from current climate to future climate (Bishop et al., 2015). In a climate change context, highly nested areas are regions of highest species loss from which species are moving to get to higher elevation.

Range size

The proportion of the map predicted as present for each species was determined for current and future climate using R version 3.1.3. The comparison was done between current climate and future climate for the final ensemble binary maps for both MaxEnt and Biomod and was done for no dispersal future and full dispersal future. ANOVA and Tukey HSD posthoc analyses were done to determine the significance of difference in mean species extent between current and future climate and between the two modelling methods.

Results

Model evaluation

The independently evaluated models showed no significant difference in sensitivity scores between Biomod and MaxEnt models ($W = 172.5$, $p = 0.4552$), while the cross-validated evaluation showed a significant difference in mean sensitivity, with MaxEnt models having higher scores ($W = 628$, $p < 0.001$) (Figure 3.3a). Independent evaluation showed no significant difference in mean specificity scores between Biomod and MaxEnt models ($t = 0.2057$, $df = 34.937$, $p = 0.8382$), while cross-validated evaluation showed significantly higher specificity scores for Biomod models ($t = 11.3133$, $df = 51.899$, $p < 0.001$) (Figure 3.3b). Independent evaluation between Biomod and MaxEnt models showed no significant difference between mean TSS scores ($W = 178$, $p = 0.2905$), while cross-validated evaluation showed significantly higher Biomod TSS scores ($t = 9.665$, $df = 62.417$, $p < 0.001$) (Figure 3.3c). There was no significant difference in AUC means ($t = -0.2265$, $df = 37.993$, $p = 0.822$), but Biomod had a significantly higher AUC score average for cross-validated evaluation ($t = 5.8842$, $df = 74.229$, $p < 0.001$) (Figure 3.3d).

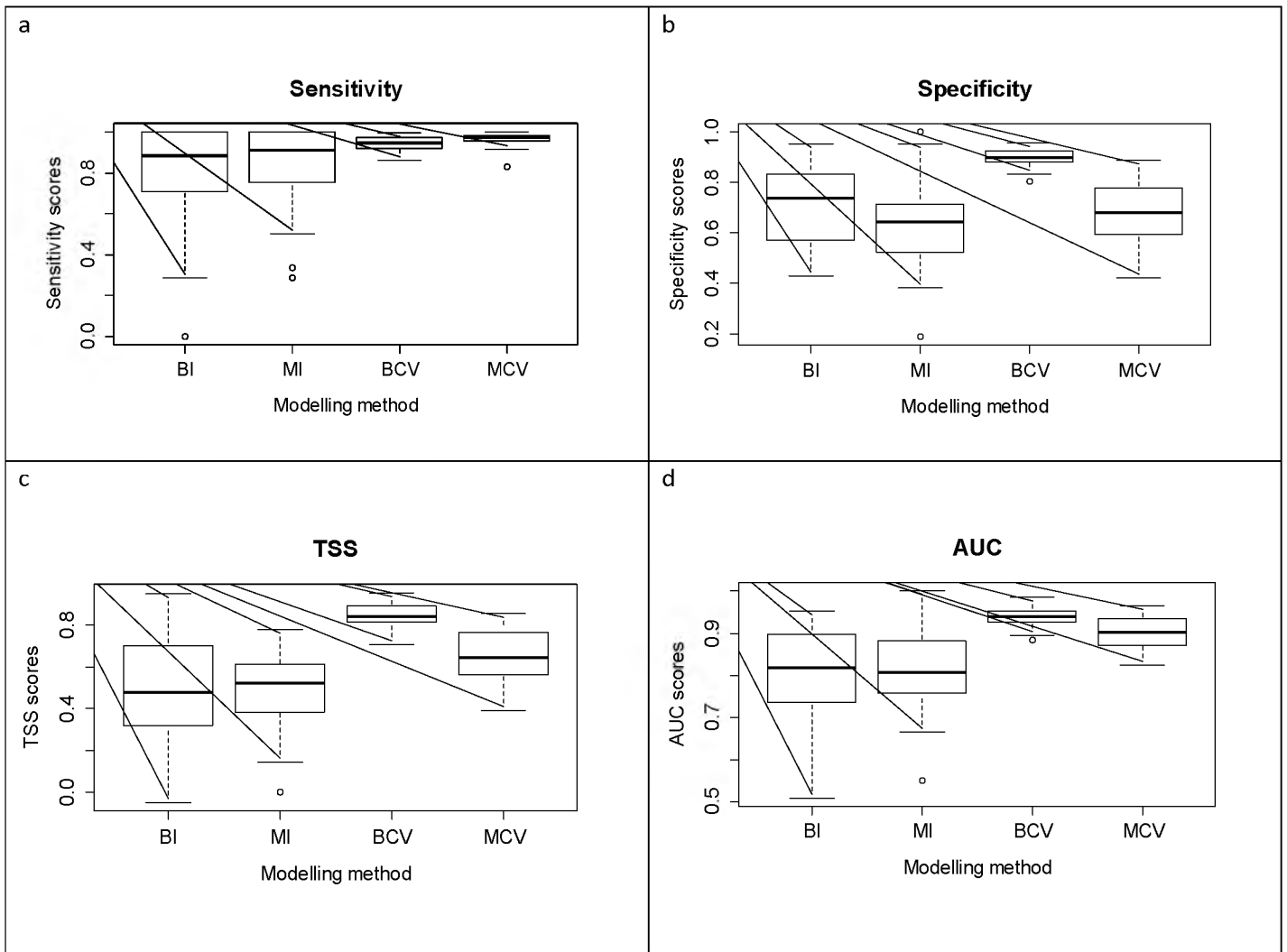


Figure 3.3: Results of model evaluation for Biomod (B) and MaxEnt (M) models that were evaluated using independent evaluation (I) and cross validation (CV) for a) sensitivity, b) specificity, c) TSS and d) AUC. The independent model evaluation was done for 20 species and the cross validated evaluation was done for all 46 species.

Species richness

Species richness showed a trend of high species richness towards the higher elevation regions of Lesotho for current climate (Figure 3.4a, b). Secondary areas of high richness in current climate were noticeable in the south-western Cape. Results were largely similar between the two modelling methods, although MaxEnt (Figure 3.4b) predicted a slightly larger area of high species richness than Biomod. Under future climate, the region of high richness contracted towards Lesotho (Figure 3.4c, d, e, f), while surrounding low elevation regions had lower species richness than in current climate. Results were similar for both modelling methods. The secondary regions of relatively high richness in the south-western Cape also showed similar trends of species richness contraction towards high elevation in the future for both modelling methods. Both methods showed a marginally greater contraction towards high elevation regions under the no dispersal assumption (Figure 3.4e, f).

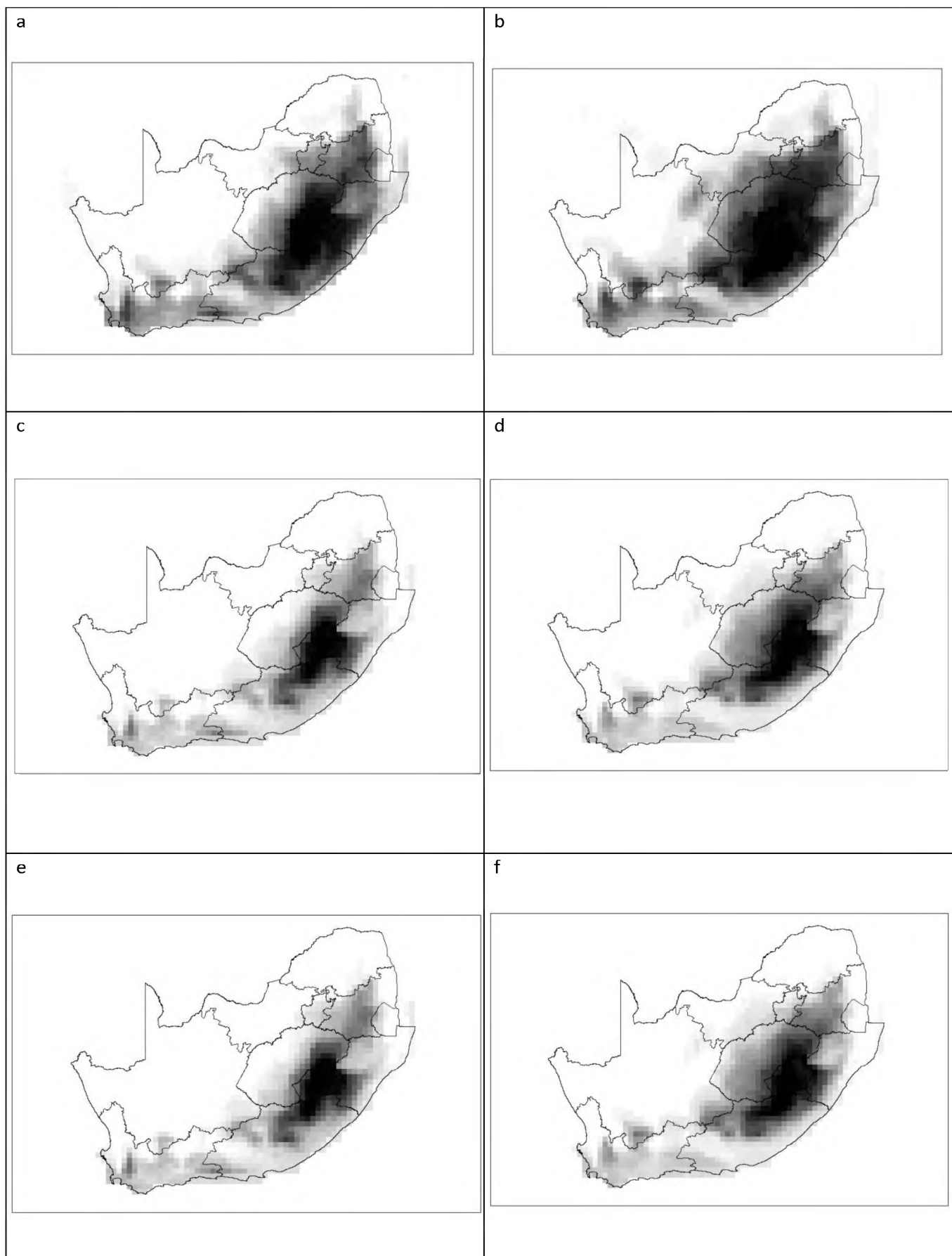


Figure 3.4: Results of species richness analysis for current climate (1971-2005) for the a) Biomod modelling method and b) MaxEnt modelling method. Future climate (2040-2080) results are for c) Biomod to full dispersal, e) Biomod to no dispersal, d) MaxEnt to full dispersal and f) MaxEnt to no dispersal.

Beta diversity

Total beta diversity showed high beta diversity scores in the low elevation regions of the south-western Cape, central Free State, Gauteng, lowveld and eastern and southern coastal plains surrounding the high elevation Lesotho area (Figure 3.5a, b, 3.6a, b). Under the no dispersal assumption, beta diversity values were marginally lower in some low elevation places because turnover cannot be taken into account (Figure 3.6a, b). This is because turnover can only occur if dispersal allows a species to disperse into new, suitable areas – a no dispersal assumption predicts a future climate range entirely within a current climate range. There were high levels of turnover in the south-western Cape, the central Free State and in the north-east of the country for the MaxEnt (Figure 3.5c) and Biomod (Figure 3.5d) models. Nestedness scores were high in the low elevation regions surrounding the Drakensberg highlands (Figure 3.5e, f, 3.6c, d). Under no dispersal (Figure 3.6c, d), nestedness values were higher than under full dispersal (Figure 3.5e, f) in the low elevation regions for both the MaxEnt (Figure 3.5f, 3.6d) and Biomod (Figure 3.5e, 3.6c) models.

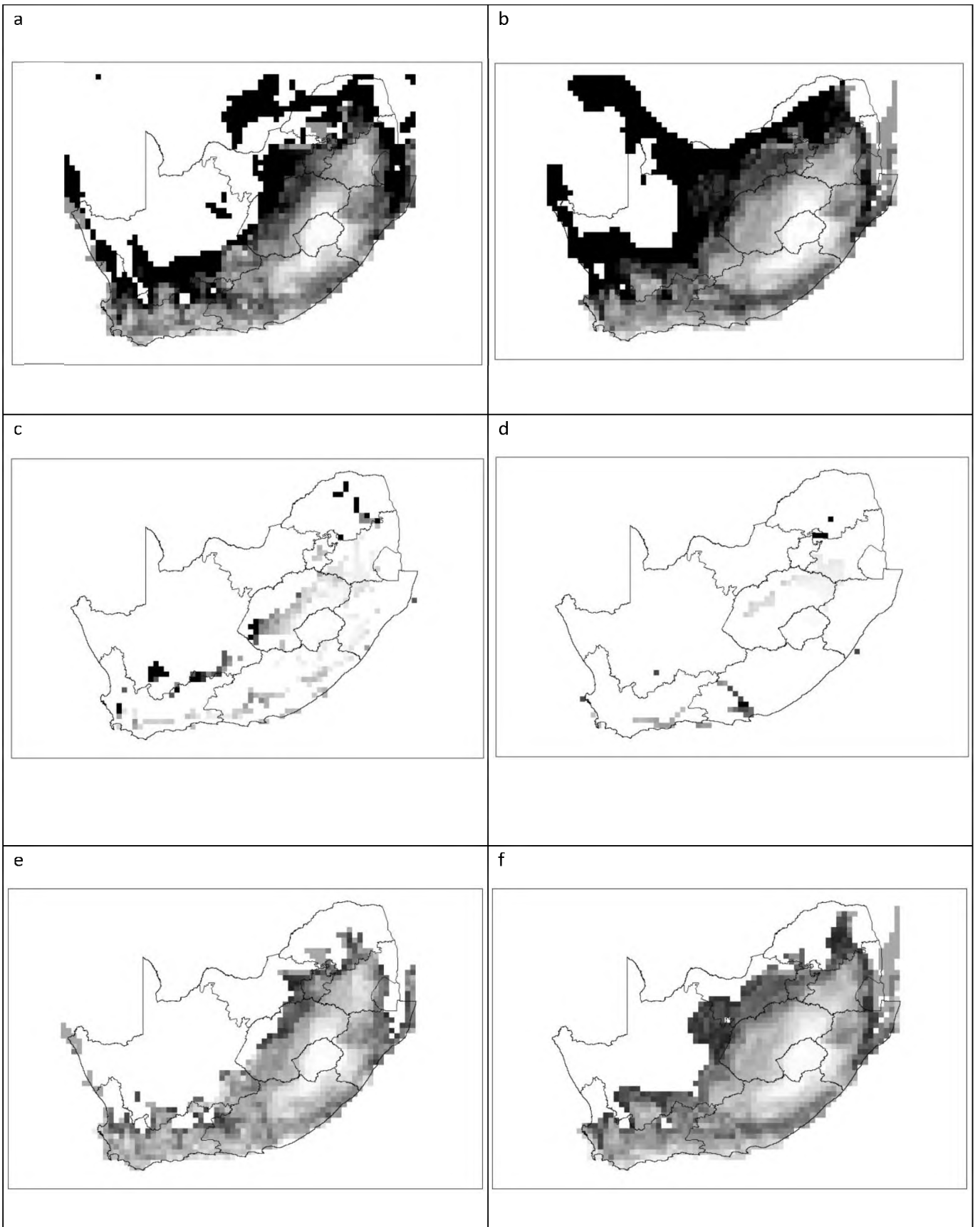


Figure 3.5: Biomod a) total beta diversity, c) turnover and e) nestedness results, and MaxEnt b) total beta diversity, d) turnover and f) nestedness results with the full dispersal assumption. Dark denotes a higher value and all indices are measured between 0 and 1.

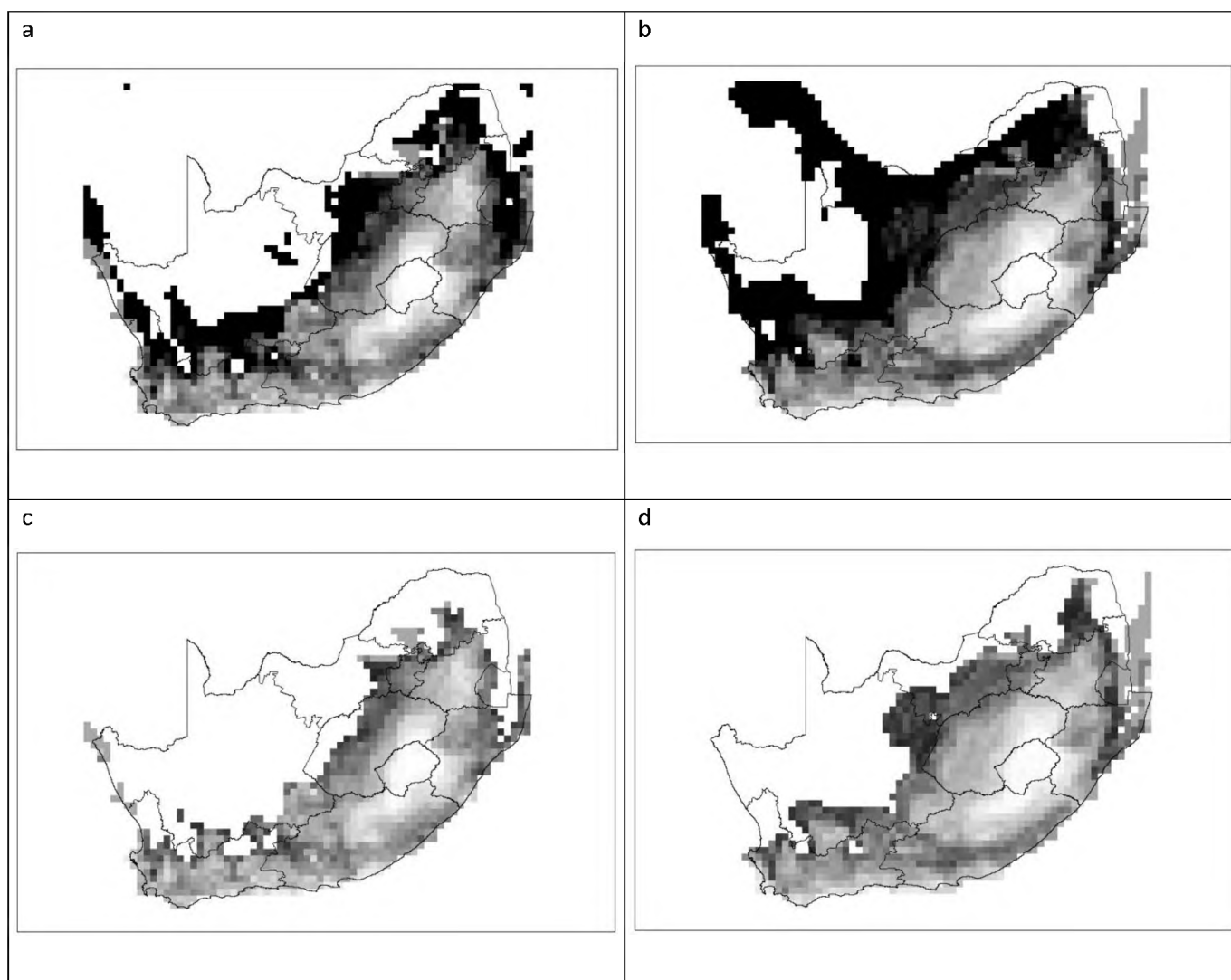


Figure 3.6: Biomod a) total beta diversity and c) nestedness results, and MaxEnt b) total beta diversity and d) nestedness results with the no dispersal assumption.

Species extent of occurrence comparison

The predicted potential extent of occurrence (Figure 3.7) for current climate and future climate was compared and showed significant reductions in predicted occurrence between current climate and future climate for both Biomod ($p < 0.001$) and MaxEnt ($p < 0.001$) to full dispersal. In the case of no dispersal, Biomod ($p < 0.001$) and MaxEnt ($p < 0.001$) also showed a significant reduction. There was a significant difference between predicted area of occurrence for current climate for MaxEnt and Biomod ($p = 0.017$).

Species extent

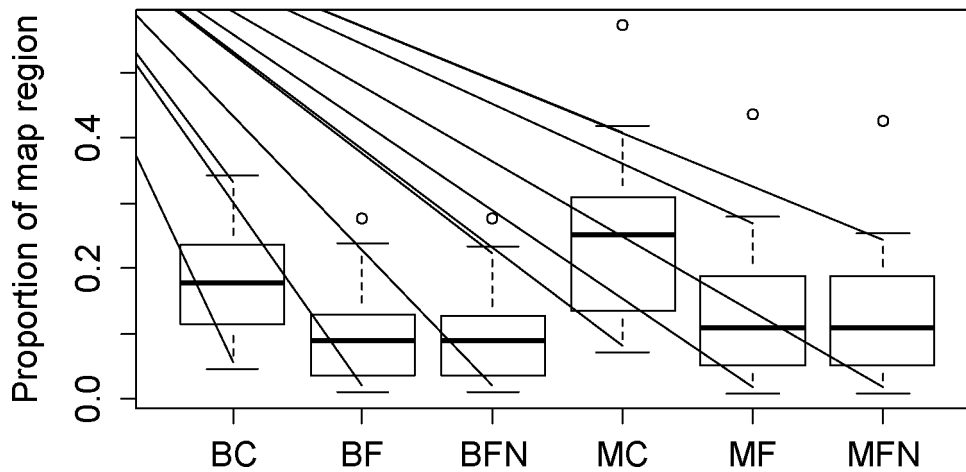


Figure 3.7: The proportion of map region predicted as present for current climate (C) and future climate to full (F) and no dispersal (FN) for Biomod (B) and MaxEnt (M) modelling methods.

All species analysed showed a decline in the extent of occurrence proportion of map region predicted as present between current and future full dispersal for both the MaxEnt (Figure 3.8) and Biomod (Figure 3.9) modelling methods. The no dispersal assumption, in some cases, showed a greater decline than the full dispersal assumption, although in most cases they were identical.

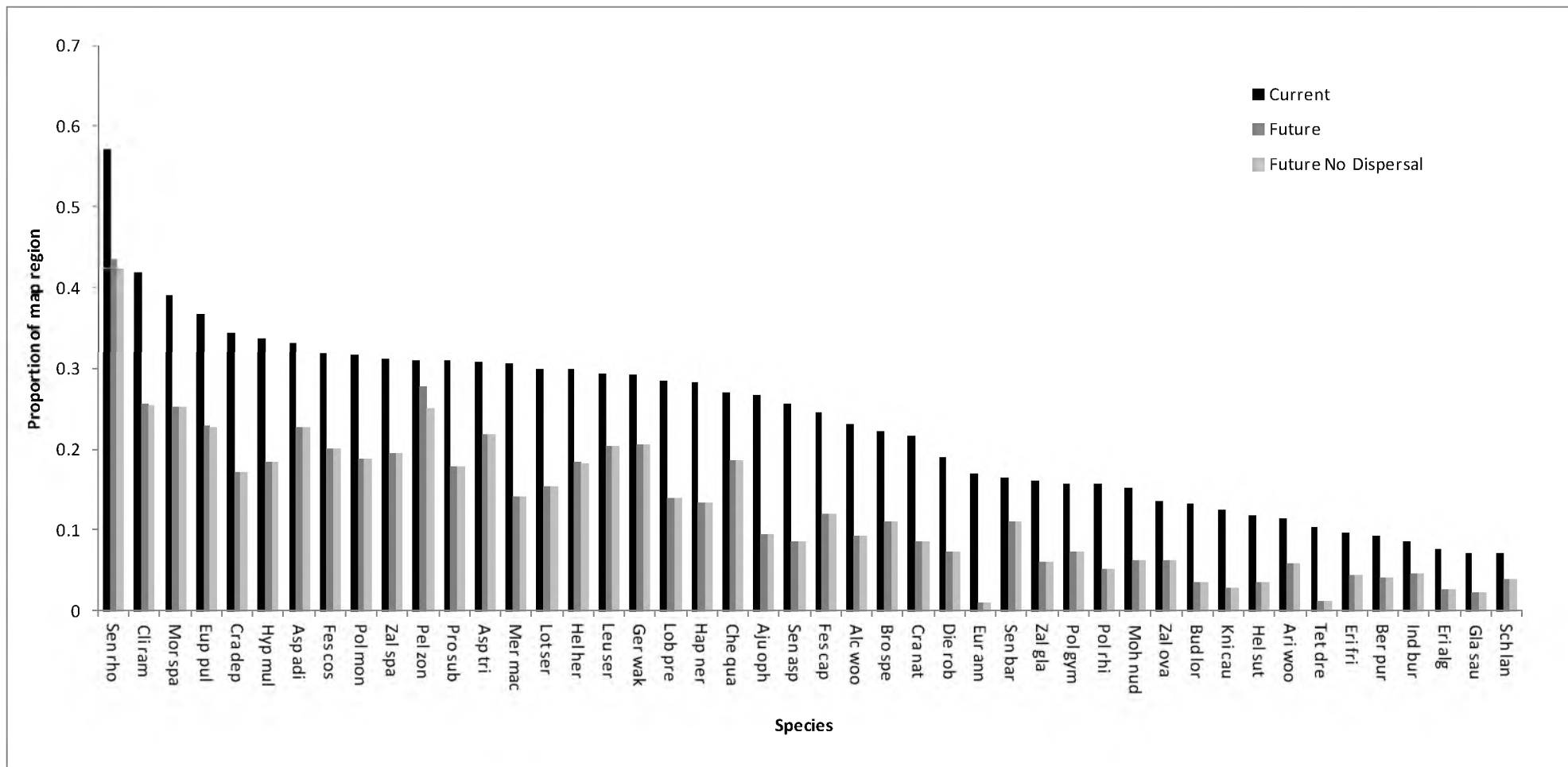


Figure 3.8: The proportion of the map region predicted as present for current climate and future climate to full and no dispersal for the MaxEnt models. Species abbreviations are as follows: Aju oph - *Ajuga ophrydis*; Alc woo - *Alchemilla woodii*; Ari woo - *Aristea woodii*; Asp adi - *Asplenium adiantum-nigrum* var. *adiantum-nigrum*; A. tri - *Asplenium trichomanes* subsp. *quadrivalens*; Ber pur - *Berkheya purpurea*; Bro spe - *Bromus speciosus*; Bud lor - *Buddleja loricata*; Che qua - *Cheilanthes quadripinnata*; Cli ram - *Cliffortia ramosissima*; Cra dep - *Crassula dependens*; C. nat - *Crassula natalensis*; Die rob - *Dierama robustum*; Eri alg - *Erica algida*; E. fri - *Erica frigida*; Eup pul - *Euphorbia pulvinata*; Eur ann - *Euryops annae*; Fes cap - *Festuca caprina*; F. cos - *Festuca costata*; Ger wak - *Geranium wakkerstroomianum*; Gla sau - *Gladiolus saundersii*; Hap ner - *Haplocarpha nervosa*; Hel sut - *Helichrysum sutherlandii*; H. Her - *Helichrysum herbaceum*; Hyp mul - *Hypoxis multiceps*; Ind bur - *Indigofera burchellii*; Kni cau - *Kniphofia caulescens*; Leu ser - *Leucosidea sericea*; Lob pre - *Lobelia preslii*; Lot ser - *Lotononis sericophylla*; Mer mac - *Merxmuellera macowanii*; Moh nud - *Mohria nudiuscula*; Mor spa - *Moraea spathulata*; Pel zon - *Pelargonium zonale*; Pol gym - *Polygala gymnoclada*; Pol mon - *Polystichum monticola*; P. Rhi - *Polygala rhinostigma*; Pro sub - *Protea subvestita*; Sch lan - *Schoenoxiphium lanceum*; Sen asp - *Senecio asperulus*; S. bar - *Senecio barbatus*; S. rho - *Senecio rhomboideus*; Tet dre - *Tetrachne dregei*; Zal gla - *Zaluzianskya glareosa*; Z. ova - *Zaluzianskya ovata*; Z. Spa - *Zaluzianskya spathacea*

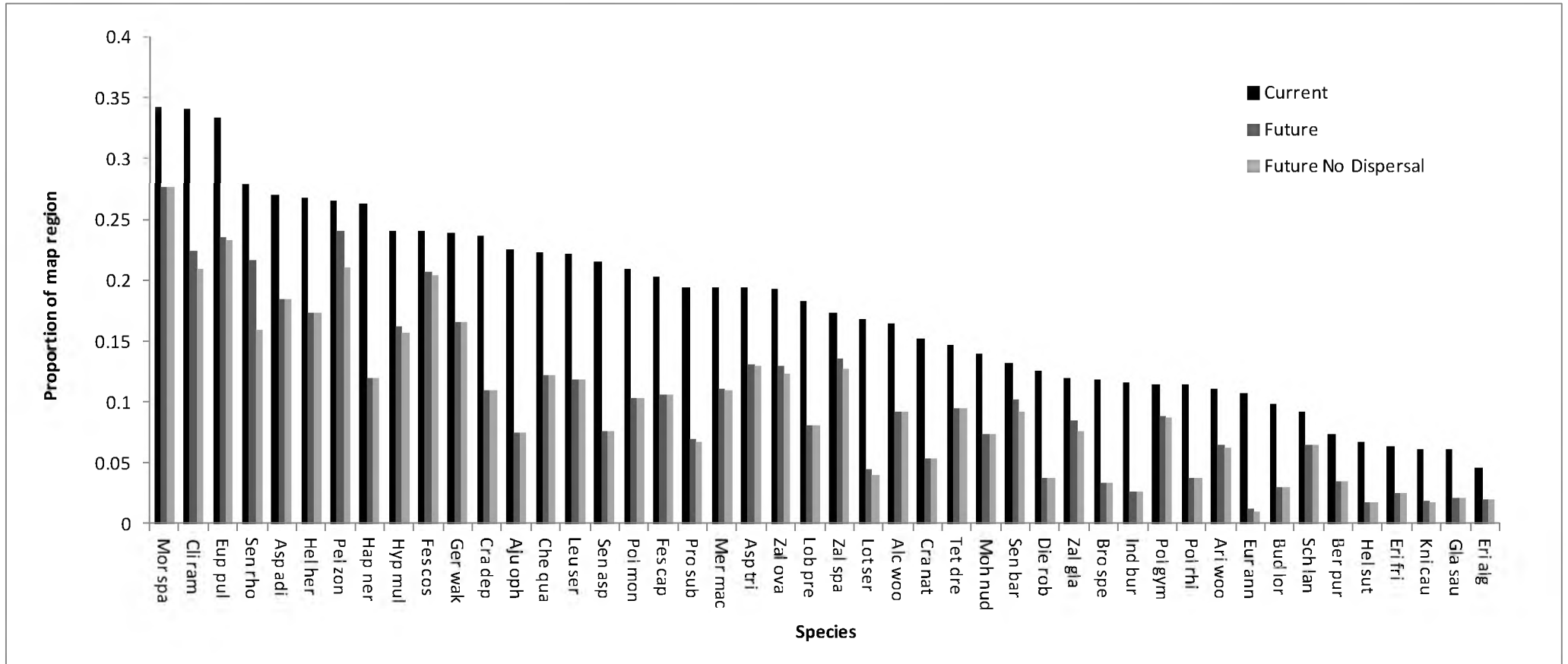


Figure 3.9: The proportion of the map region predicted as present for current climate and future climate to full and no dispersal for the Biomod models. Species abbreviations are as follows: Aju oph - *Ajuga ophrydis*; Alc woo - *Alchemilla woodii*; Ari woo - *Aristea woodii*; Asp adi - *Asplenium adiantum-nigrum* var. *adiantum-nigrum*; A. tri - *Asplenium trichomanes* subsp. *quadrivalens*; Ber pur - *Berkheya purpurea*; Bro spe - *Bromus speciosus*; Bud lor - *Buddleja loricata*; Che qua - *Cheilanthes quadripinnata*; Cli ram - *Cliffortia ramosissima*; Cra dep - *Crassula dependens*; C. nat - *Crassula natalensis*; Die rob - *Dierama robustum*; Eri alg - *Erica algida*; E. fri - *Erica frigida*; Eup pul - *Euphorbia pulvinata*; Eur ann - *Euryops annae*; Fes cap - *Festuca caprina*; F. cos - *Festuca costata*; Ger wak - *Geranium wakkerstroomianum*; Gla sau - *Gladiolus saundersii*; Hap ner - *Haplocarpha nervosa*; Hel sut - *Helichrysum sutherlandii*; H. Her - *Helichrysum herbaceum*; Hyp mul - *Hypoxis multiceps*; Ind bur - *Indigofera burchellii*; Kni cau - *Kniphofia caulescens*; Leu ser - *Leucosidea sericea*; Lob pre - *Lobelia preslii*; Lot ser - *Lotononis sericophylla*; Mer mac - *Merxmuellera macowanii*; Moh nud - *Mohria nudiuscula*; Mor spa - *Moraea spathulata*; Pel zon - *Pelargonium zonale*; Pol gym - *Polygala gymnoclada*; Pol mon - *Polystichum monticola*; P. Rhi - *Polygala rhinostigma*; Pro sub - *Protea subvestita*; Sch lan - *Schoenoxiphium lanceum*; Sen asp - *Senecio asperulus*; S. bar - *Senecio barbatus*; S. rho - *Senecio rhomboideus*; Tet dre - *Tetrachne dregei*; Zal gla - *Zaluzianskya glareosa*; Z. ova - *Zaluzianskya ovata*; Z. Spa - *Zaluzianskya spathacea*

All 46 species ranked by percentage decline in predicted occurrence from current climate to full dispersal future climate is shown in Table 3.2. The highest ranked species thus have the greatest potential extent of occurrence decline as a consequence of a changing climate. Species which rank highly for both modelling methods (shown in bold) are therefore potentially good candidates for monitoring early changes in montane vegetation patterns as a consequence of climate change. Despite their being general similarity in species rankings, some species show large discrepancies between the rankings for the two modelling methods. The modelling methods used were very different - the Biomod method included a number of regression algorithms in a total of five algorithms and the average prediction was taken across all five. The MaxEnt method used only MaxEnt, a machine learning prediction algorithm, in a nuanced manner. The different methodologies used to produce the predictions will lead to slight differences in the predictions, even if the predicted general trends are the same.

Table 3.2: Rankings for predicted species occurrence decline for MaxEnt and Biomod methods.

Species	Biomod	MaxEnt
<i>Euryops annae</i>	1	1
<i>Indigofera burchellii</i>	2	30
<i>Helichrysum sutherlandii</i>	3	5
<i>Lotononis sericophylla</i>	4	27
<i>Bromus speciosus</i>	5	24
<i>Dierama robustum</i>	6	12
<i>Buddleja loricata</i>	7	4
<i>Kniphofia caulescens</i>	8	3
<i>Polygala rhinostigma</i>	9	6
<i>Ajuga ophrydis</i>	10	10
<i>Gladiolus saundersii</i>	11	7
<i>Senecio asperulus</i>	12	8
<i>Crassula natalensis</i>	13	13
<i>Protea subvestita</i>	14	31
<i>Erica frigida</i>	15	17
<i>Erica algida</i>	16	9
<i>Lobelia preslii</i>	17	22
<i>Haplocarpha nervosa</i>	18	21
<i>Crassula dependens</i>	19	25
<i>Berkheya purpurea</i>	20	16
<i>Polystichum monticola</i>	21	32
<i>Festuca caprina</i>	22	23
<i>Mohria nudiuscula</i>	23	15
<i>Leucosidea sericea</i>	24	42
<i>Cheilanthes quadripinnata</i>	25	41
<i>Alchemilla woodii</i>	26	14
<i>Merxmuellera macowanii</i>	27	20
<i>Aristea woodii</i>	28	26
<i>Tetrachne dregei</i>	29	2
<i>Helichrysum herbaceum</i>	30	34
<i>Cliffortia ramosissima</i>	31	33
<i>Asplenium trichomanes subsp. quadrivalens</i>	32	44
<i>Hypoxis multiceps</i>	33	29
<i>Zaluzianskya ovata</i>	34	19
<i>Asplenium adiantum-nigrum var. adiantum-nigrum</i>	35	40
<i>Geranium wakkerstroomianum</i>	36	43
<i>Schoenoxiphium lanceum</i>	37	28
<i>Zaluzianskya glareosa</i>	38	11
<i>Euphorbia pulvinata</i>	39	35
<i>Senecio barbatus</i>	40	39
<i>Polygala gymnoclada</i>	41	18
<i>Senecio rhomboideus</i>	42	45
<i>Zaluzianskya spathacea</i>	43	36
<i>Moraea spathulata</i>	44	38
<i>Festuca costata</i>	45	37
<i>Pelargonium zonale</i>	46	46

Discussion

Assessment of model performance

Model performance indicators are poorer for the independent evaluation in contrast to the cross-validated evaluation. Independent evaluation uses an independent dataset, not the occurrence record dataset used to run the models, so an independent dataset is likely to show poorer model performance as the models have not been trained to this dataset. Independent evaluation results show higher sensitivity scores than specificity and total TSS scores. TSS scores have a median of 0.5 for Biomod and 0.55 for MaxEnt. These are poor to acceptable for TSS scores (Hodd et al., 2014). Median AUC scores are 0.85 for Biomod models and 0.8 for MaxEnt models which are close to or higher than the 0.8 proposed by Beaumont et al. (2009) as the score for a fair to good model. Model sensitivity is high, with a median correct prediction of present on independent datasets of approximately 0.9 for Biomod and MaxEnt.

Despite the Biomod and MaxEnt methods having marginally different median independent evaluation scores for the four evaluation metrics, none of these differences is significant. Based on independent evaluation, model performance is mixed with relatively good AUC and sensitivity scores and poorer specificity and total TSS scores. These models are therefore often correctly predicting presence, yet have low specificity scores and so are incorrectly predicting pseudo-absence. Pseudo-absences are an approximation of absence when true absences, as in this case are not available, and based on that approximation these are not conservative models.

Cross-validated evaluation reports significantly higher average scores for Biomod specificity, TSS and AUC than MaxEnt, although MaxEnt maintains significantly higher sensitivity than Biomod. The significantly higher TSS scores are a result of the much higher specificity scores in the Biomod models. AUC scores show better performing Biomod models, though the MaxEnt models, with a median AUC of over 0.9 and minimum AUC of above 0.8, still perform well. As is expected, cross-validated model scores are higher than independent scores because of the use of dependent data to evaluate the model. The scores show models which, on average, performed well.

From this evaluation, MaxEnt seems to perform well in sensitivity, outperforming Biomod in the cross-validated evaluation, and having a higher median score (though not significantly different) in the independent evaluation. Specificity is higher in Biomod which has a significantly higher mean score for cross-validated evaluation, and a marginally higher (though also not significantly different) mean score for independent evaluation. MaxEnt models seem to be sensitive, on average, and

produce less conservative models than the Biomod method, which is more specific than the MaxEnt method. AUC scores are significantly higher for the Biomod cross-validated evaluation than MaxEnt.

In terms of total performance of the models, improvement in model evaluation indices could theoretically be attained by adjusting model calibration in either MaxEnt or Biomod, or by adjusting the manner of selecting pseudo-absences (Elith and Graham, 2009; Chefaoui and Lobo, 2008; Barbet-Massin et al., 2012, Van Der Wal et al., 2009). Pseudo-absences were selected following recommendations in the literature and part of the comparison between Biomod and MaxEnt was to select high-performing modelling algorithms on default settings in Biomod and to adjust only MaxEnt. MaxEnt was set up following best-practice recommendations from other research and the ability to individually recalibrate specific modelling algorithms according to recommendations in Biomod (e.g. Elith and Graham, 2009) is limited and beyond the scope of this work.

The distribution models, based on independent and cross-validated evaluation, largely perform well. The MaxEnt models have higher sensitivity than the Biomod models and hence are less conservative than the Biomod models. The Biomod models may be more conservative predictions because they take the mean of a selection of modelling algorithms which, according to Marmion et al. (2009) has a 'cleaning' effect on predicted presence and minimizes spurious predictions of occurrence. Biomod models, though, with higher sensitivity scores than specificity scores, are conservative relative to the MaxEnt models, although they are not conservative in absolute terms.

Models which are not conservative may be more useful for climate change research in montane regions than more conservative models as they are more inclined to predict presence. Considering climatic changes in these regions predict species range declines, less conservative models mean that any range decline predicted by the model is more likely to occur than from a more conservative model.

Predicted responses of montane plants to climate change

Species richness shows a contraction in the potential region of high species richness from current climate to future climate which is in accordance with the hypothesized plant response. There is a large region of high richness over the high elevation Lesotho, eastern Free State, south-western Kwazulu-Natal and north-eastern Eastern Cape regions, as well as small regions of relatively high richness in the south-western Cape under current climate. These regions decline in size for both modelling methods in the future, although the MaxEnt method, due to its less conservative models, shows a larger region of high richness at current and future climate than Biomod. Species extent analysis corroborates this response with significant declines in predicted extent between current

climate extent and future climate extent for both modelling methods. MaxEnt, because of its more sensitive, less conservative models, has a significantly higher mean prediction of a potential area of occurrence at current climate than Biomod models. Plant species which have a high predicted decline in occurrence between current and future climate for both modelling methods are potential species for monitoring. If both modelling methods, based on climatic niche, agree on large decreases for a particular species, it is worth determining, through monitoring, if the empirical response of species distribution matches what models are predicting.

Beta diversity predictions show high beta diversity at the low elevation regions surrounding the Drakensberg highlands centred over Lesotho. Nestedness scores show high levels of nestedness in low elevation areas surrounding Lesotho. The plant assemblages in these regions are therefore a subset of the core region. High species turnover is predicted in parts of the south-western Cape, the central Free State and the north-east of South Africa. Turnover would not be expected in the high elevation, main Drakensberg region because this is the high altitude refugium for these species. Turnover, being a replacement of some species with other species, only occurs in areas from which species are moving i.e. low altitude regions. MaxEnt models, with their less conservative predictions than Biomod, show a larger area of low beta diversity centred on the high elevation, Lesotho area, as well as a larger surrounding area of high beta diversity at low elevation than Biomod.

These results correspond with numerous empirical studies: Kelly and Goulden (2008) found a 65m elevation increase of the dominant plant species in the Santa Rosa Mountains of southern California between surveys in 1977 and 2006-2007. Elevation increases in the treeline in Europe and New Zealand (Meshinev et al., 2000; Kullman, 2001), in Norwegian mountain plants (Klanderud and Birks, 2003), and in lowland birds in Costa Rica (Pounds et al., 1999), as well as general shifts of species to higher elevation (e.g. Harsh et al., 2009; Chen et al., 2011) have been reported in the recent scientific literature.

Qualifying these results

These results show an area of potential occurrence for each species and only take the rainfall and temperature, and the changes in these predictors, into account. Further geological and edaphic factors are not taken into account. Pearson and Dawson (2003) note the issues of biotic interactions, species dispersal and evolution in affecting where species move during a climatic change. Biotic interactions may make a species survive in a smaller region than its climatic niche, or move downslope rather than upslope (Lenoir et al., 2010). These models assume no adaptive evolution; only migration. Full dispersal and no dispersal assumptions have been made, with the no dispersal

assumption predicting greater contraction of the modelled species towards high elevation regions under future climate than the full dispersal assumption. Most of the species being modelled are known or suspected to be wind dispersed, with a few, such as the legumes *Lotononis sericophylla* and *Indigofera burchellii*, having exploding pods which drop their seeds in the vicinity of the parent plant (Pers. Comm. Prof. Barker). Wind dispersal is potentially long range dispersal and the majority of the modelled species use this method, leading to possible future distribution patterns which resemble the full dispersal assumption which assumes no lag between climate change and species distribution.

Implications

Biodiversity loss is one of the major potential impacts of changing montane land cover (Beniston, 2003). A smaller potential extent of occurrence, as southern Africa's montane species move to a higher elevation has serious biodiversity implications because southern Africa's mountainous regions are home to numerous current and proposed centres of endemism. The Drakensberg Alpine Region is a centre of endemism (Carbutt and Edwards, 2004). Further centres of endemism are proposed by Matthews et al. (1993) and Clark et al. (2014) in the north-eastern escarpment and southern escarpment respectively. Part of the reason for high levels of endemism in different South African mountain ranges is because mountainous regions have acted as refugia in past climate changes (Medail and Diadema, 2009). Regions, such as mountainous regions, which are topographically heterogeneous, allow the persistence of species in small, suitable microhabitats when climates change. These species' ranges expand and contract, as climate becomes more or less favourable, and speciation can occur. The modelled response of plants in these areas shows a declining potential distribution as climate changes. This declining potential distribution, coupled with human induced habitat destruction is a cause for concern in our important, mountain-based biodiversity hotspots.

Conclusion

Predictive correlative modelling, using both an ensemble modelling approach and a nuanced method with the MaxEnt algorithm only, has found a general trend of a contraction of the potential areas of occurrence in a montane plant assemblage to high elevation based on future climate projections. This result was determined when running these predictive models to mid-century under the A2 climate change scenario. Species richness shows a smaller area of high richness at high elevation under future climate, beta diversity shows high beta diversity in low elevation regions and species extent shows a statistically significant decline in predicted species occurrence extent between current climate and future climate. The nuanced MaxEnt method was, on average, more sensitive

than the ensemble model. Both modelling paradigms predict a similar response for South Africa's mountain vegetation which strengthens the prediction. These responses have important biodiversity implications and are discussed in the next chapter. The Drakensberg and Lesotho highlands seem to be the important refugium for future montane biodiversity.

Chapter 4

General discussion and conclusion

This thesis undertook a historical and predictive analysis of climate change impacts in the great escarpment region of southern Africa. The historical analysis assessed rainfall trends in the escarpment in the south-east of South Africa. This was to attempt to determine a definitive direction of change and to determine if the trajectory of rainfall change matches the climate models. This historical data also served an important purpose for chapter three, as it acted as verification for the predictions made by the climate models and for the accuracy of the current climate rainfall projections in comparison to recorded rainfall.

The predictive analysis used correlative species distribution modelling to predict the potential distribution response of montane plants to a changing climate. It used only rainfall and temperature predictor variables and compared two distribution modelling methodological paradigms and their predictions and performance.

Contemporary climate change determined from historical data

The analysis of historical rainfall records determining the trajectory of rainfall change in South Africa's Eastern Cape Mountains shows a marginal increase in rainfall, particularly for the single station tau analysis. This marginal trend is occurring as is generally predicted in the Global Circulation Models which have been downscaled to southern Africa (Hewitson and Crane, 2006; Engelbrecht et al., 2009; Tadross et al., 2011). These trends determined from recorded data are useful to add credibility to the predictive modelling results. Modelling and attempting to predict the way species distributions change under novel climates is inherently complex requiring many assumptions (Elith et al., 2010). Researchers will have different opinions as to how best to go about modelling a range change. When this uncertainty is coupled with uncertainty in the Global Climate Models used as the basis for predicting the range change, credible predictions are difficult to attain. The historical rainfall records validate the predictions made by the climate modellers and this allows confidence in species distribution projections. Predictions which have been validated with current data are more likely to be accepted by the broad community than purely hypothetical models. When predictions are accepted by the broad community, they can be seriously considered and management practices can be introduced to mitigate potential results.

The comparison between current climate model projections for mean annual rainfall and historical rainfall records is important to further validate the species distribution models in chapter three.

Fridley (2009) and Van Niekerk and Joubert (2011) note the difficulty of modelling climate in mountainous terrain. Results suggested good agreement between the current climate model projections and historical rainfall records. Over 50% of the rainfall collection locations had predicted rainfall amounts within 100 mm above or below the recorded records for 15 and 9 minute resolution projections allowing for greater confidence in the results from chapter three of the thesis.

The rainfall records also support the assertion that climate change is already happening in southern Africa. A wetter eastern South Africa, in particular in this case the south-east, is described by Chase and Meadows (2007) as characteristic of a period of a warmer, interglacial climate. They detail past Quaternary changes in the southern African climate system, particularly focussing on the size and strength of the frontal winter rainfall zone in the south-western Cape. They note how this zone has expanded or contracted based on the state of the climate system. The current climatic shift is, however, occurring at a much faster rate than has happened in the past because of anthropogenic forcing: Current CO₂ concentrations of around 400 ppm are similar to concentrations in the mid-Miocene (around 15 million years ago) when global temperatures were 3 to 6°C higher and sea levels were 25 to 40 meters higher than currently (Tripadhi et al., 2009).

Comparing the ensemble and nuanced distribution modelling methods

The use of two methodological paradigms to make these distribution predictions was important to firstly compare the two as they are two commonly used methods in the literature (e.g. Buermann et al., 2008; Buckland et al., 2014; Hodd et al., 2014), and so that further credibility can be given to the final results. The results can be accepted with greater confidence if both modelling methods predict similar trends.

After comparing the two, the nuanced method using only the MaxEnt algorithm can be accepted as less conservative than the ensemble method. This is thought to be because an ensemble of multiple algorithms uses a group discrimination technique and this 'cleaning' effect creates a more conservative model as described by Marmion et al. (2009). This contrast may mean a particular method is more useful in a certain scenario depending on the sort of predictions to be made. For example, less conservative models are more inclined to predict presence than more conservative models, so for a reduction in extent of occurrence, any reductions predicted by a less conservative model are more likely to occur than those predicted by a more conservative model.

Climate change and its predicted impact on montane vegetation

Following empirical validation of the downscaled Regional Climate Models (RCMs) being used here, the impact of climate change on future plant distribution in the Great Escarpment was determined. Models predicted a general contraction to high elevation for the assemblage of plant species in response to climate change. Predictor variables included rainfall and temperature variables and the first order response of an ecosystem to a warming climate – to move to higher elevation (MacArthur, 1972; Peters and Darling 1985) – was the response found in the models.

These correlative models were calculated using only climatic predictors and not any edaphic or geological predictors. This means an overarching assumption was made that the distribution of the plants modelled is ultimately limited by rainfall and temperature. This, according to Pearson and Dawson (2003), is a credible assumption to make when calculating species distribution models at a large scale over a large area.

The results predicted here can give an initial indication and warning for planners and project managers about the future of our montane vegetation. However, more detailed, small-scale correlative and mechanistic distribution modelling needs to be done in order to make more accurate predictions for pertinent endemic species in our mountainous regions to a changing climate. This analysis was unfortunately affected by the depauperate nature of empirical information in southern Africa – particularly for plant records, geology and soil types. Furthermore, future climate projections can be attained to only a 9 minute spatial resolution at the finest scale. Database plant occurrence records across the region are generally documented to a 15 minute resolution precluding small-scale analyses. This needs to be addressed before small-scale, single species predictions can be made.

The applied implications of these predicted montane trends for protected areas

The predicted high elevation refugium for montane plant diversity covers most of Lesotho and the surrounding highlands of the Eastern Cape, Free State and Kwazulu-Natal (Figure 4.1).

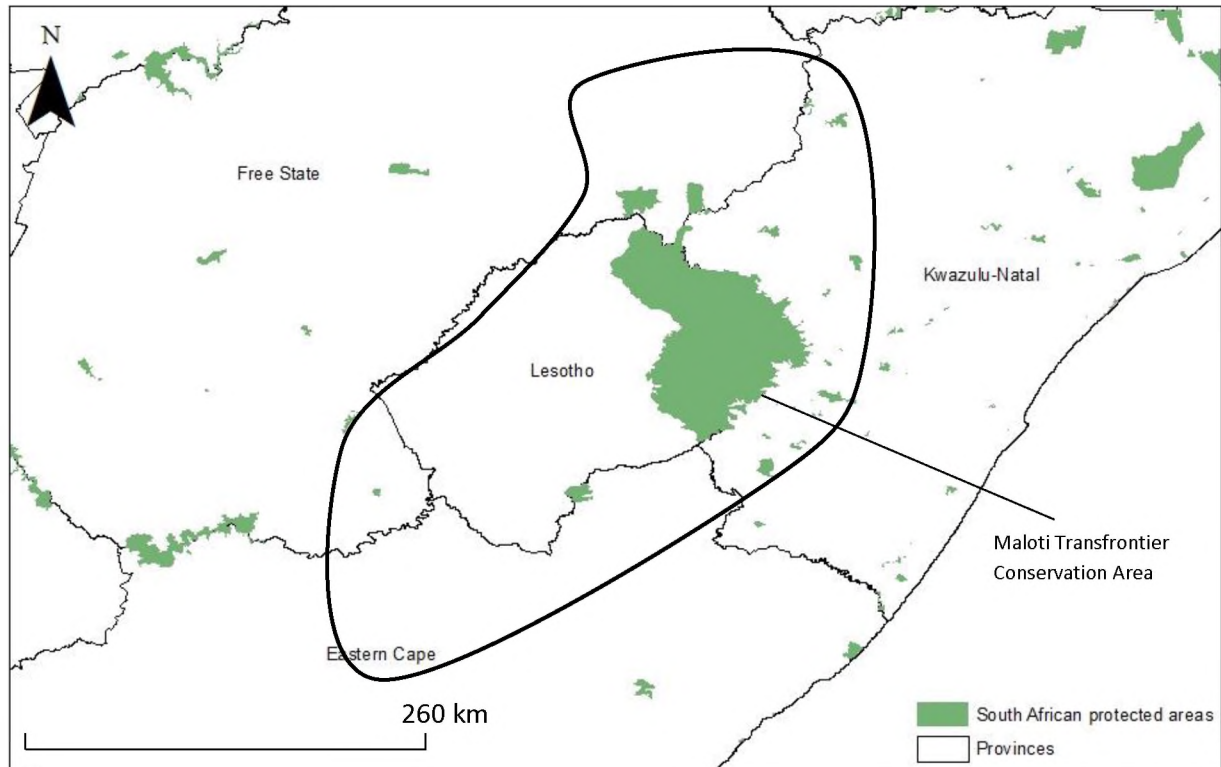


Figure 4.1: The predicted high elevation refugium for southern Africa's montane plant diversity and the protected areas within it.

All major protected areas in this region have been merged into a Maloti Drakensberg Transfrontier Conservation Area (Maloti Drakensberg Transfrontier Programme, 2012) (Figure 4.1). These include the Ukhahlamba Drakensberg Park World Heritage Site and the Sehlabatebe National Park (Maloti Drakensberg Transfrontier Programme, 2012)

SANParks (2006) promotes landscape connectivity and increasing the size of protected areas as a climate change response. SANParks believe that barriers to migration as climate and vegetation change may lead to species extinctions. Increasing the extent of protected areas is therefore their main response to climate change challenges. The Transfrontier Project for the Maloti Drakensberg is consequently a great initiative to provide a greater protected region for this important and fragile climate change refugium.

This project, however, needs to be expanded and the theoretical protection it provides to the biodiversity in the area needs to be properly enforced. Large parts of Lesotho in particular remain

unprotected and, with a total of 2961 recorded flora, of which 30% are endemic, it is a centre of biodiversity and endemism which needs better protection (Department of Environment, 2009). Currently the main threats to biodiversity include alien invasive plants, unplanned human settlement, overuse of plants for medicinal purposes, overgrazing and the extensive clearing of land for developments such as dam construction (National Environment Secretariat, 2002) and these need to be addressed before they seriously impact Lesotho biodiversity. Heller and Zavaleta (2009) note the importance of a holistic approach to conservation, particularly by getting the local rural population on board to protect regional biodiversity. This buy-in is imperative to properly conserving this region of Lesotho.

Another important part of climate change mitigation and adaptation is regular monitoring to determine if global changes are having an impact on natural systems. In terms of this research and these predictions, monitoring plant species in strategic locations and the changes in their populations is important to empirically corroborate the modelled predictions made. In the Drakensberg highlands, this is the mission of the South African Environmental Observation Network (SAEON) Grasslands-Forests-Wetlands node. Results garnered from research institutes and universities (such as in this thesis) need to be communicated to policy-makers in nature reserves in the pertinent regions so that well-informed decisions regarding nature reserve management can be made.

Conclusion

Historical rainfall records have shown a marginal increase in total and summer rainfall in particular in South Africa's south-east, although there was insufficient data to support the prediction of an increasing regularity of extreme events. This has a number of implications for that area and helps to validate the climate change projections being used to predict the response of montane vegetation to a changing climate. The predictive modelling analysis predicted a general contraction in the potential distributions of the plants in the selected assemblage towards the Drakensberg highlands and acts as an early forecast for the empirical trends to be expected in montane vegetation in the future. This predicted elevational shift highlights the importance of the Maloti Drakensberg Transfrontier Conservation Area, although this initiative needs to be expanded and correctly enforced to ensure human impacts on this centre of biodiversity can be mitigated and it can act as an important climate change refugium in the future.

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Appendix 1

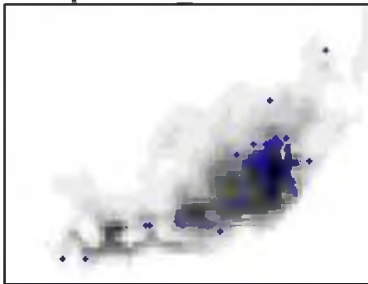
Table A1: Localities from which rainfall records were attained and the length of time over which the records span.

Study locations	Length of rainfall record (years)	Longitude	Latitude
Adelaidepol	93	26.3	-32.7
Albertvalefrm	105	26	-32.73
Aliwalnorthplaatkop	23	26.88	-30.8
Amatolastateforest	106	27.28	-32.67
Bacelapol	31	27.48	-32.2
Bassonskloof	56	25.7855	-33.25639
Baziya (Mthatha)	15	28.43301	-31.568331
Bedford	35	26.08	-32.68
Belvedere	33	25.912778	-32.566667
Bisho	24	27.28	-32.9
Bradgate	32	26.921667	-31.401944
Broughton	96	26.56748	-31.28137
Buffelsfonteina	26	26.7	-31.37
Buffelsfonteinb	109	26.6969	-31.3694
Cathcartpol	79	27.13	-32.3
Cradock	23	25.6253	-32.1672
Craig Doone	17	26.47697	-33.358578
De Klerksdal	98	25.9047	-32.6004
Derek Painter	90	26.461519	-32.735044
Dirko	96	25.728186	-32.750719
Dohne	35	27.4675	-32.535
Dordrechttnk	102	27.05	-31.37
Driehoek	33	26.598831	-31.206925
Dwayne Wallace	14	26.385197	-32.635639
Exwellpark	107	27.12	-32.2
Fortbeaufort	74	26.63	-32.78
Fortcunnyngame	27	27.4	-32.48
Glen Avon (Intake)	19	25.652611	-32.697067
Glen Avon (Mountain)	22	25.62211	-32.690736
Glen Avon (Stutt)	35	27.493753	-32.636997
Grootdam	86	25.83	-31.97
Hazelmere	28	26.680833	-31.501667
Hendersenpol	37	27.35	-32.32
Hillside	28	26.659722	-31.458889
Hofmeyrmun	100	25.8	-31.63
Hotfire	69	27.37	-32.18
Indwe-mun	102	27.33	-31.47
Izeleniplantation	88	27.42	-32.67
Jamestownpolice	119	26.8	-31.12

Study locations	Length of rainfall record (years)	Longitude	Latitude
Kalkoenkrans	91	26.100556	-31.25
Kareefontein	93	25.67	-31.58
Kingwilliamstownmun	43	27.4	-32.87
Kologhabos	111	27.37	-32.53
Komanihospitaal	17	26.9	-31.93
Kubusiestateforest	101	27.28	-32.58
Larry King	59	26.249	-32.1
Leeufontein	34	26.18	-31.12
Mattie de Bruyn	28	27.428139	-32.575678
Molteno	88	26.37	-31.4
Moltenommarshmoor	79	26.37	-31.4
Mpofugamereserve	7	26.55	-32.57
Noupoort	85	24.9603	-31.1864
Old homestead glen avon	64	25.647314	-32.711825
Qoqodala	12	26.95	-31.72
Queenstownvet	20	26.87	-31.88
Rossouw	63	27.28	-31.17
Somerseteast-tnk	100	25.72	-33.05
Spitskopagr	82	26	-31.58
Spring Valley	18	25.53	-31.245
Sterkstroom	22	26.55	-31.55
Strydfontein	53	26.6239	-31.3067
Stutterheimtnk	51	27.43	-32.57
Tarkastad	98	26.27	-32
Thomasriver	73	27.25	-32.45
Vogelvlei	98	26.855	-31.388889
Wellfound	58	24.91	-32.7732
Whytebank	29	26.243092	-32.406777
Wildeperdehoek	91	26.3	-31.57
Willow Park	40	26.942778	-31.499444
Chris Hobson	136	24.3902	-32.5215
De Rust	56	24.156	-32.256
Bassonskraal	56	24.156	-32.402
Oordonantie	80	24.835	-32.459
Wellwood	138	24.644	-32.006
Wheatfields	45	24.767	-32.616
Ganora	26	24.5856	-31.88
Asante sana	25	24.9703	-32.3908
Mount Camdeboo	10	24.9249	-32.3332

Appendix 2

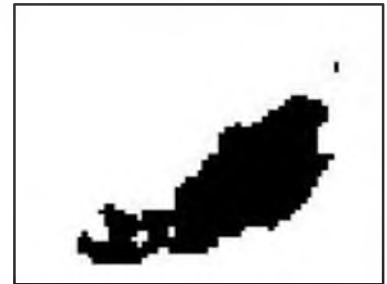
Asplenium trichomans



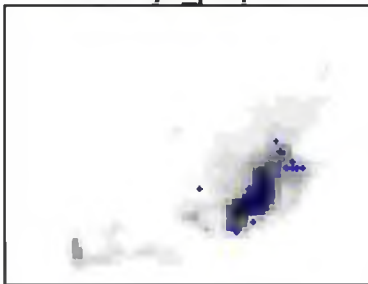
Current



Future



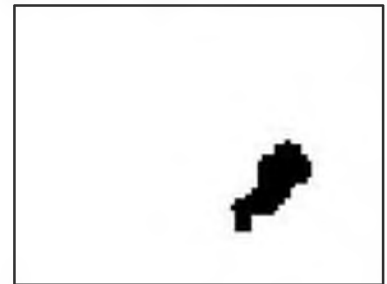
Berkheya purpurea



Current



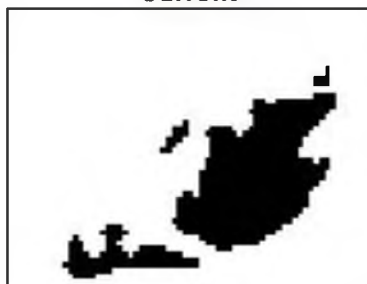
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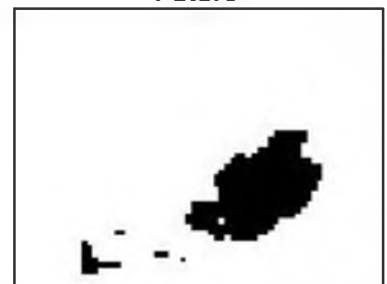
Bromus speciosus



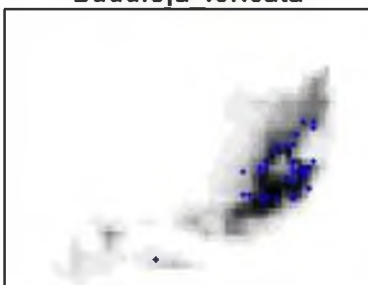
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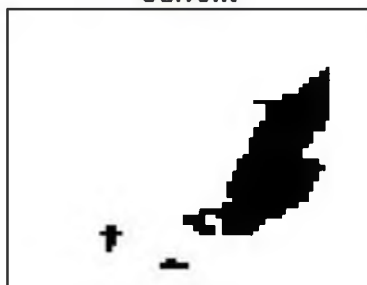
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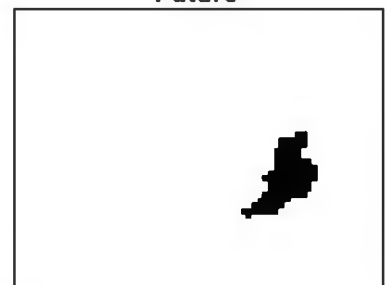
Buddleja loricata



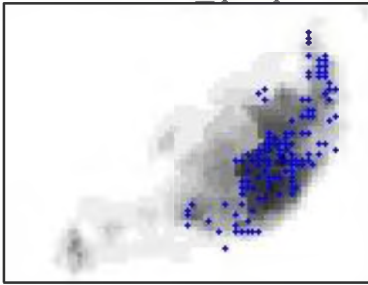
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Future



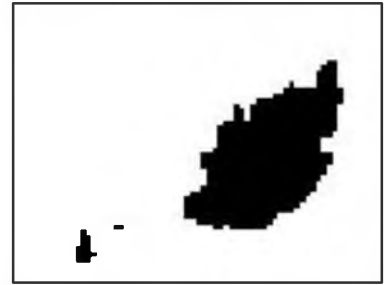
Cheilanthes qudrpnnt



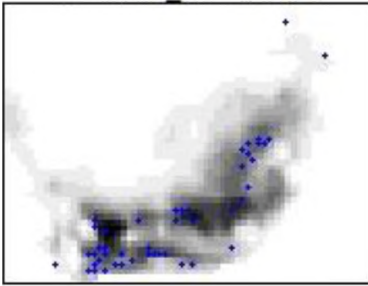
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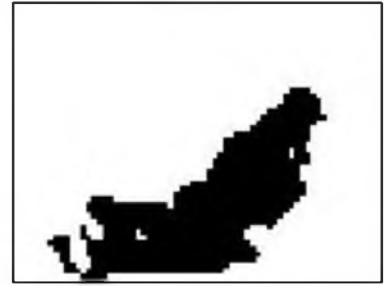
Cliffortia ramosissm



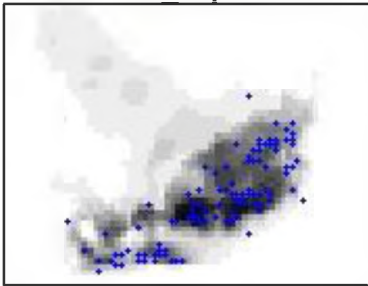
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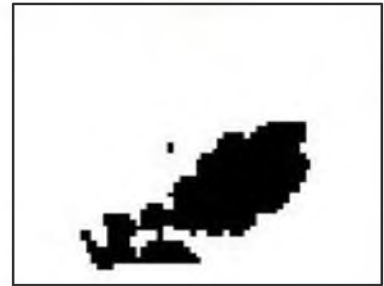
Crassula dependens



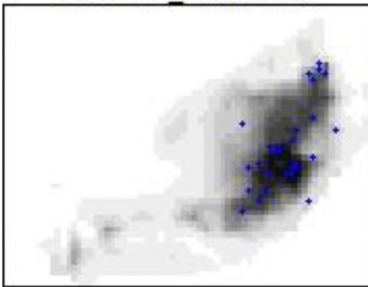
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Future



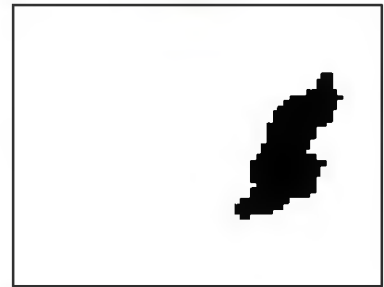
Crassula natalensis



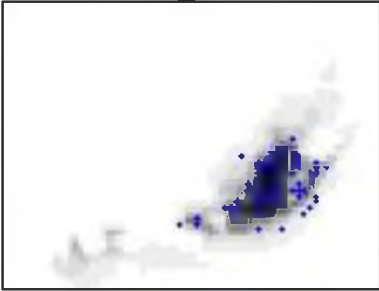
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Future



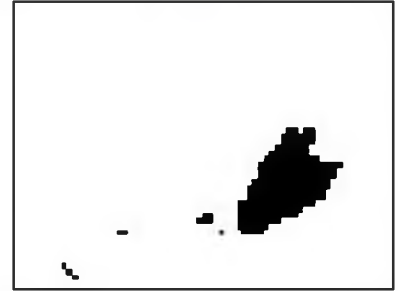
Dierama robustum



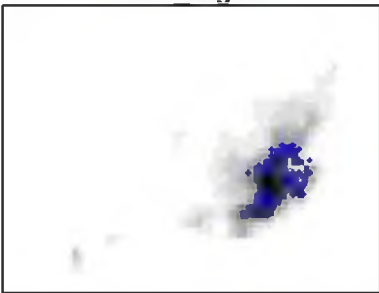
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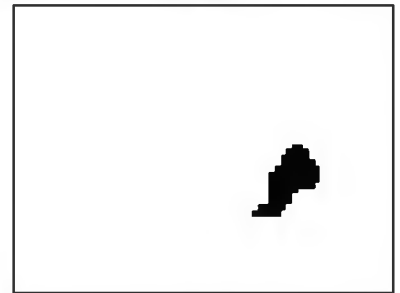
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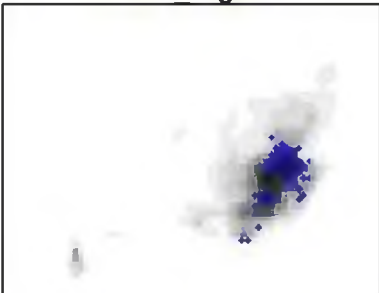
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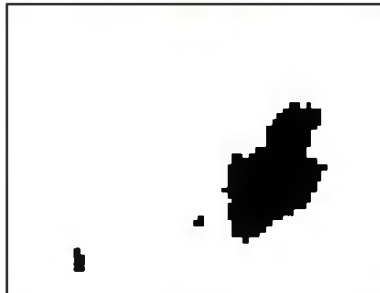
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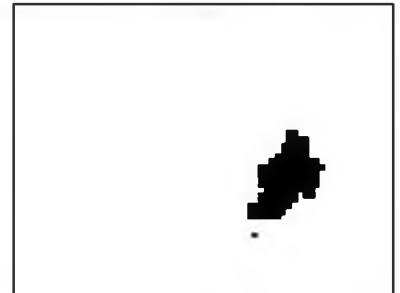
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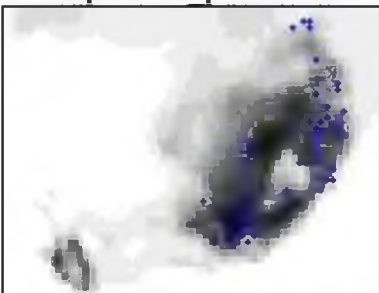
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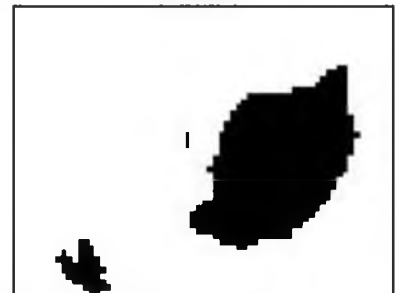
Euphorbia pulvinata



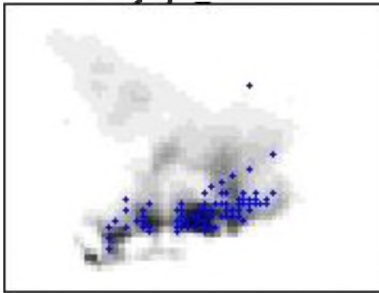
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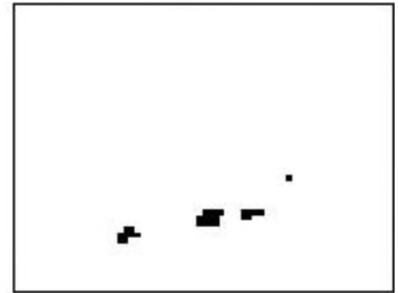
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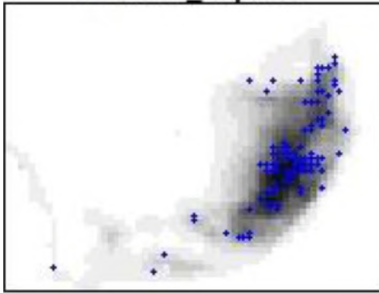
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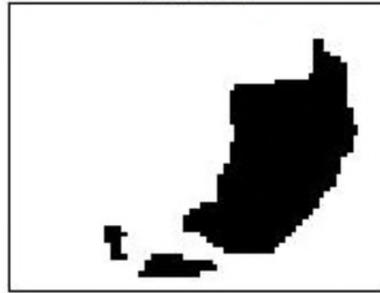
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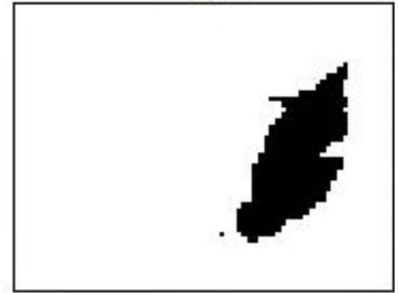
Festuca caprina



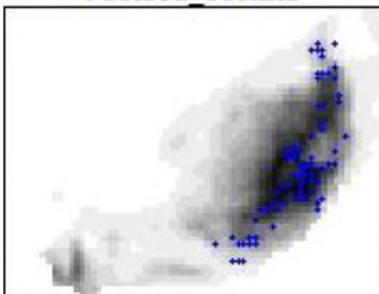
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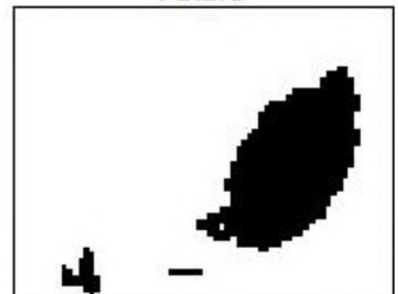
Festuca costata



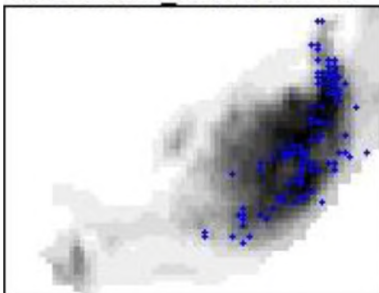
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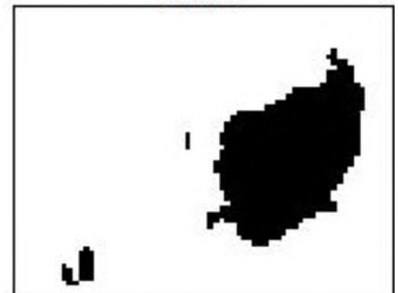
Geranium wakkstrmnm



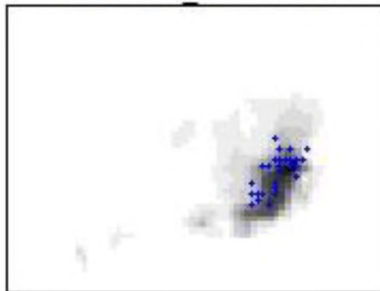
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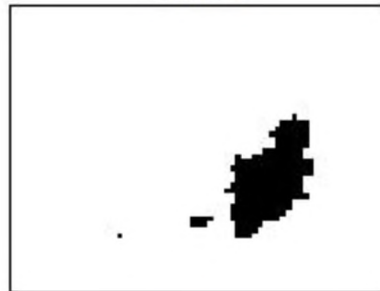
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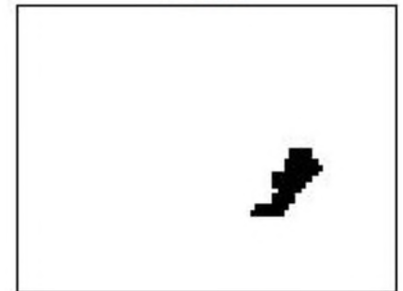
Gladiolus saundersii



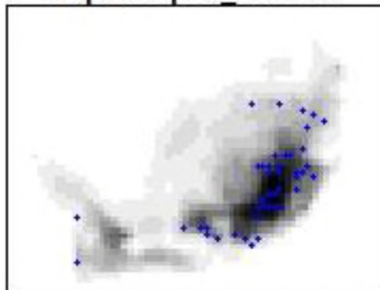
Current



Future



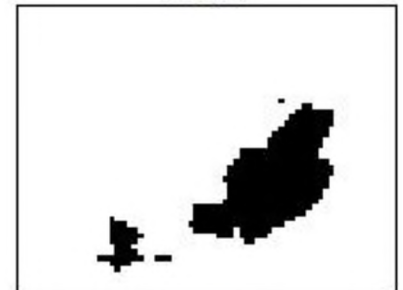
Haplocarpha nervosa



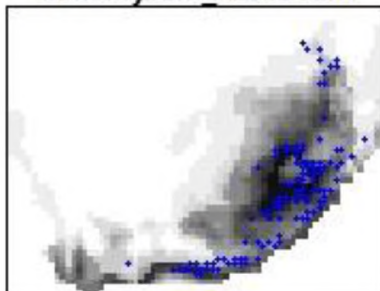
Current



Future



Helichrysum herbacem



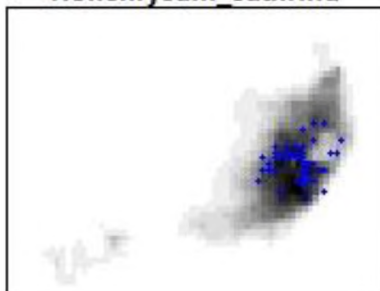
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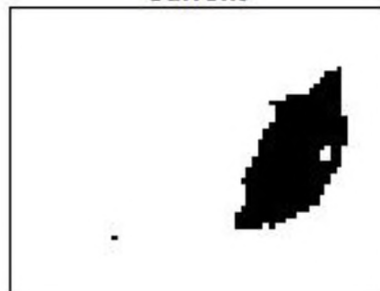
Future



Helichrysum sutherlandii



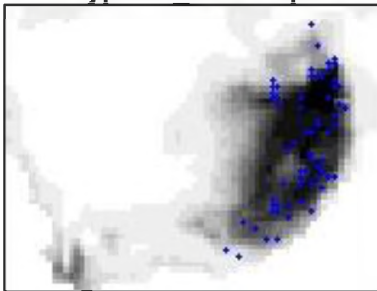
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Future



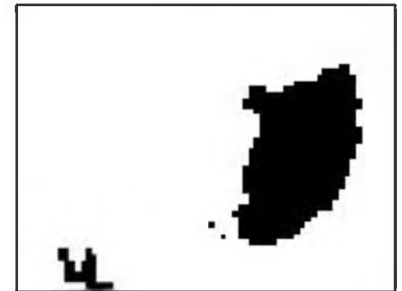
Hypoxis multiceps



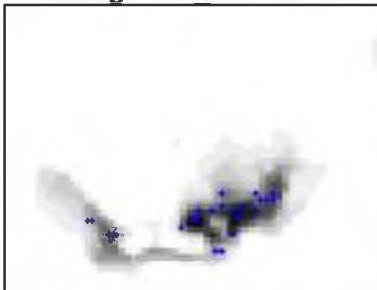
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Future



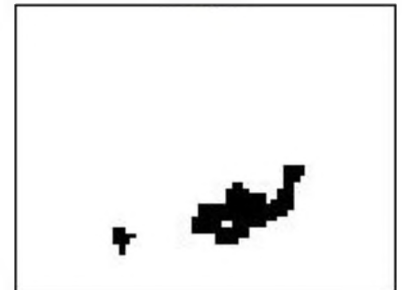
Indigofera burchelli



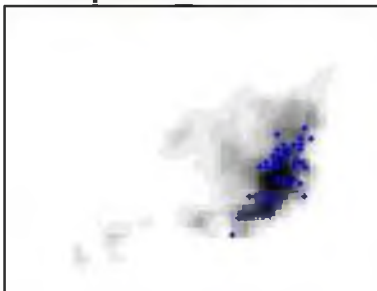
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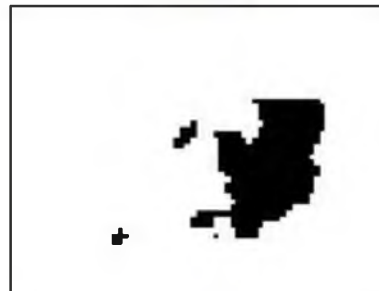
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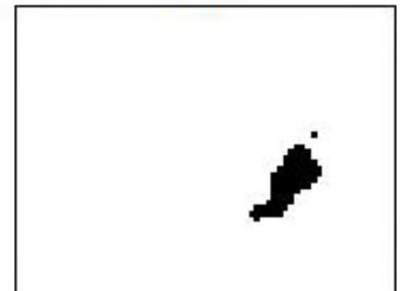
Kniphofia caulescens



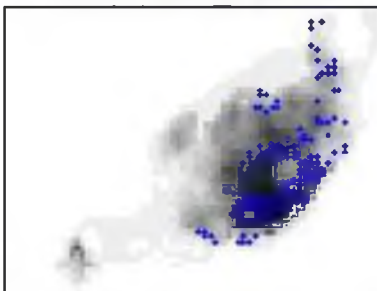
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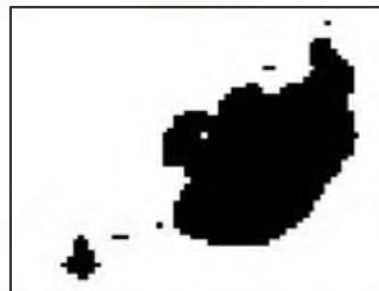
Future



Leucosidea sericea



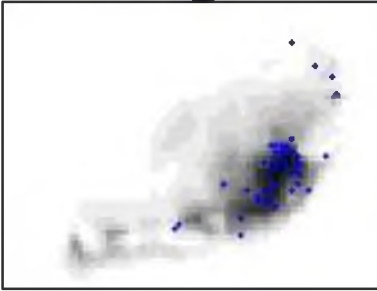
Current



Future



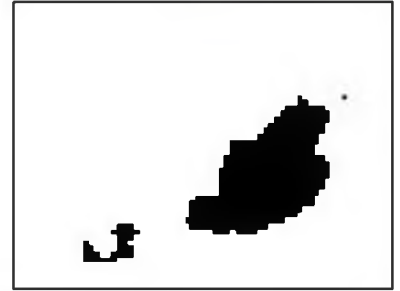
Lobelia preslii



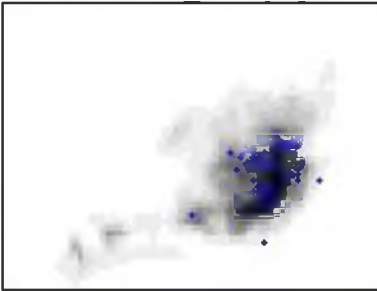
Current



Future



Lotononis sericphyll



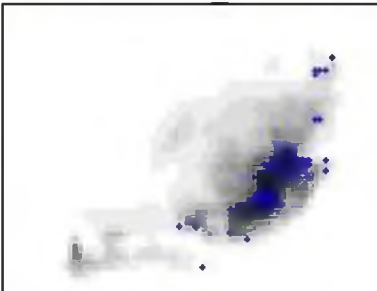
Current



Future



Merxmuellera macowan



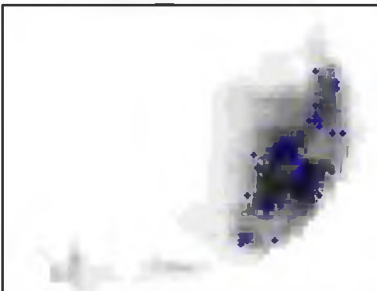
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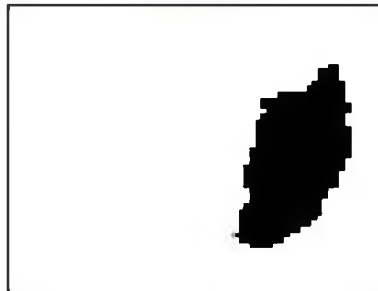
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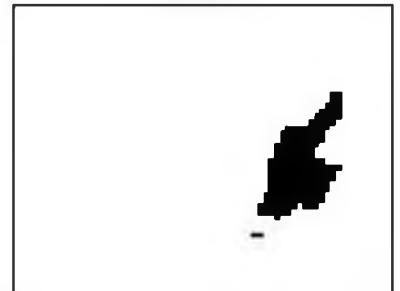
Mohria nudiuscula



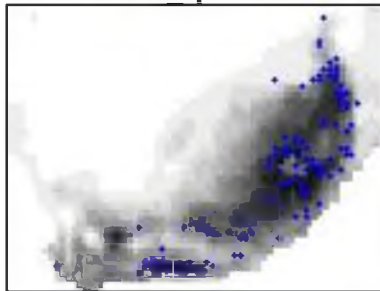
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Future



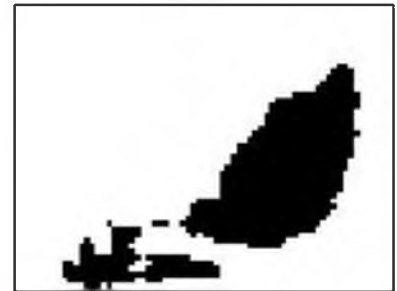
Moraea spathulata



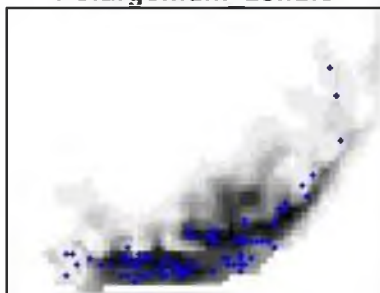
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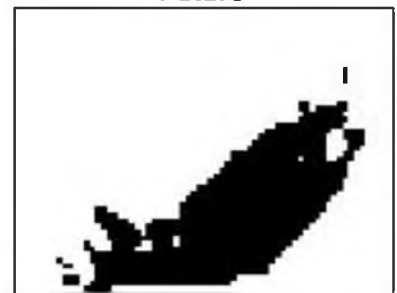
Pelargonium zonale



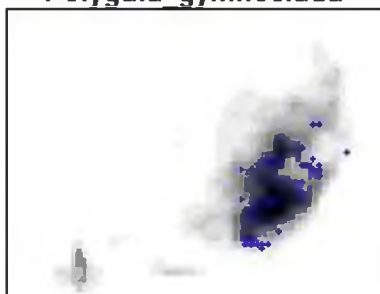
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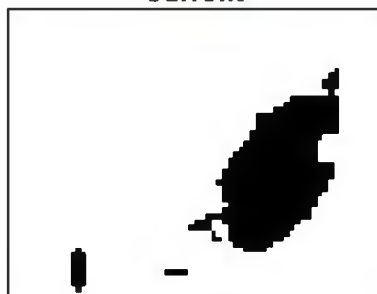
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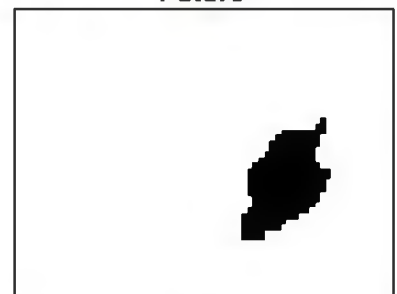
Polygala gymnoclada



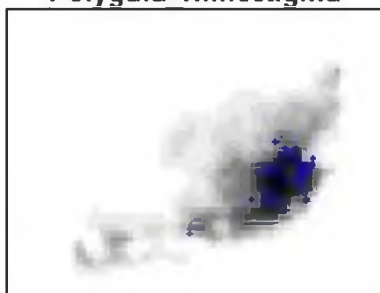
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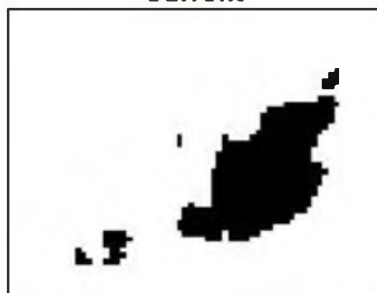
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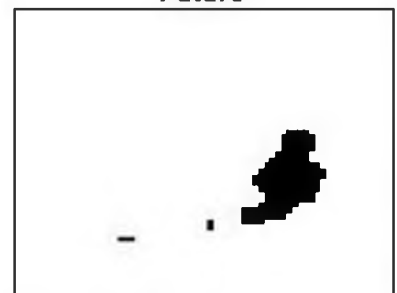
Polygala rhinostigma



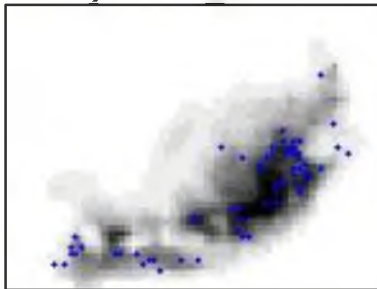
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Future



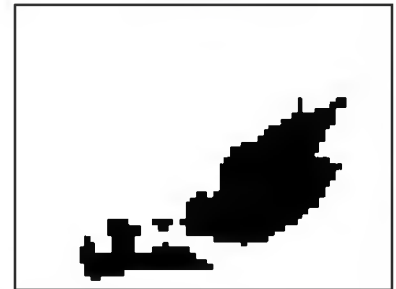
Polystichum monticol



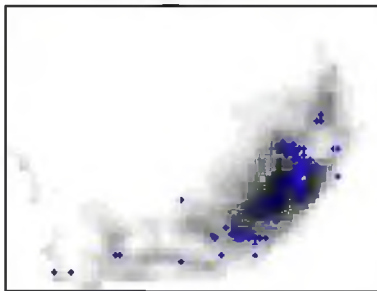
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Future



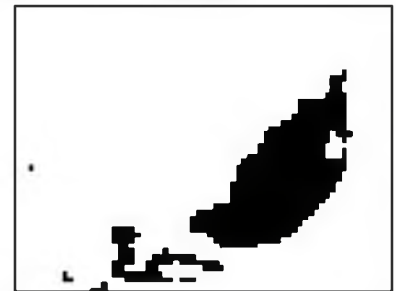
Protea subvestita



Current



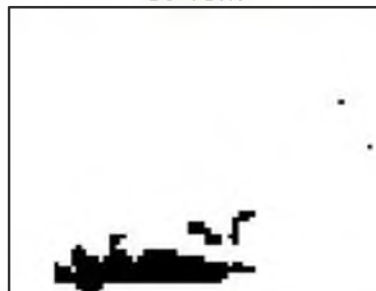
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Schoenoxiphium lancm



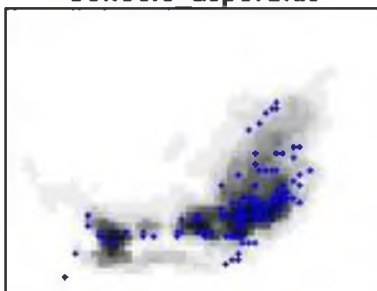
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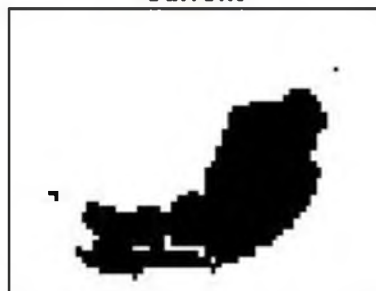
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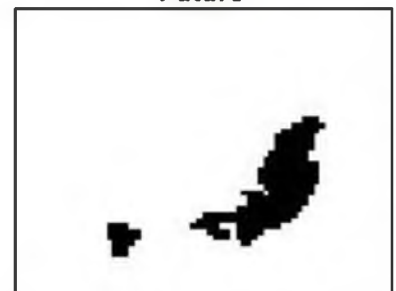
Senecio asperulus



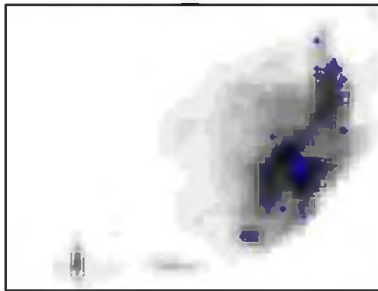
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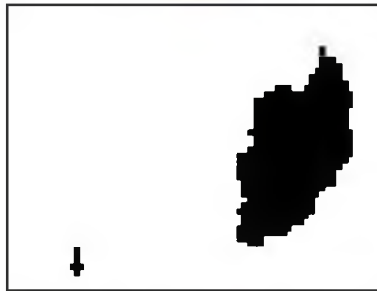
Future



Senecio barbatus



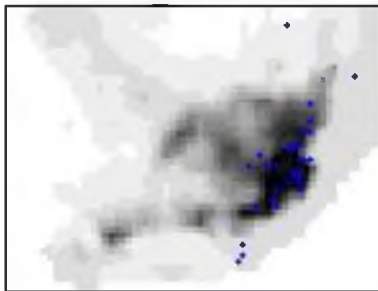
Current



Future



Senecio rhomboideus



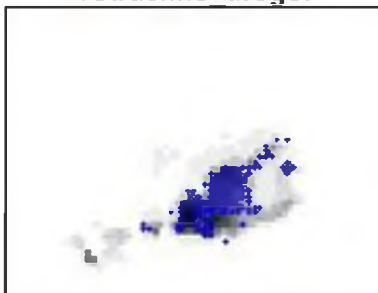
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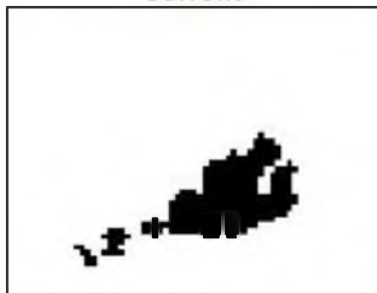
Future



Tetrachne dregei



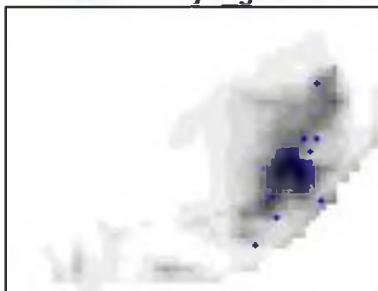
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Future



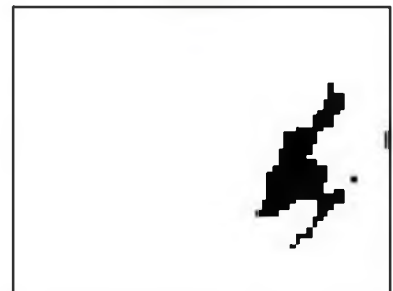
Zaluzianskya glareos



Current



Future



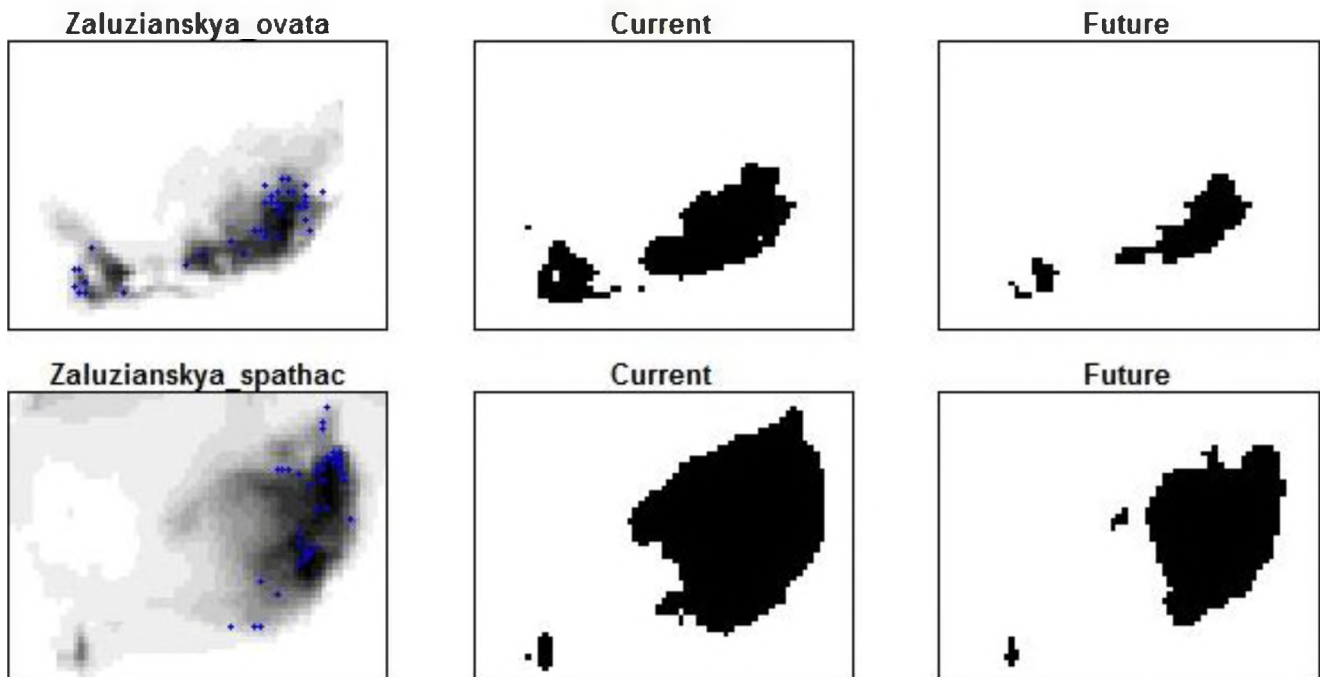
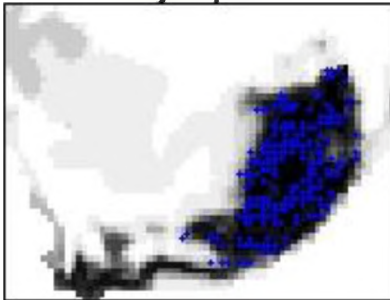


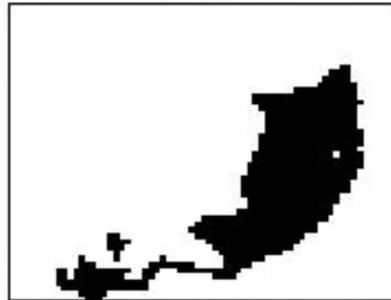
Figure A2: Final ensemble probability of occurrence and binary current and future predictions for the MaxEnt modelling method for each of the 46 species. Species abbreviations are as follows: *Asplenium adntm-ngrm* – *Asplenium adiantum-nigrum* var. *adiantum-nigrum*; *Asplenium trichomans* – *Asplenium trichomanes* subsp. *quadrivalens*; *Cheilanthes qudrpnnt* – *Cheilanthes quadripinnata*; *Cliffortia ramosissm* – *Cliffortia ramosissima*; *Geranium waakstrmnm* – *Geranium wakkerstroomianum*; *Helichrysum herbacem* – *Helichrysum herbaceum*; *Helichrysum suthrlnd* – *Helichrysum sutherlandii*; *Lotononis sericophyll* – *Lotononis sericophylla*; *Merxmuellera macowan* – *Merxmuellera macowanii*; *Polystichum monticol* – *Polystichum monticola*; *Schoenixiphium lancm* – *Schoenixiphium lanceum*; *Zaluzianskya glareos* – *Zaluzianskya glareosa*; *Zaluzianskya spathac* – *Zaluzianskya spathacea*.

Appendix 3

Aju.oph.



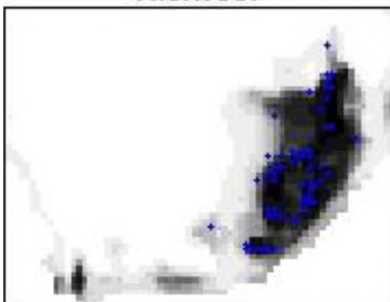
Current



Future



Alc.woo.



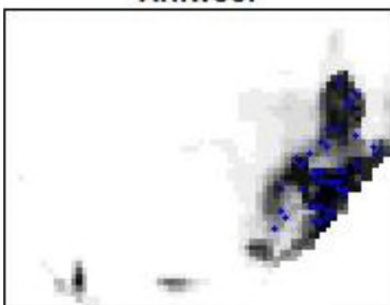
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Future



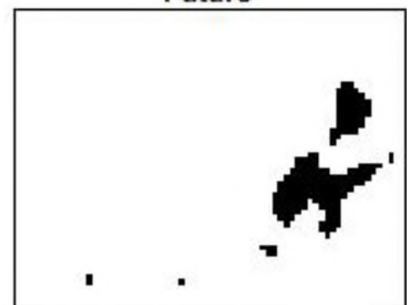
Ari.woo.



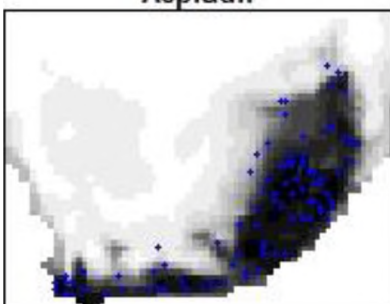
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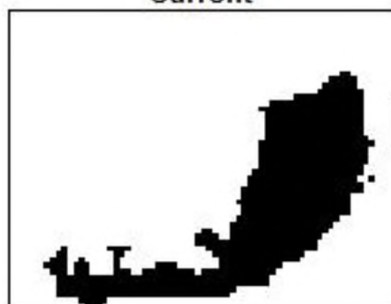
Future



Asp.adi.



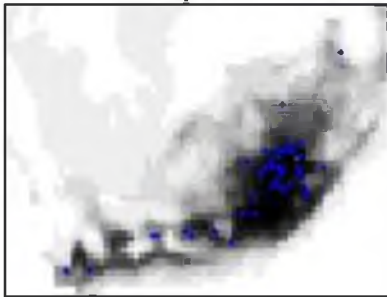
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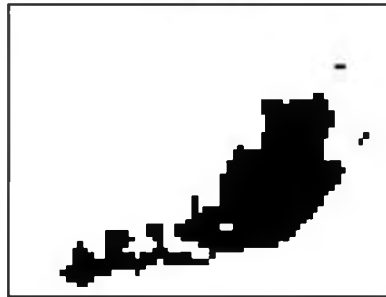
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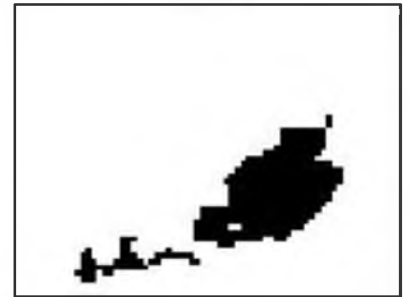
Asp.tri.



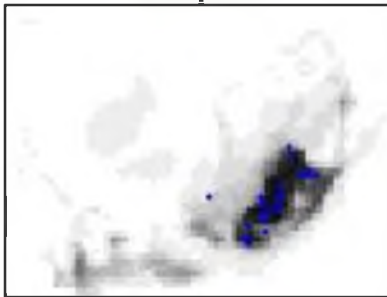
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Future



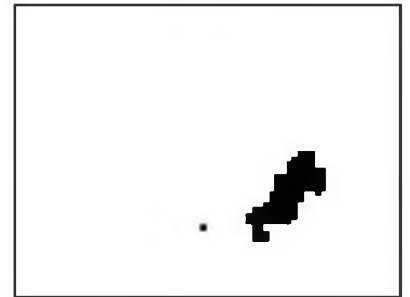
Ber.pur.



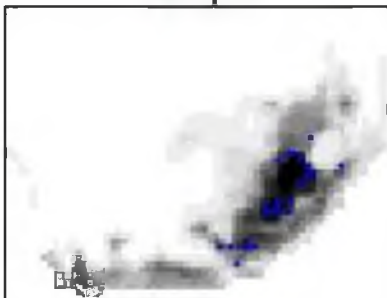
Current



Future



Bro.spe.



Current



Future



Bud.lor.

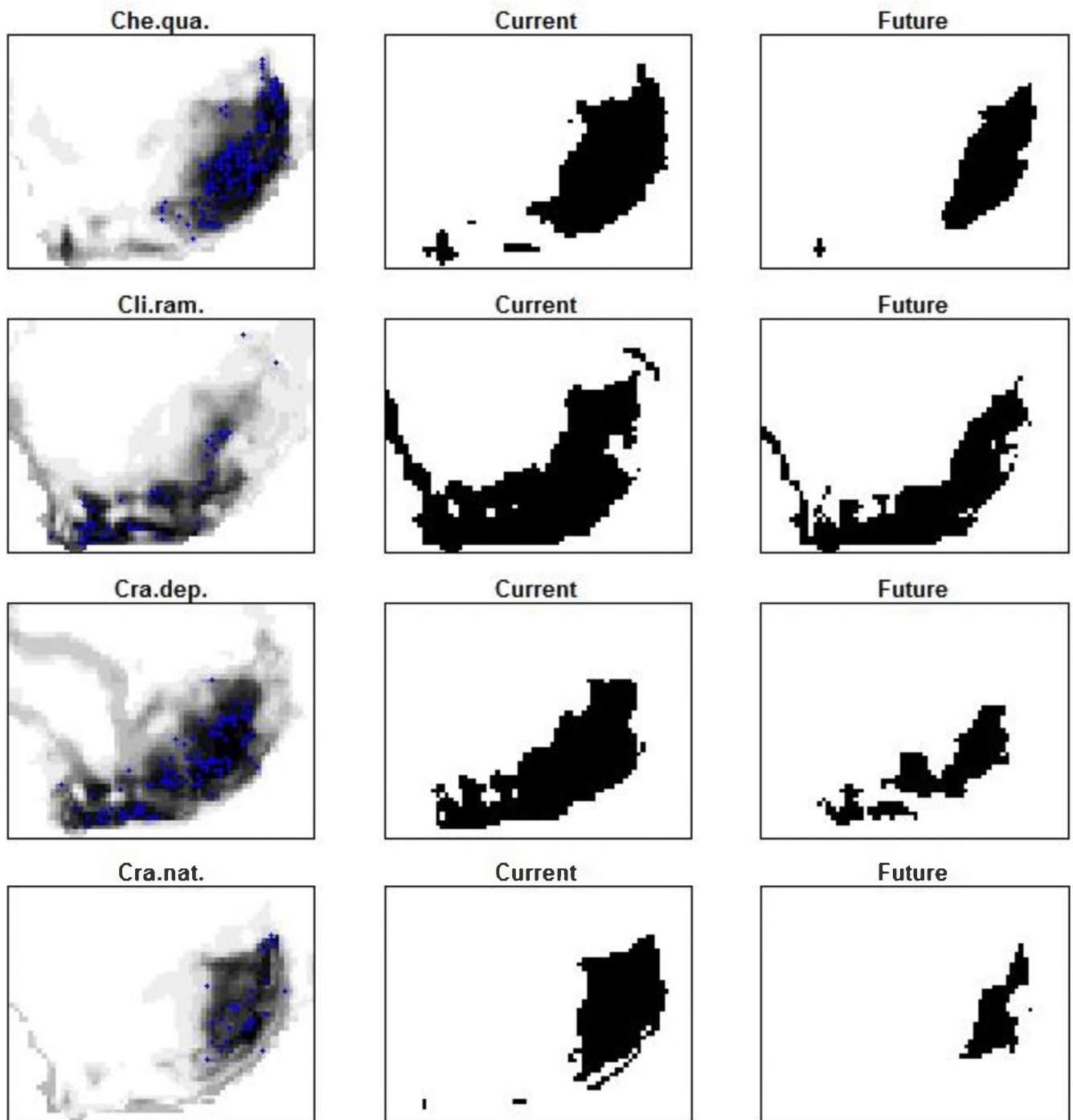


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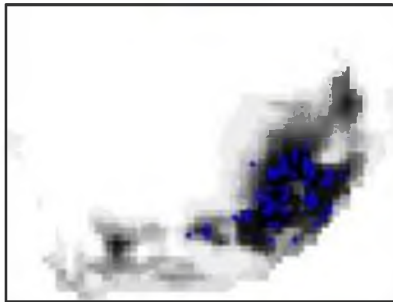


Future





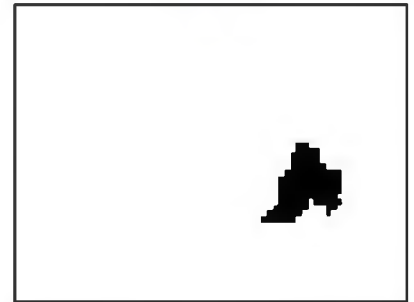
Die.rob.



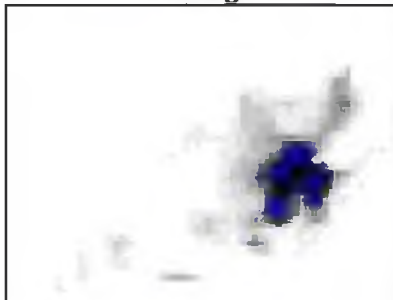
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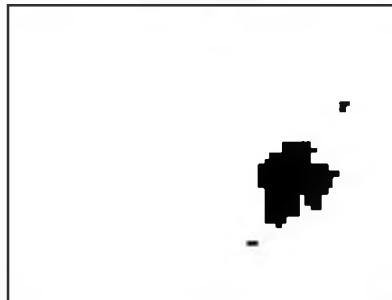
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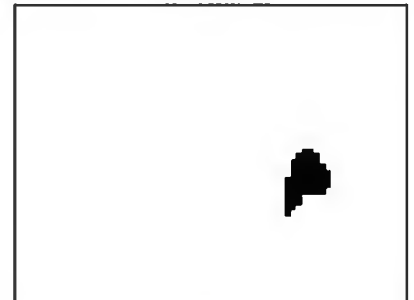
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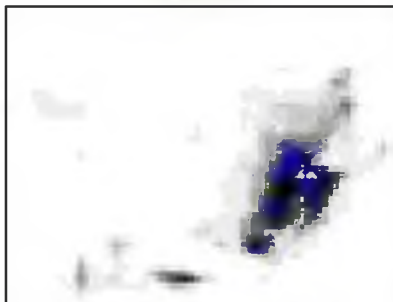
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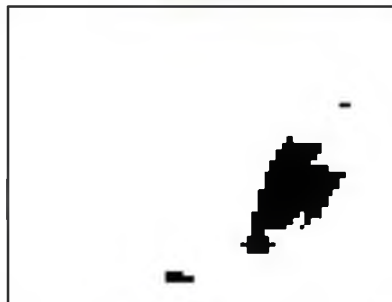
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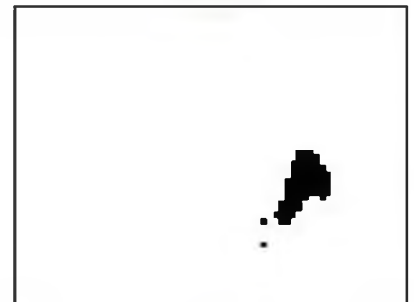
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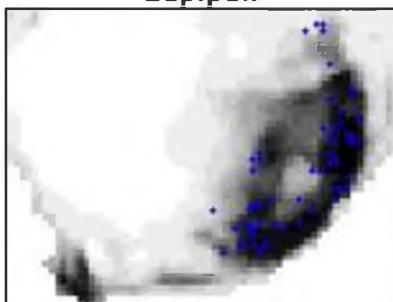
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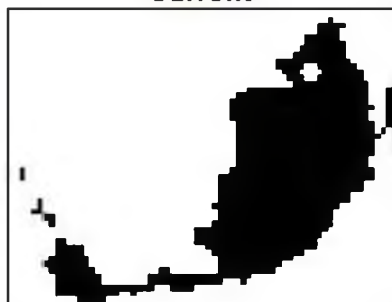
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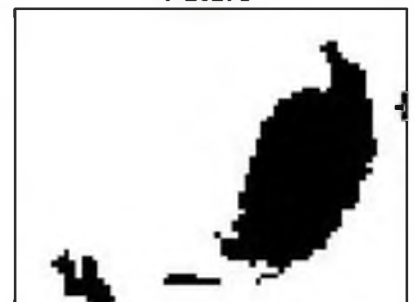
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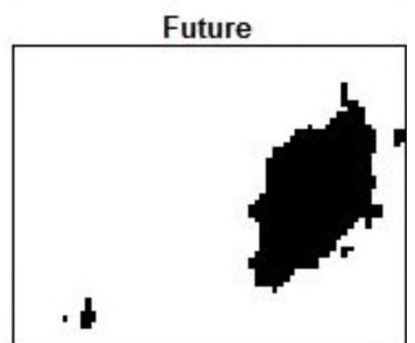
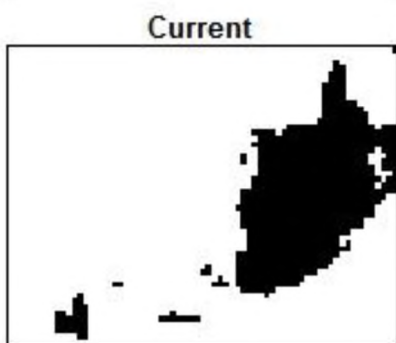
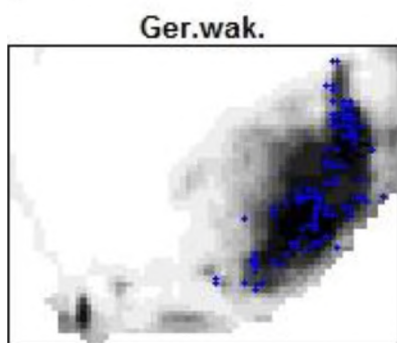
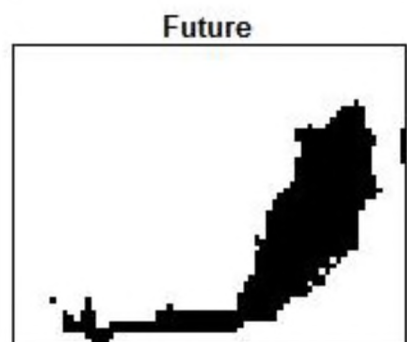
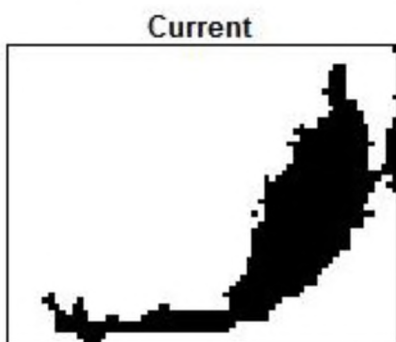
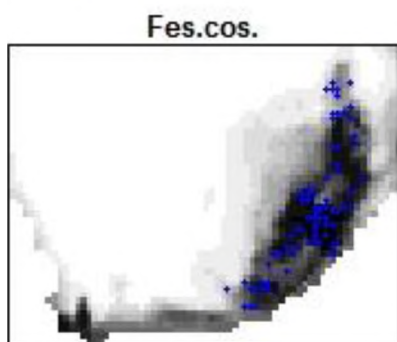
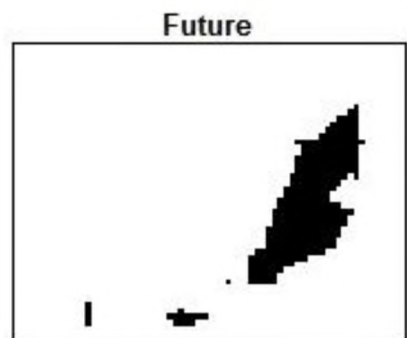
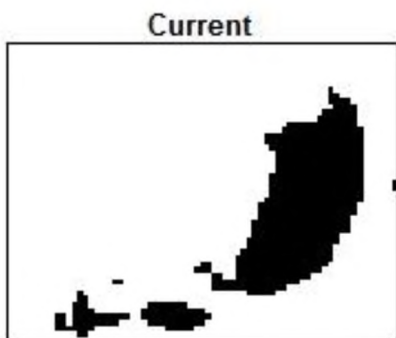
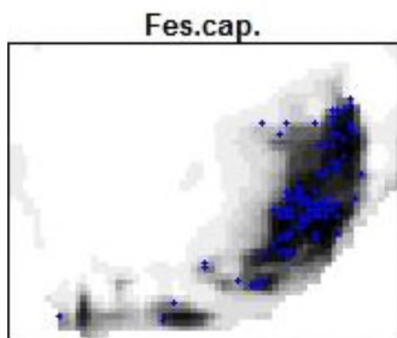
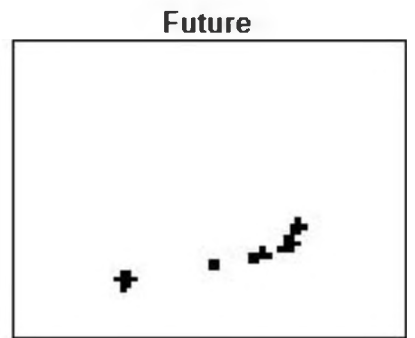
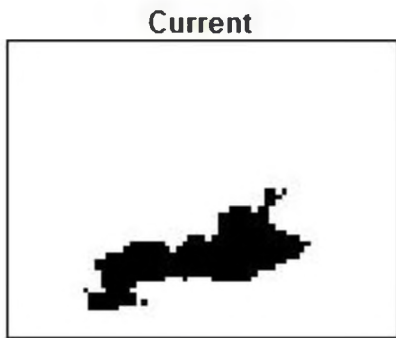
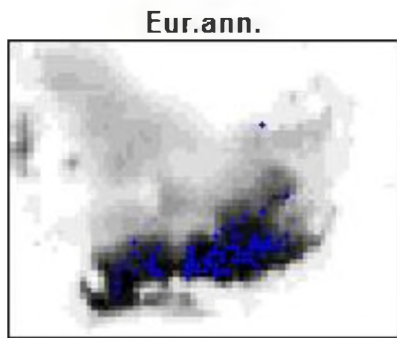


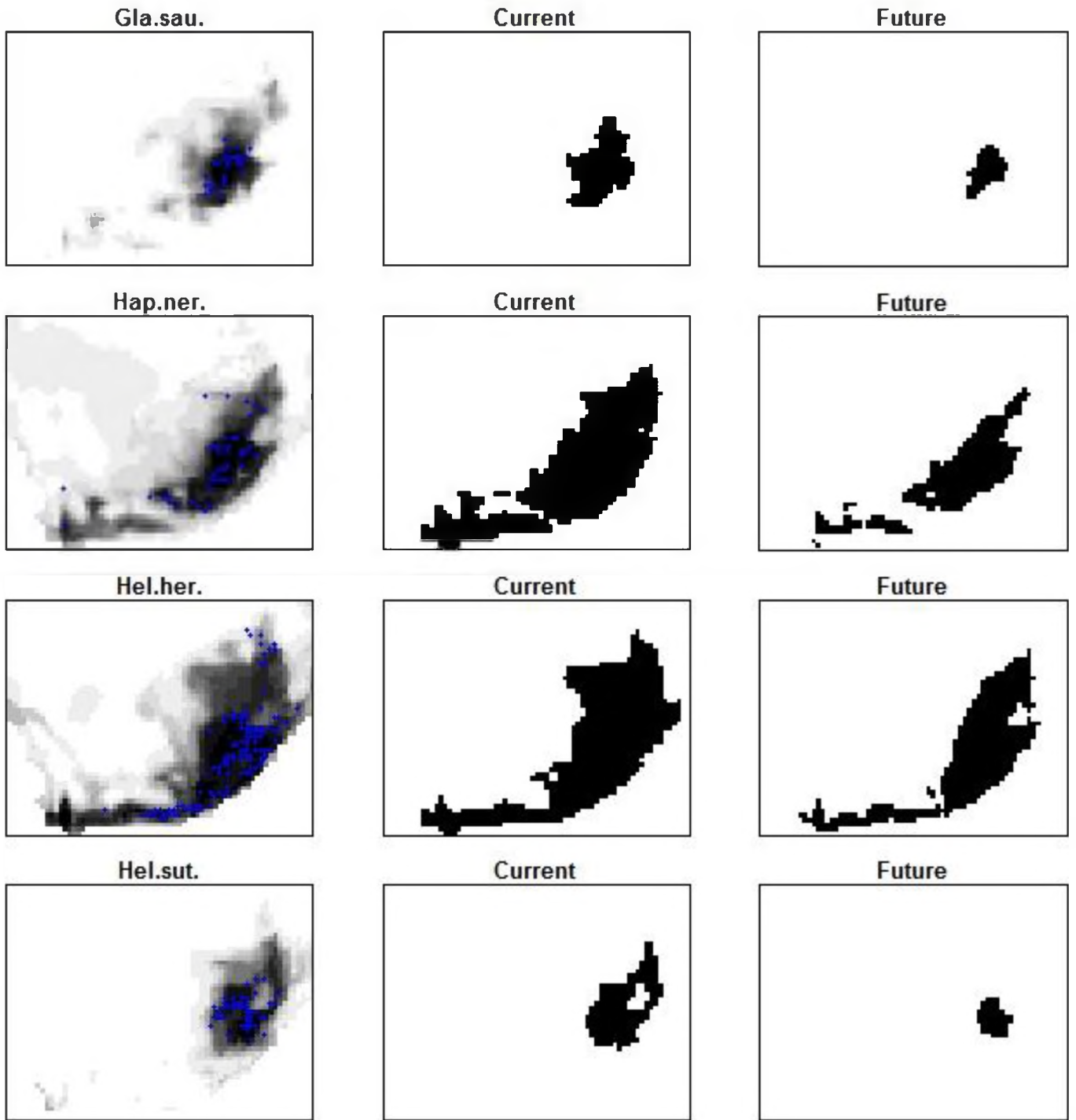
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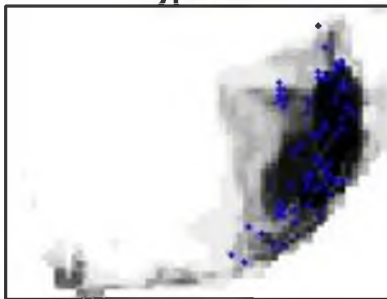
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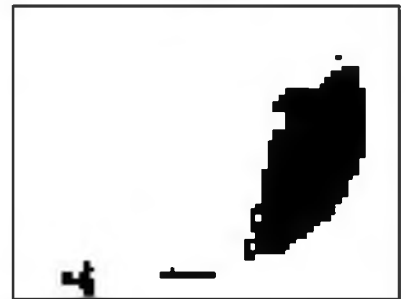
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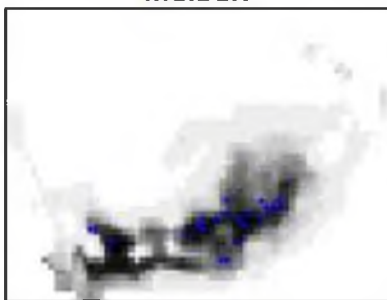
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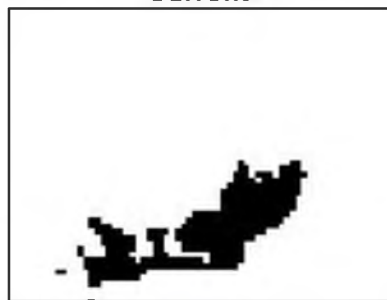
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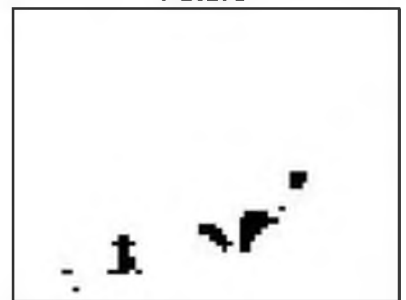
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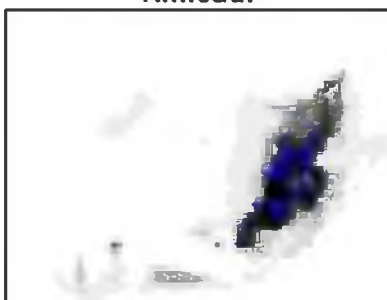
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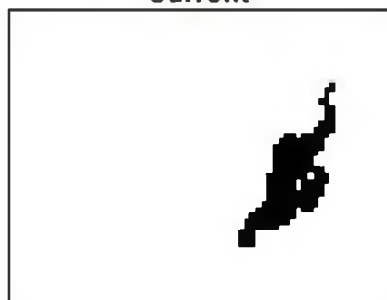
Future



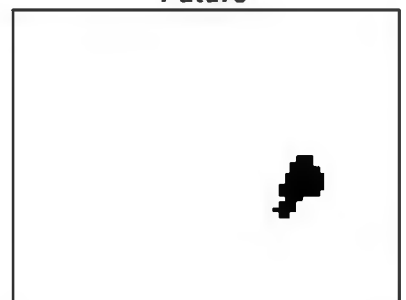
Kni.cau.



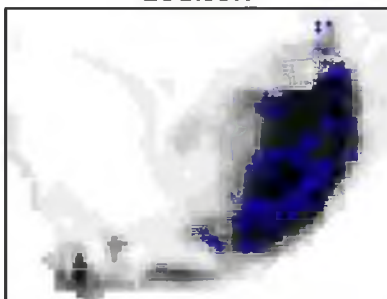
Current



Future



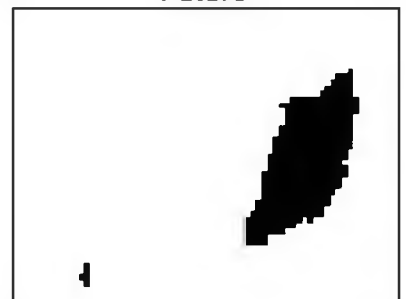
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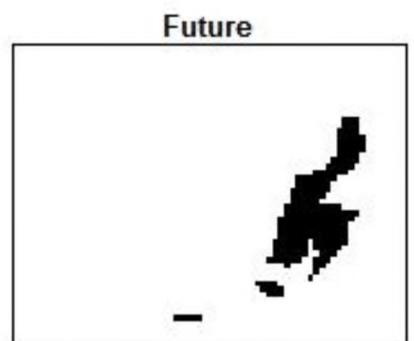
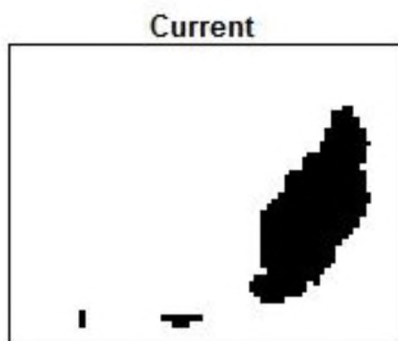
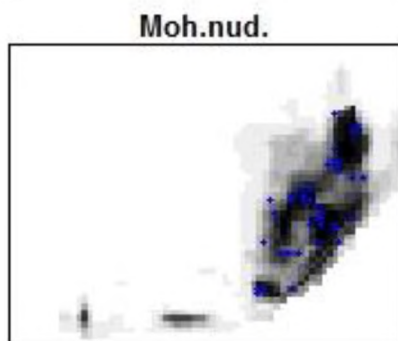
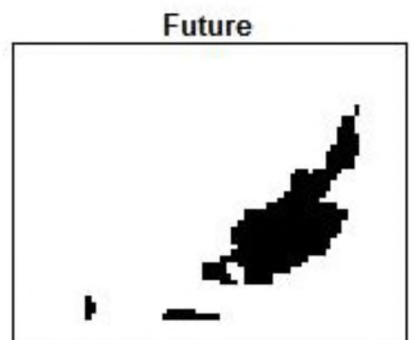
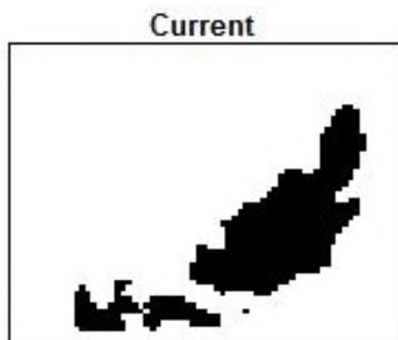
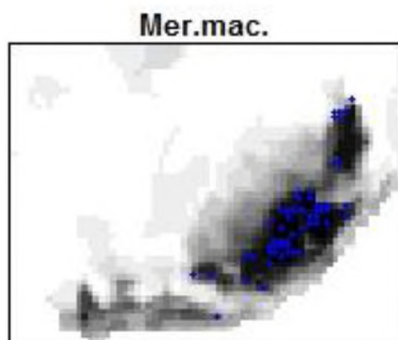
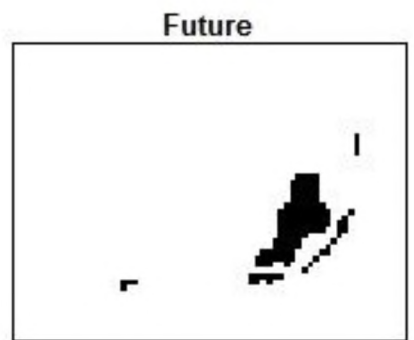
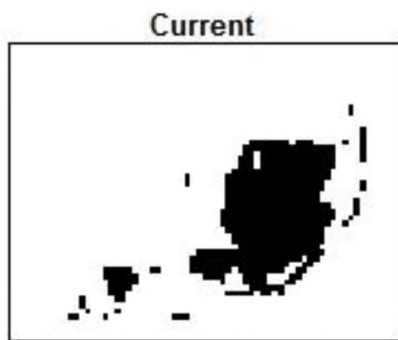
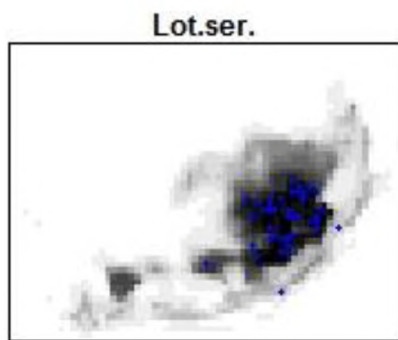
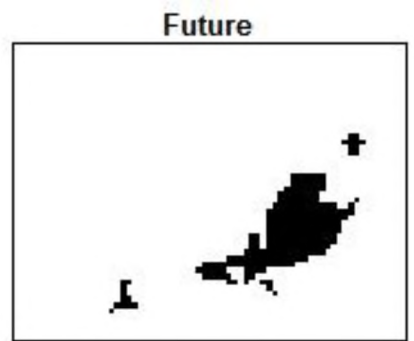
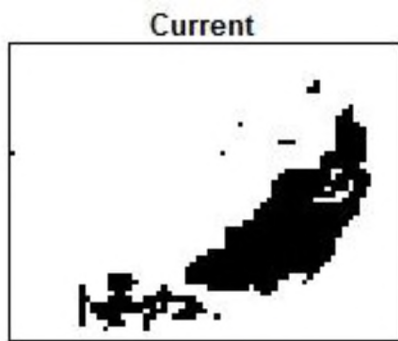
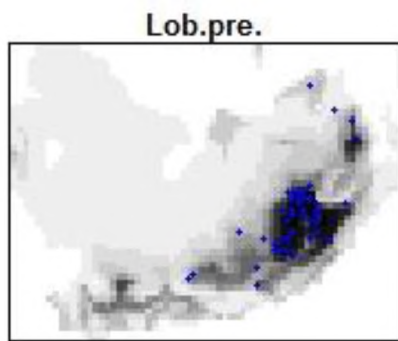


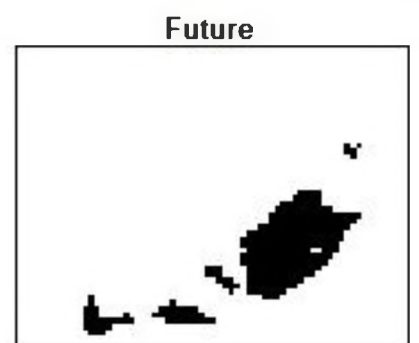
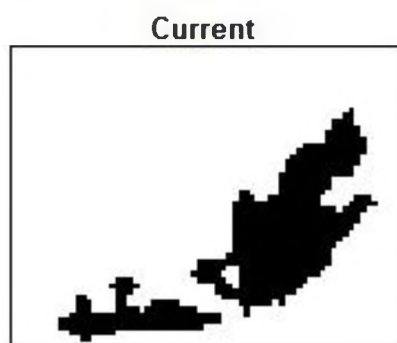
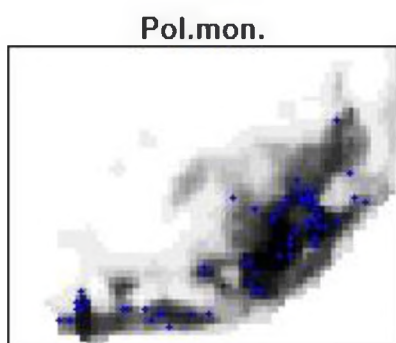
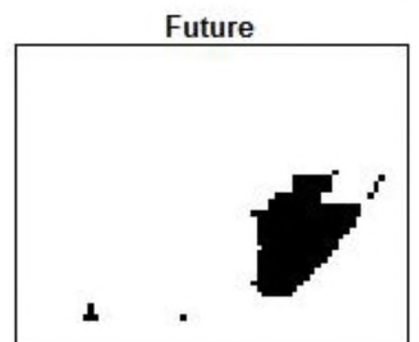
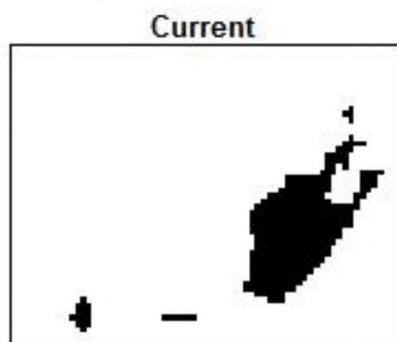
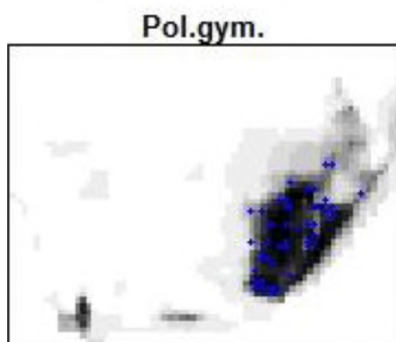
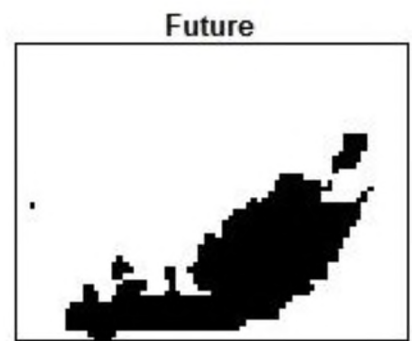
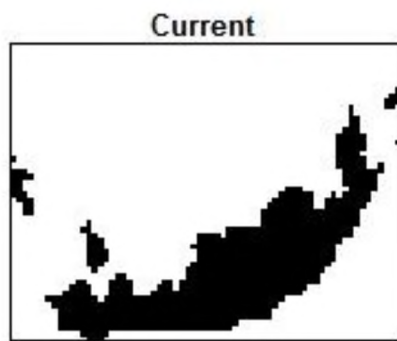
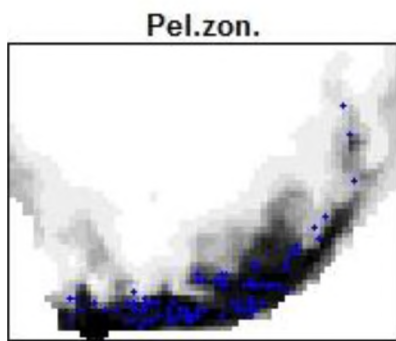
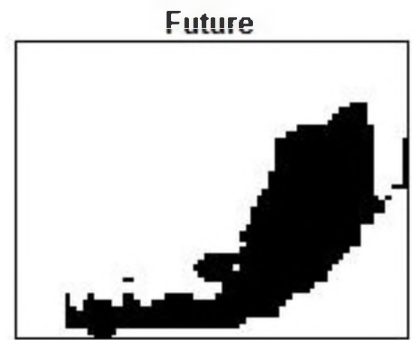
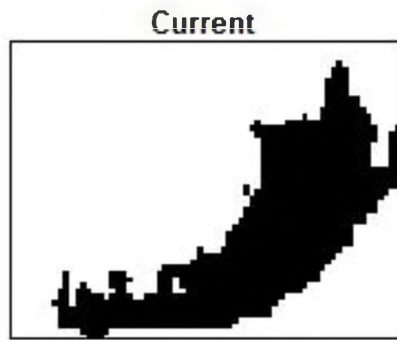
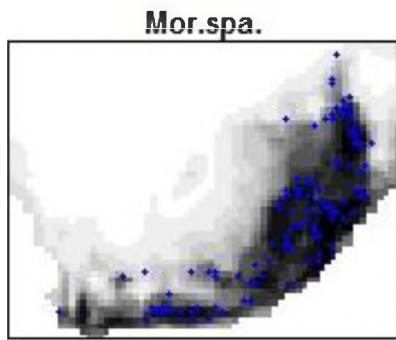
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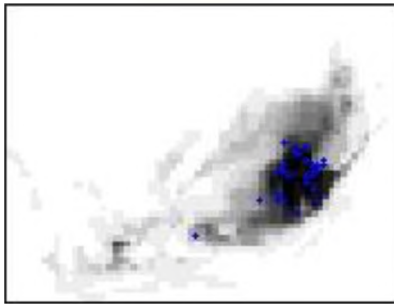
Future



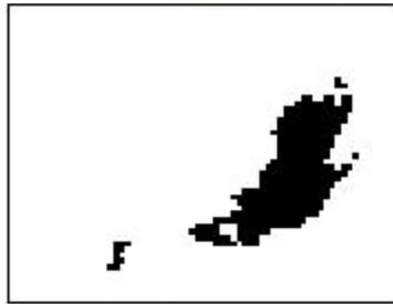




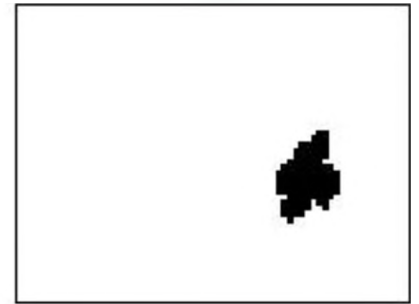
Pol.rhi.



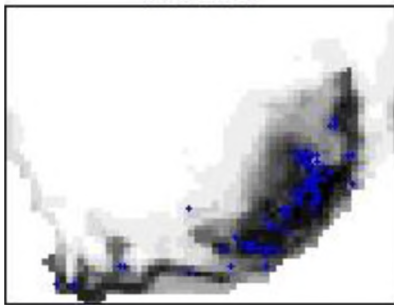
Current



Future



Pro.sub.



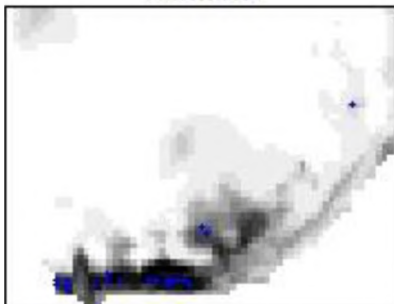
Current



Future



Sch.lan.



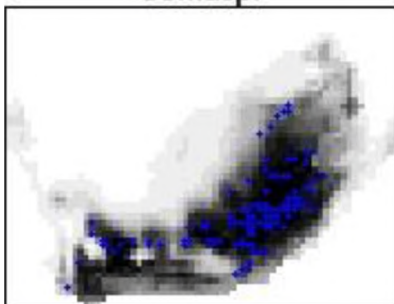
Current



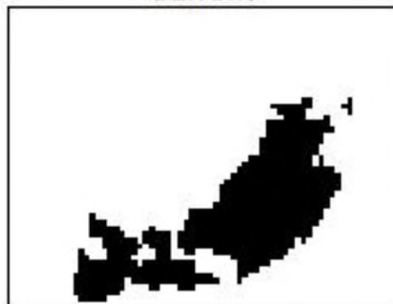
Future



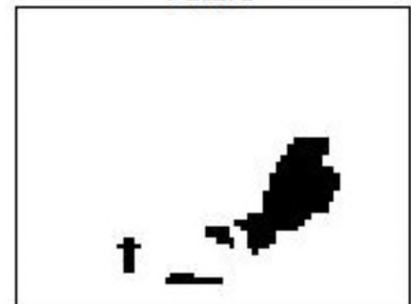
Sen.asp.

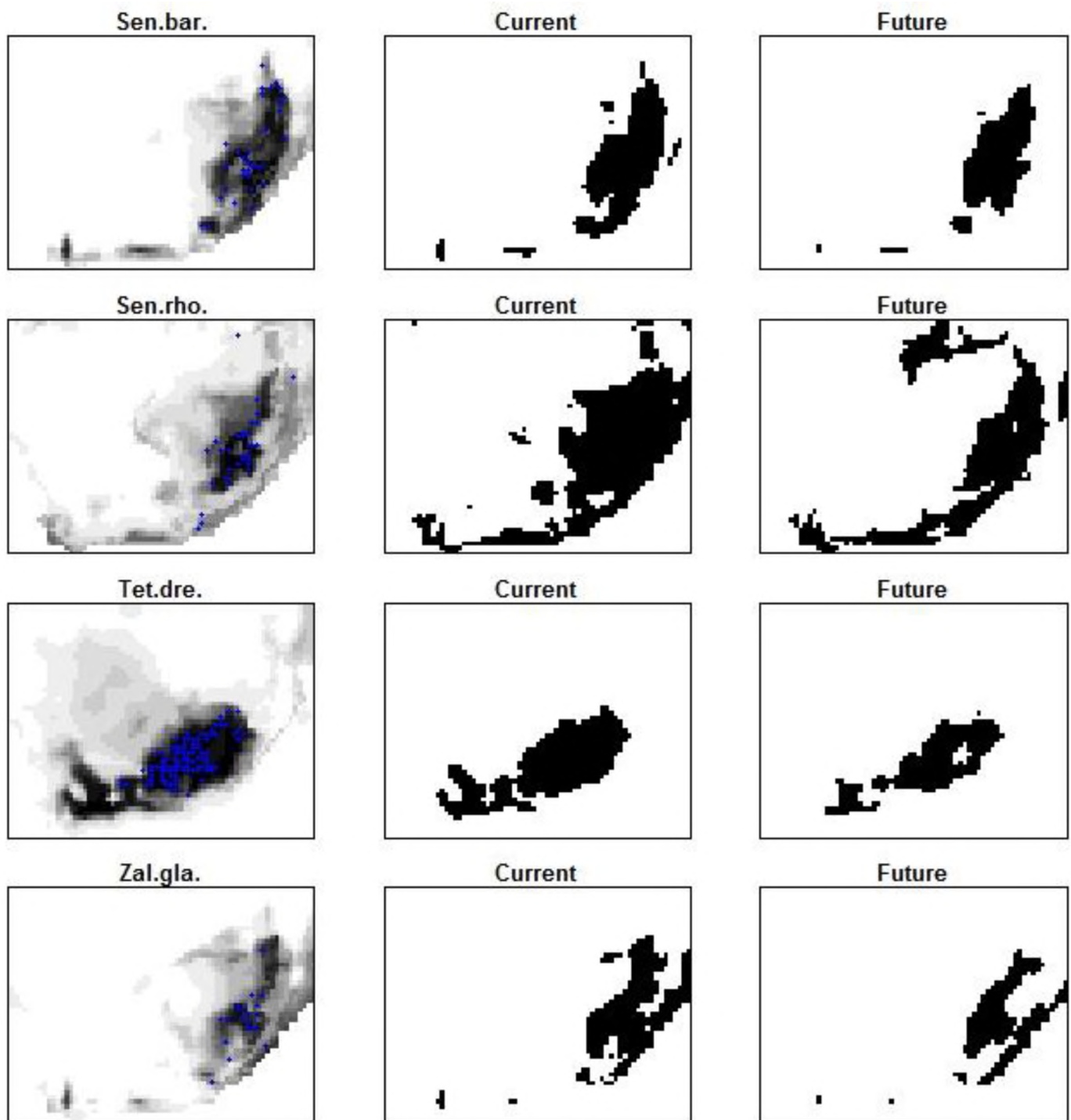


Current



Future





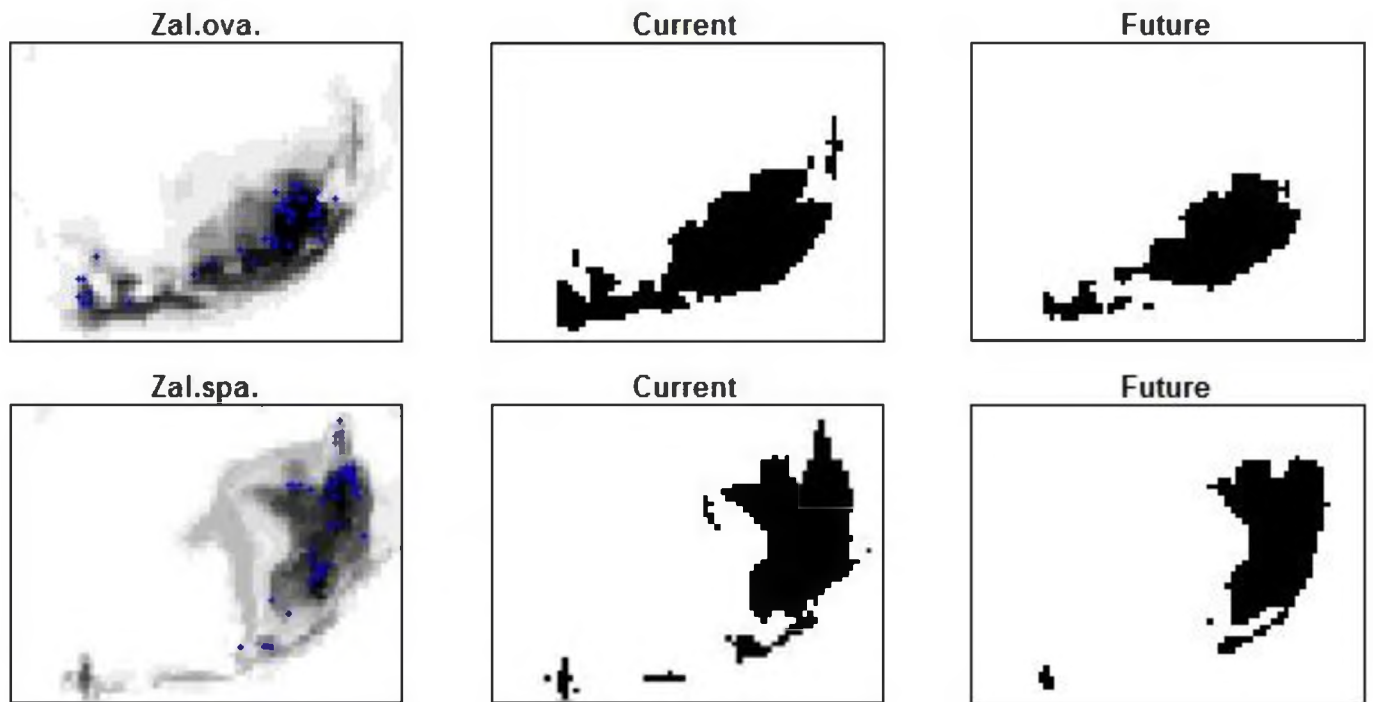


Figure A3: Final ensemble probability of occurrence and binary current and future predictions for the Biomod modelling method for each of the 46 species. Species abbreviations are as follows: Aju oph - *Ajuga ophrydis*; Alc woo - *Alchemilla woodii*; Ari woo - *Aristea woodii*; Asp adi - *Asplenium adiantum-nigrum* var. *adiantum-nigrum*; A. tri - *Asplenium trichomanes* subsp. *quadrivalens*; Ber pur - *Berkheya purpurea*; Bro spe - *Bromus speciosus*; Bud lor - *Buddleja loricata*; Che qua - *Cheilanthes quadripinnata*; Cli ram - *Cliffortia ramosissima*; Cra dep - *Crassula dependens*; C. nat - *Crassula natalensis*; Die rob - *Dierama robustum*; Eri alg - *Erica algida*; E. fri - *Erica frigida*; Eup pul - *Euphorbia pulvinata*; Eur ann - *Euryops annae*; Fes cap - *Festuca caprina*; F. cos - *Festuca costata*; Ger wak - *Geranium wakkerstroomianum*; Gla sau - *Gladiolus saundersii*; Hap ner - *Haplocarpha nervosa*; Hel sut - *Helichrysum sutherlandii*; H. Her - *Helichrysum herbaceum*; Hyp mul - *Hypoxis multiceps*; Ind bur - *Indigofera burchellii*; Kni cau - *Kniphofia caulescens*; Leu ser - *Leucosidea sericea*; Lob pre - *Lobelia preslii*; Lot ser - *Lotononis sericophylla*; Mer mac - *Merxmuellera macowanii*; Moh nud - *Mohria nudiuscula*; Mor spa - *Moraea spathulata*; Pel zon - *Pelargonium zonale*; Pol gym - *Polygala gymnoclada*; Pol mon - *Polystichum monticola*; P. Rhi - *Polygala rhinostigma*; Pro sub - *Protea subvestita*; Sch lan - *Schoenoxiphium lanceum*; Sen asp - *Senecio asperulus*; S. bar - *Senecio barbatus*; S. rho - *Senecio rhomboideus*; Tet dre - *Tetrachne dregei*; Zal gla - *Zaluzianskya glareosa*; Z. ova - *Zaluzianskya ovata*; Z. Spa - *Zaluzianskya spathacea*

