

Species Distribution modelling of Egyptian Plants under Climate Change

Emad Kaky, BSc, MSc

Thesis submitted to the University of Nottingham for the degree of Doctor of
Philosophy

September 2017

Dedication

To the most cherished people in my life:

My wife

To my eyes: my children

To my dear mother's spirit

Abstract

It is thought that climate change will have a major impact on species distributions by changing the habitat suitability for species. Species distribution modelling is a modern approach to assess the potential effect of climate change on biodiversity. We used 11 environmental variables with the MaxEnt algorithm to model the distributions of 114 Egyptian medicinal plant species under current conditions, then projecting them into three different future times (2020, 2050, and 2080) under two different climate-change emission scenarios (A2a and B2a), under two hypotheses about the capability of the species for dispersal (unlimited and no dispersal). Species richness maps for current and future times were produced. We tested the value of Egypt's Protected Areas under climate change by estimating the species richness inside and outside under each scenario. We assessed Egyptian medicinal plants based on IUCN Red List categories and criteria, and then used the SDMs for conservation planning with and without consideration of socioeconomic factors using Zonation software.

The A2 emission scenario was more harmful than B2 under all assumptions. Species richness inside Protected Areas was significantly higher than outside for all models. Based just on the records, between 75% and 90% of species could be classified as Least Concern, according to the assumptions made. Similarly, based on SDMs all species could be classified as LC at the current time, whilst in the future under climate change, up to 18% of species face the risk of extinction, depending on assumptions and based on the absolute time gap between the two future times. Based on 10 years, most species were assigned as Least Concern. Areas within PAs were no better in conservation prioritization value than area outside when socioeconomic costs (especially the Human Influence Index) were taken into account.

Species distribution models appear to be extremely useful for conservation planning under climate change, particularly when only sparse data are available.

Socioeconomic information adds a new dimension to conservation planning, which is actually misleading and incomplete without it.

Acknowledgements

I would like to thank my supervisor Dr Francis Gilbert for his valuable effort, advice and support through this project.

I would like to thank my wife Nasrin, who has supported me throughout these five years; without her support it would have been impossible to complete this work. My thanks to Ahmed El-Gabbas for his valuable advice, Ahmed Dhair for GIS help and advice, and Drs Anni Arponen and Heini Kujala for advice about Zonation. I would like thank my Institute, the 'Kalar Technical Institute', for this opportunity and permission to study outside Iraq. I thank the BioMap project for sharing the data upon which this study is based.

I would like thank all the members of my family abroad, who have supported me throughout these five years at all times.

I thank all my friends in the University of Nottingham, especially the people in my office for their support and encouragement.

Finally, special thanks to my sponsor, 'The Higher Committee for Education Development in Iraq' for funding and supporting me, giving me this opportunity to study at the University of Nottingham.

Publications

A list of peer-reviewed publications based on work presented in this thesis:

Kaky, E. & Gilbert, F. 2016. Using species distribution models to assess the importance of Egypt's protected areas for the conservation of medicinal plants. *Journal of Arid Environments*, 135, 140-146.

Kaky, E. & Gilbert, F. 2017. Predicting the distributions of Egypt's medicinal plants and their potential shifts under future climate change. *Journal of PLOS one*. In revision.

Kaky, E. & Gilbert, F. 2017. Using species distribution modelling to assess regional risk under climate change in data-sparse countries: the case of Egypt's medicinal plants. *Conservation Biology*. In revision.

Kaky, E. & Gilbert, F. 2017. Allowing for human socioeconomic impacts in the conservation of plants under climate change. *Landscape and Urban Planning*. In review.

Contents

1 Chapter One: General introduction	1
1.1 Niche theory	1
1.2 Dispersal limitation	3
1.3 Species distribution models	6
1.4 Environmental data	11
1.5 Predictions of the effects of climate change.....	13
1.6 Applications of species distribution modelling	17
1.6.1 Managing biodiversity under climate future.....	17
1.6.2 Predicting invasions	18
1.6.3 Biodiversity conservation.....	19
1.7 Medicinal plants	22
1.8 Thesis outline.....	24
2 Chapter Two: Using MaxEnt to select the best model compromise between complexity and performance	27
2.1 Introduction.....	28
2.2 Methods	33
2.3 Results.....	39
2.4 Discussion	50
3 Chapter Three: Using species distribution models to assess the importance of Egypt's Protected Areas for the conservation of medicinal plants	54
3.1 Introduction.....	55
3.2 Methods	57
3.3 Results.....	60
3.4 Discussion	69
4 Chapter Four: Plant distributions, climate change and Protected Areas in data-sparse countries	72
4.1 Introduction.....	73
4.2 Methods	76
4.3 Results.....	81
4.4 Discussion	99
5 Chapter Five: Using species distribution modelling to assess regional risk under climate change in data-sparse countries: the case of Egypt's medicinal plants	106
5.1 Introduction.....	107
5.2 Methods	111
5.3 Results.....	119
5.4 Discussion	127

6	Chapter Six: Allowing for human socioeconomic impacts in the conservation of plants under climate change.....	131
6.1	Introduction.....	132
6.2	Methods	134
6.3	Results.....	140
6.4	Discussion	158
7	Chapter Seven: General discussion	161
7.1	Conclusions	167
8	Bibliography.....	169
9	Appendices.....	189

Table of figures

Figure 1.1. The interaction between two abiotic environmental variables to give the fundamental (potential) niche. The central point is the optimum niche by this two-dimensional model. Organisms will be stressed at the extremes of tolerance, creating the limits. This simple model is helpful in recognizing how in reality a niche consists of many different abiotic factors with potentially complex interactions.	2
Figure 1.2. The niche is controlled by environmental variables (e.g. moisture and temperature). The gray area shows the combinations of temperature and moisture which the organism needs for survival and reproduction in its habitat; this resource space is known as the fundamental niche. The white area illustrates the subset of the fundamental niche known as the realized niche, what is left to an organism after its interactions with other species...	3
Figure 1.3. Diagram showing the relationship between geographical and environmental space for a hypothetical distribution. Geographical space is referenced by x and y coordinates; environmental space is n-dimensional in Hutchinson's niche concept, but here is explained by two dimensions (the two environmental variables, e1 and e2). The grey area of C in geographical space shows the known distribution, but there may be unknown areas (e.g. area A). In environmental space the grey area D represents occupied parts of the niche; notice that the entire area of the occupied niche may not contain occurrence records. The fundamental niche is indicated by the solid line in environmental space (D+E), which represents the range of abiotic conditions in which the species can live. In geographic space the solid lines describes the places that fall inside the fundamental niche (the potential distribution), including some areas unoccupied because of dispersal limitations or biotic interactions. For instance, area B is environmentally appropriate, but not within the actual distribution because the species does not have the ability to disperse across inappropriate environments to reach it. Equally, area C in geographical space is also within the potential distribution, but is also not occupied due to competition from a different species. Modified from (Pearson, 2007).	7
Figure 1.4. Area A represents the range of abiotic variables creating the fundamental niche (FN). Area B represents the region where the right combination of species occurs, which may or not interaction with area A to produce the realized niche (RN). Area M represents areas without barriers in which species can move and colonize. The interaction between A, B and M together produce the actual distribution (P). Modified from (Soberón and Peterson, 2005).....	8
Figure 1.5. Diagram of the steps essential for building and validating species distribution models. From (Pearson, 2007).	10
Figure 3.1. Frequency distribution of the mean AUC values achieved in the distribution models of plant species.....	66
Figure 3.2. Contribution to the final species distribution models made by each environmental predictor, illustrated by the mean permutation importance.	66
Figure 3.3. Numbers of species where particular variables were the best predictor in species distribution models. One of the variables (ndvi_max) included in modelling was never the best predictor.	67

Figure 3.4. Locations which Egyptian plants were sampled (square circle), and protected areas of Egypt (pink shading).	67
Figure 3.5. Species richness for predicting current distributions: (A) probability richness map resulting from summing all individual species probability maps then rescaled to the same range as that of the binary map; (B) binary richness map, produced from adding all individual species thresholded maps. The colours ranged from blue to red, which blue indicate for low species richness and red indicated for high species richness.	68
Figure 3.6. A) Comparison of binary predicted species richness (mean $\pm$ SE) between inside and outside protected areas, expected by adding all individual species distribution models; B) Comparison of probability predicted species richness (mean $\pm$ SE) between inside and outside protected areas.	68
Figure 4.1. An example to show predicted gain and loss areas in the future distribution of one species.	81
Figure 4.2. Predicted patterns of species richness using probability distributions for the present-day ('current') and into the future (2020, 2050, 2080) under two climate-change scenarios (A2a and B2a), created by adding together the maps of all 114 species and assuming unlimited dispersal. The colours indicate predicted species richness ranging between dark red (high) and blue (low).	85
Figure 4.3. Potential effect of different climate-change scenarios (A2a and B2a) on changes in future species richness (using probability species distributions and assuming unlimited dispersal); maps created as differences between future and current species richness maps (presented in Fig. 2). Red means increasing future species richness, and blue means declining future species richness.	86
Figure 4.4. Predicted patterns of species richness using binary distributions for the present-day ('current') and into the future (2020, 2050, 2080) under two climate-change scenarios (A2a and B2a), created by adding together the maps of all 114 species and assuming unlimited dispersal. The colours indicate predicted species richness ranging between dark red (high) and blue (low).	87
Figure 4.5. Potential effect of different climate change scenarios (A2a and B2a) on changes in future species richness (using binary species distributions and assuming unlimited dispersal); maps created as differences between future and current species richness maps (presented in Fig 3). Red means increasing future species richness, and blue means declining future species richness.	88
Figure 4.6. Predicted patterns of species richness using binary distributions for the present-day ('current') and into the future (2020, 2050, 2080) under two climate-change scenarios (A2a and B2a), created by adding together the maps of all 114 species and assuming no-dispersal. The colours indicate predicted species richness ranging between dark red (high) and blue (low).	89
Figure 4.7. Potential effect of different climate change scenarios (A2a and B2a) on changes in future species richness (using binary species distribution and assuming no-dispersal); maps created as differences between future and current species richness maps (presented in Fig 4). Red means decline future species richness, and blue means increasing future species richness.	90

Figure 4.8. Average predicted mean species richness assuming unlimited dispersal for binary and probability distributions, A): Current and future times with the A2a scenario; B): current and future times with the B2a scenario.	91
Figure 4.9. Predicted mean species richness assuming no-limited dispersal for binary distributions for the two scenarios A2a (left) and B2a (right).	91
Figure 4.10. Mean of the difference in predicted species richness between inside and outside each of the Egyptian PAs for both probability and binary distributions. Only this predictor was retained in the GLM model (scenario, time, and dispersal were not significant). Note that the mean differences are both highly significantly different from zero, implying that species richness is higher inside than outside PAs.	92
Figure 4.11. Species richness excess inside relative to outside PAs through time, using probability and binary distributions (both assuming unlimited dispersal). A): A2a scenario; B): B2a scenario.	92
Figure 4.12. Species richness excess inside relative to outside PAs using binary distribution (assuming no dispersal).	93
Figure 4.13. Spatial pattern of the number of species gained under climate change in the future (assuming unlimited dispersal). Colours indicate few (blue) to many (red) species gained.	94
Figure 4.14. Spatial pattern of the number of species lost under climate change in the future (assuming unlimited dispersal). Colours indicate few (blue) to many (red) species lost.	95
Figure 4.15. Spatial pattern of the number of species lost under climate change in the future (assuming no dispersal). Colours indicate few (blue) to many (red) species lost.	96
Figure 4.16. Predicted future species turnover (change in species composition), assuming unlimited dispersal. The colours indicate ranges, from low (blue) to high (red) change in species composition).	97
Figure 4.17. Predicted patterns of temperature distributions (Bio 6) across Egypt for the present-day ('current') and into the future (2020, 2050, 2080) under two climate-change scenarios (A2a and B2a). The colours indicate predicted temperature ranging between dark red (high) and blue (low).	98
Figure 5.1. Binarized map for <i>Chiliadenus montanus</i> showing the calculation of the Jaccard similarity index (in this case equal to $0.61 = C / (A+B-C)$, where A is the EOO derived from the SDM model, B is the EOO derived from the records, and C is the area of overlap between A and B.	117
Figure 5.2. Scatterplots showing the relationships between the Extent of Occupancy (EOO) measurements for the records ($EOO_{records}$), the species distribution models (EOO_{model}) and the model quality (area under the curve, AUC) of the SDMs: a) $EOO_{records}$ and EOO_{model} ; and b) EOO_{model} and AUC. These indicate how good the SDMs are in relation to the more traditional IUCN methods of calculating the EOO.	122
Figure 5.3. Scatterplots exploring variables affecting the validity of measuring the Extent of Occupancy from species distribution models (EOO_{model}). The relationships between: a) the number of records and $EOO_{records}$; b) the number of records and EOO_{model} ; c) the number of records and the differences between $EOO_{records}$ and EOO_{model}	123
Figure 5.4. Scatterplots with Spearman rank correlations showing: a) the relationship between EOO_{model} and Jaccard Similarity Index; b) the relationship between $EOO_{records}$ and Jaccard Similarity Index; c) the number of the records and Jaccard Similarity Index.	124

Figure 6.1. Cost layer used in Zonation and Egyptian Protected Areas. a) is Human Influence Index (HII), b) Population density grids both used with unlimited and no dispersal assumptions. Both layers rescaled to be in the same scale. c) Egyptian Protected Areas overlying on Egypt's political boundaries.....	139
Figure 6.2. Conservation prioritization ranked values using Additive Benefit Function removal cell for current and future assuming unlimited dispersal without using costs. The colours ramp from red colour high conservation values, for blue colour low conservation value.....	143
Figure 6.3. Conservation prioritization ranked values using Core – Area Zonation removal cell for current and future assuming unlimited dispersal without using costs. The colours ramp from red colour high conservation value, for blue colour low conservation value.....	144
Figure 6.4. Conservation prioritization ranked values using Additive Benefit Function removal for current and future assuming no dispersal without using a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.....	145
Figure 6.5. Conservation prioritization ranked values using Core – Area Zonation removal for current and future assuming no dispersal without using a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.....	146
Figure 6.6. Conservation prioritization ranked values using Additive Benefit Function removal cell for current and future assuming unlimited dispersal using HII cost layer. The colours ramp from red colour high conservation values, for blue colour low conservation value.....	147
Figure 6.7. Conservation prioritization ranked values using Core – Area Zonation removal cell for current and future assuming unlimited dispersal using HII cost layer. The colours ramp from red colour high conservation value, for blue colour low conservation value.....	148
Figure 6.8. Conservation prioritization ranked values using Additive Benefit Function removal for current and future assuming unlimited dispersal using population density as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.....	149
Figure 6.9. Conservation prioritization ranked values using Core – Area Zonation removal for current and future assuming unlimited dispersal using population density as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.....	150
Figure 6.10. Conservation prioritization ranked values using Additive Benefit Function removal for current and future assuming no dispersal using HII as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.....	151
Figure 6.11. Conservation prioritization ranked values using Core – Area Zonation removal for current and future assuming no dispersal using HII as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.....	152
Figure 6.12. Conservation prioritization ranked values using Additive Benefit Function removal for current and future assuming no dispersal using population density as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.....	153
Figure 6.13. Conservation prioritization ranked values using Core – Area Zonation removal for current and future assuming no dispersal using population density as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.....	154

Figure 6.14. a) mean Zonation PA value excess for different cost layers (human influence index HII, population density Pop, and No-cost) for both dispersal assumptions; b) mean Zonation PA value excess for each PA, across all assumptions; c) mean Zonation PA value excess for each PA just for the HII cost, across all other assumptions. 156

Table of Tables

Table 2.1. Environmental variables used to build the models (The highlighted one thrown), after applying Variance Inflation Factor (VIF) to reduce the collinearity.....	42
Table 2.2. Mean and SD of AUC values for each feature type (model A with 10-fold partitioning).....	43
Table 2.3. AUC values and standard deviation with all feature combinations for model A with single partitioning, 70% for model building and 30% for model testing.	43
Table 2.4. Mean and SD of AUC values for each feature type (model B with 10-fold partitioning).....	44
Table 2.5. AUC values and standard deviation for model B with single partitioning, 90% for model building and 10% for model testing.....	44
Table 2.6. Mean and SD of AUC values for each feature type (model C with 10-fold partitioning).....	45
Table 2.7. AUC values and standard deviation for model C with single partitioning, 90% for model building and 10% for model testing.....	45
Table 2.8. Mean and SD of AUC values for each feature type (model D with 10-fold partitioning).....	46
Table 2.9. AUC values and standard deviation for model D with single partitioning, 70% for model building and 30% for model testing.....	46
Table 2.10. Mean and SD of AUC values for varying numbers of background points (model E).	47
Table 2.11. Mean and SD of AUC values for each feature type with varying values of the regularisation multiplier (model F).....	47
Table 2.12. Effect of single partitioning and 10 K-fold partitioning on the omission rate and the difference between train and test AUCs (model A).	49
Table 2.13. Omission rate and the difference between mean train and test AUC values with varying regularisation multipliers (QPT model only, with default setting 1).	49
Table 3.1. The plant species used for species distribution models, showing the model fit in terms of the mean and standard deviation of the AUC values of the 10 replicates.....	63
Table 4.1. Overview of greenhouse gas emissions between 1990 – 2100, modified from the IPCC special report on emission scenarios (Nakicenovic <i>et al.</i> , 2000). Units are given in the table.....	104
Table 4.2. Standardized anthropogenic emissions (CO ₂ , N ₂ O, CH ₄ , and NO _x) for the ALM region (Africa and Latin America), the region containing our study area; modified from (Nakicenovic <i>et al.</i> , 2000) Units given in the table. ..	104
Table 4.3. Mean number of species gained, lost, and turnover under both dispersal assumptions (unlimited and no dispersal) for both scenarios (A2 and B2) at various future times (2020, 2050, and 2080).	105
Table 4.4. Mean value for all environmental variables related to temperature and precipitation.....	105
Table 5.1. IUCN Red List Categories and Criteria used to assess the plant species. Because of a lack of information, the highlighted sub-Criteria were not able to be used, resulting in preliminary assessments only for the 'current' assessments (IUCN, 2016).	118
Table 5.2. Number of plant species categorized into each of the preliminary National IUCN categories based on EOOrecords, and on AOOrecords under three different assumptions about the minimum distance between 'locations'.	

These are 'preliminary' because the lack of data does not allow us to assess the sub-Criteria 'continuing decline' or 'extreme fluctuations'.	125
Table 5.3. Number of plant species assessed in each IUCN category assuming unlimited dispersal.....	126
Table 5.4. Number of plant species assessed in each IUCN category assuming no dispersal.....	126
Table 6.1. Results of Anova based on GLM for difference inside - outside PAs in Zonation Score.....	157
Table 6.2. Species weighting based on different kind of scoring.....	157

1 Chapter One: General introduction

1.1 Niche theory

There are still a variety of points of view about the concept of the niche in a variety of different ecological disciplines (Holt, 2009). Niche theory is one of the fundamental concepts underlying the building of species distribution models in biodiversity, and therefore it is very important to clarify it carefully right at the start. There are many uses of the niche concept in different area of biodiversity, but also a lack of clarity in its definition because there are many and varied meanings for the term (McInerny and Etienne, 2012). Despite its crucial importance, the concept has been interpreted differently throughout the history of ecology, but frequently it is depicted descriptively as a match between habitats and abundances (Chase and Leibold, 2003; Kearney *et al.*, 2010). The first person to use the term 'niche' was Joseph Grinnell (1917, 1924), who thought of it as the environmental conditions under which species survive and reproduce mainly abiotic factors such as temperature or precipitation (Grinnell, 1924; Vandermeer, 1972). However, Charles Elton (1927) explained the niche of a species as its habitat or role in the community, thus focusing on the relationship between species more than abiotic factors (Vandermeer, 1972), as well as the effect that species have on their environment (Leibold, 1995; Chase and Leibold, 2003).

G Evelyn Hutchinson (1957) was the first to formalize niche theory properly. Hutchinson proposed that the niche could be modelled as an imaginary space with many dimensions, in which each dimension or axis represents the range of some environmental condition or resource that is required by the species. Consequently, the niche of a plant may include the range of temperature or humidity that it can tolerate, the amount of light required for photosynthesis, and smallest levels of essential soil nutrients that it can take up (Figure 1.1). This ecological concept of the niche involves the interface between species and their environment (Kearney *et al.*, 2010).

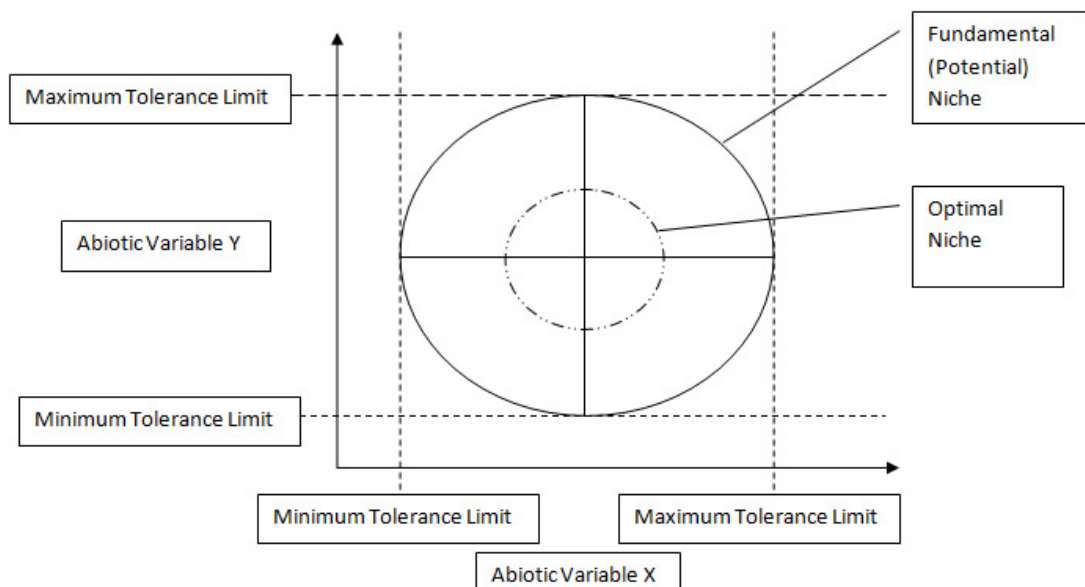


Figure 1.1. The interaction between two abiotic environmental variables to give the fundamental (potential) niche. The central point is the optimum niche by this two-dimensional model. Organisms will be stressed at the extremes of tolerance, creating the limits. This simple model is helpful in recognizing how in reality a niche consists of many different abiotic factors with potentially complex interactions.

In niche theory, it is important to distinguish between fundamental and realized niches. The fundamental (potential) niche of a species includes the entire scope of environmental conditions that are appropriate for continued existence without the impact of interspecific competition or predation by other species. The realized (actual) niche defines that part of the fundamental niche actually occupied by the species (Hutchinson, 1957; Serra-Diaz *et al.*, 2012): see Figure 1.2. Despite the fact that the most common and readily available predictors which are used to describe the niche are environmental variables, others involving interactions with other species (e.g. land cover use, competition) or dispersal barriers also could be significant contributors to determining the distribution. It can be very difficult to include these kinds of factors in models of species distributions (Pulliam, 2000).

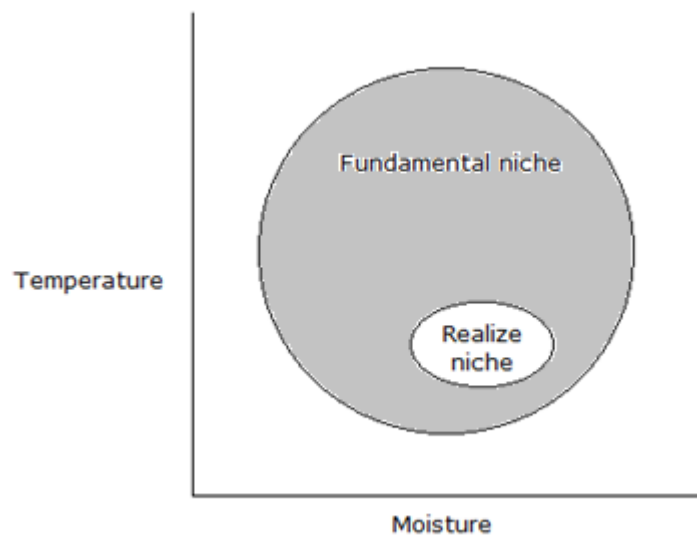


Figure 1.2. The niche is controlled by environmental variables (e.g. moisture and temperature). The gray area shows the combinations of temperature and moisture which the organism needs for survival and reproduction in its habitat; this resource space is known as the fundamental niche. The white area illustrates the subset of the fundamental niche known as the realized niche, what is left to an organism after its interactions with other species

According to Grinnell (1917) two species cannot persist together in the same habitat when they have exactly the same niche. This understanding is now termed “competitive exclusion”, and can be illustrated experimentally by creating competition in the laboratory between two or more species for the same resource. The first such experiment was done by Gause (1934) using protozoan species, and a famous later experiment by Park (1948) used flour beetles. It is much harder to test competitive exclusion in the field. Therefore, based on above explanation it is important for ecologists who deal with geographical distributions of species to understand Grinnellian and the Eltonian niche theory, and compared with new perspectives about realized and fundamental niche for more understanding (Soberón, 2007).

1.2 Dispersal limitation

There are many species living on the earth that are restricted to small geographical areas with small ranges of environmental conditions. Geographical patterns in global biodiversity result from the overlap in distribution of thousands of

species with limited geographic ranges (Lomolino *et al.*, 2006). There are three overarching factors that determine species distributions. Firstly, there are abiotic conditions involving physical environmental variables (e.g. rainfall, temperature, substrate type, etc.). Secondly, there are biotic interactions; competition and predation are two significant processes determining geographical spatial patterns of distribution and abundance (MacArthur, 1972). Finally, there are dispersal limitations. All these three factors can constrain the occurrence of species in suitable areas (Soberón and Peterson, 2005), and species distributions are shaped by overlapping multiple factors (Algar *et al.*, 2013) acting at different scales (Soberón, 2007; Soberón and Nakamura, 2009). Dispersal is one of the most important processes for the survival of species under climate change, which requires a spatial response from a population (Hanski and Gilpin, 1997; Berg *et al.*, 2010).

Individual movement of organisms from their original habitats to new breeding sites is called biological dispersal. The action of dispersal includes three important stages, departure, transfer and settlement, where each phase has a different balance of fitness costs and benefits (Bonte *et al.*, 2012). The factors can be complex. For example, plant species colonizing the northern regions of Western Europe from the south as a result of climate change may escape temporarily from soil pathogenic action. These plant species are dispersed more rapidly than their natural enemies, and this spatial divergence results in a less net negative plant–soil response than similar natural species in the new variety (Berg *et al.*, 2010). Biotic interaction dispersal barriers are important factors impacting and determining geographical distributions (Holt, 2009).

Geographical barriers or long distances from suitable habitats may be the effective factors leading to the absence of some species from climatically suitable areas (Pulliam, 2000). Franklin *et al.*, (2013) used a good rainforest survey dataset from three archipelagos (Fiji, Tonga, and Samoa) to test the roles of dispersal limitation, speciation, environmental filtering, and competitive displacement on species structure of forest tree populations. They found that dispersal limitation was

very clearly influential inside rainforests through the three archipelagos, and also for coastal forests derived from water-dispersed species (Franklin *et al.*, 2013). However, biotic factors also have a vital role in species dispersal. White (2016) showed the role of wing morphology in limiting dispersal in birds: wing shape and landscape topography together explained twice the variance in range expansion than climate.

There are many studies that have tried to explain dispersal limitation at local scales. Most of these concentrate on aquatic species, for example calculating the similarity of species structure among water bodies as a function of the distance between them (Newbold, 2009). Studies about dispersal limitation in terrestrial species are very few (Newbold, 2009). One study shows that the differences in community composition of plant communities can be related to environmental differences or distances between valleys (Linares-Palomino and Kessler, 2009). Most plants cannot scatter their seeds over long distances, sometimes no more than a few metres away, demonstrating limited dispersal (van Rheede van Oudtshoorn and van Rooyen, 1999; Cain *et al.*, 2000). This lack of data is unfortunate because, for example, Engler and Guisan (2009) show that dispersal limitation is more effective for predictions of future plant dispersal under climate change than the simple dichotomy of unlimited vs. no-dispersal assumptions.

Body size is related to dispersal ability for active dispersers, but this relationship does not apply to passive dispersers (Jenkins *et al.*, 2007). Active dispersal means that a species can control its own locomotion or contribute actively to the dispersal process. Differences in active dispersal can be attributed to variation in the ability to move, and in dispersal tendency or stimulus (Matthysen, 2012). Passive dispersal means that the movement of species is largely outside its own direct control, and depends on external factors such as the wind, gravity, water and other organisms. In general passive dispersal occurs in plants, microorganisms, and small invertebrates including many insects, all with low powers of movement (Bonte *et al.*, 2007). Even where movement is passive, small insects usually position themselves

actively into and out of airstreams (e.g. aphids, ballooning spiders, etc). Some claim that there are no organisms smaller than one millimetre where the word 'biogeography' has meaning (Finlay, 2002), because dispersal of small organisms is rarely affected by geographical barriers (Whitfield, 2005).

1.3 Species distribution models

The application of species distribution models (SDMs) to plants and animals over the last two decades has increased enormously, at least partly because current developments in SDMs actually help us to project the likely effects of human beings on biodiversity at different spatial scales via the impact of climate change (Guisan and Thuiller, 2005; Franklin, 2009). There are different names for species distribution models and with different meanings (for instance: ecological niche models, climate envelopes, habitat models, bioclimatic models, resource selection functions, range maps and spatial models: (Elith and Leathwick, 2009). The development of SDMs resulted from the growing need for information about the geographical distribution of biodiversity, leading to improvements in techniques suitable to estimate this information using remote sensing (RS), global position system (GPS), geographical information systems (GIS), and new methods in statistics and machine learning (Franklin, 2009). The development of the ability to project SDMs in ecology has increased rapidly with increasing new powerful techniques in statistics and GIS tools (Guisan and Zimmermann, 2000).

The most common strategy used at this time to estimate the actual geographical distribution of the species involve identifying and describing the appropriate environment for this species, and then determining the distribution of these appropriate environments in space (Pearson, 2007; Pearson *et al.*, 2007). For instance, a model is created of a plant distribution for a plant that grows very well in wet clay soils; then we identify habitats with clay soils and high rainfall to generate an estimate of the distribution of this species (Pearson, 2007).

To develop understanding about SDMs it is necessary to take into account or think about the occurrence of species in the environmental space defined by environmental variables to which the species responds (Chase and Leibold, 2003; Pearson, 2007). Visualizing the distribution of species in environmental and geographical space together explains simple concepts of species distribution modelling (Figure 1.3) (Pearson, 2007). Models of species distribution provide detailed predictions by estimating the relationships between environmental predictors and species presence or abundance (Elith and Leathwick, 2009; Warren and Seifert, 2011). Based on these, SDMs have given researchers new tools to explore and gain insights into different questions in conservation, evolution, and ecology (Elith *et al.*, 2006). Making such predictions across landscapes sometimes demands extrapolation in space and time (Elith and Leathwick, 2009).

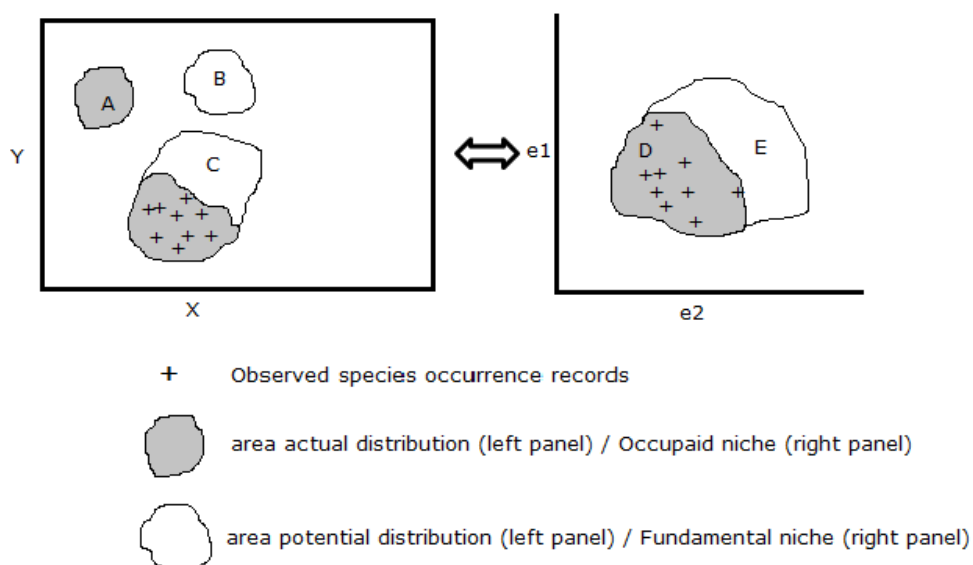


Figure 1.3. Diagram showing the relationship between geographical and environmental space for a hypothetical distribution. Geographical space is referenced by x and y coordinates; environmental space is n-dimensional in Hutchinson's niche concept, but here is explained by two dimensions (the two environmental variables, e1 and e2). The grey area of C in geographical space shows the known distribution, but there may be unknown areas (e.g. area A). In environmental space the grey area D represents occupied parts of the niche; notice that the entire area of the occupied niche may not contain occurrence records. The fundamental niche is indicated by the solid line in environmental space (D+E), which represents the range of abiotic conditions in which the species can live. In geographic space the solid lines describes the places that fall inside the fundamental niche (the potential distribution), including some areas unoccupied because of dispersal limitations or biotic interactions. For instance, area B is environmentally appropriate, but not within the actual distribution because the species does not have the ability to disperse across inappropriate environments to reach it. Equally, area C in geographical space is also within the potential distribution, but is also not occupied due to competition from a different species. Modified from (Pearson, 2007).

Soberón & Peterson (2005) identified four elements that determine the areas occupied by a species: abiotic factors (e.g. environmental variables, substrate conditions); biotic factors (interactions between species, either positive, such as pollinators or seed dispersers, or negative, such as diseases or predators); dispersal ability; and finally adaptation of the species to new conditions according to their evolutionary capacity (see Figure 1.4). All these factors dynamically interact together at different scales to create the geographical species distribution (Soberón and Peterson, 2005). In Figure 1.4 an area A (black circle) represents the abiotic factors required for the species, indicating its fundamental niche. Area B (red circle) represents the interactions between species which when combined with area A produce the realized niche. Area M (green circle) consists of those parts which the species can access without barriers to movement and hence can colonize in ecologically. The intersection of A, B and M produces the area P, the actual distribution (Soberón and Peterson, 2005).

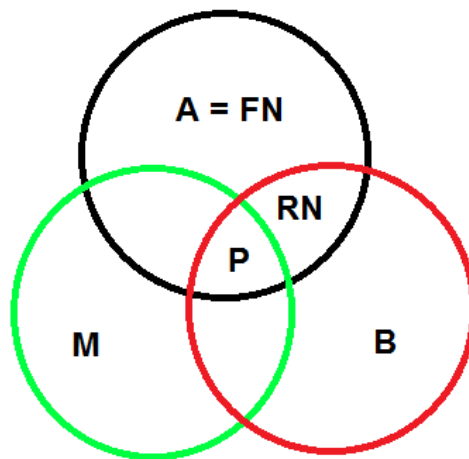


Figure 1.4. Area A represents the range of abiotic variables creating the fundamental niche (FN). Area B represents the region where the right combination of species occurs, which may or not interaction with area A to produce the realized niche (RN). Area M represents areas without barriers in which species can move and colonize. The interaction between A, B and M together produce the actual distribution (P). Modified from (Soberón and Peterson, 2005).

Some researchers (Guisan and Zimmermann, 2000; Araújo and Guisan, 2006) think that SDMs represent the realized niche even though abiotic factors alone are

used as predictors in the models, for the reason that the information about occurrence used to build model involves realized (actual) distributions. However, Soberón & Peterson (2005) argue that in general SDMs capture the fundamental niche, without taking into account variables which describe dispersal limitation or biotic interaction. There are exceptions to this rule when interactions occur between biotic and abiotic factors, because in this case the SDM is closer to the realized niche (Soberón and Peterson, 2005). There is another opinion that says that if there is no definitive confirmation that the variables used as predictors really are direct drivers of the distribution, then SDMs will be closer to the realized than the fundamental niche (Newbold, 2009).

There are many important steps necessary to build and evaluate any model of species distribution. The important thing in making spatial extrapolations of species distribution is to understand the relationship between environmental variables (biotic and abiotic) with species occurrence, or to test geographical or ecological hypotheses about the ranges and distribution of species. The main focus is to identify the pattern and magnitude of the impact of the predictors on the distribution of organisms (Franklin, 2009).

To build and validate an SDM there are two main steps: first, to identify suitable environmental variables; and second, to obtain the known records for the species (Pearson, 2007; Pearson *et al.*, 2007). There are of course several quality control elements: collecting appropriate data; evaluating their suitability; dealing with inter-correlated predictors; choosing a suitable algorithm for modelling; assessing the fit between the training data and the model; assessing the model via the realism of the fitted functions; assessing model residuals; assessing the performance of predictors on test data; producing a map of predictions in geographical space; if needed, creating a binary map of occurrence by selecting a suitable threshold; and finally improving the model in light of the information gained during its construction (Figure 1.5) (Elith and Leathwick, 2009).

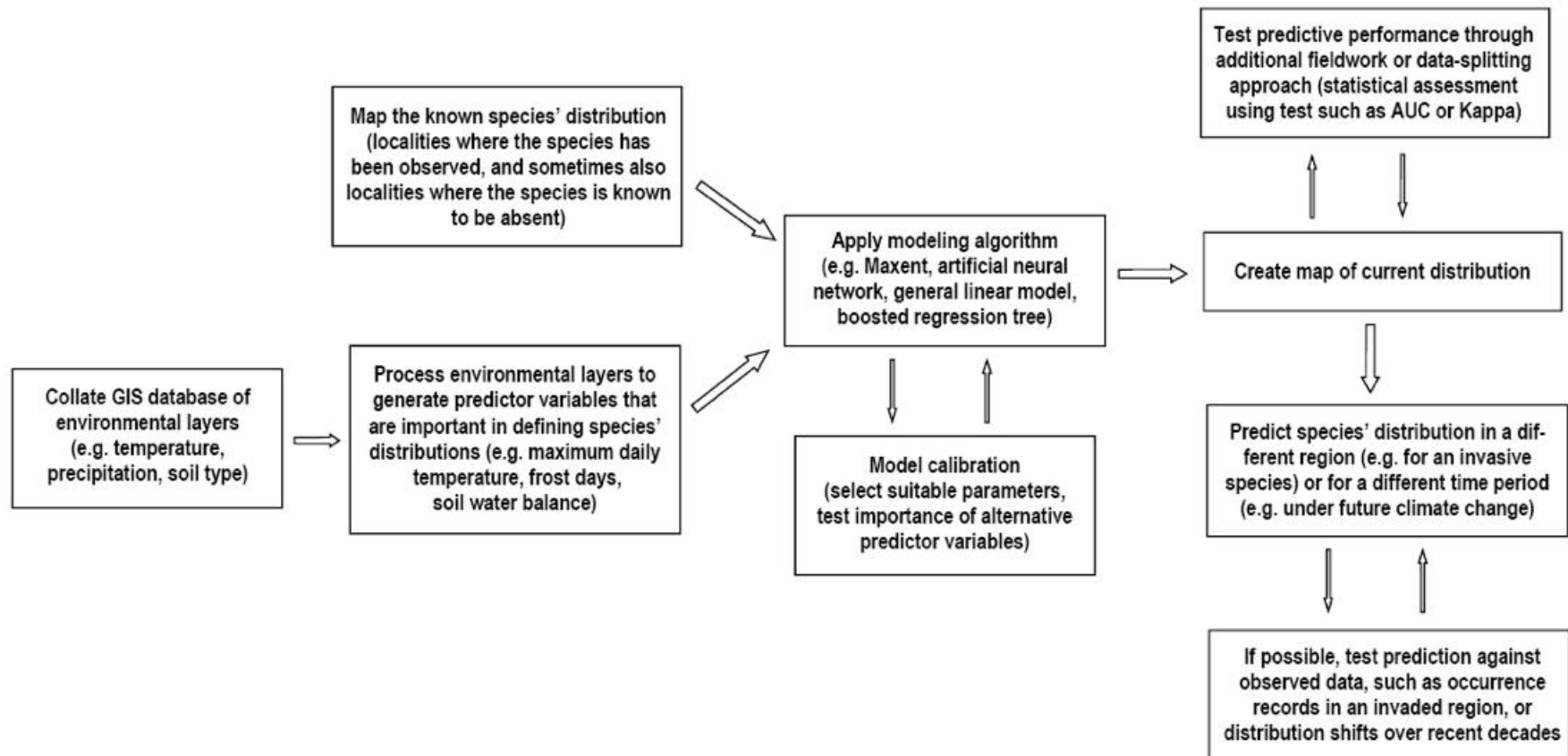


Figure 1.5. Diagram of the steps essential for building and validating species distribution models. From (Pearson, 2007).

All researchers working with the development of SDM techniques focus on the creation of models using abundance or presence/absence data from sites of interest that have been systematically sampled (Franklin, 2009). Nevertheless, real occurrence data come from collations without any scheduled plan in place to collect samples. The great majority of these records are from museums and herbaria, involving presence-only records (Soberón and Peterson, 2005). The significant problem with these occurrence data is that there is not sufficient information about the methods of collecting, and they are subject to biases and errors associated with them, reflecting the disorganized manner in which the dataset was accumulated (Elith *et al.*, 2006). Recent studies indicate that the SDMs are well able to describe the natural distribution of a species within its current range, especially if the data have been collected by good surveys and functionally pertinent indicators are examined with a suitably specified model (Elith and Leathwick, 2009).

1.4 Environmental data

There are many different environmental variables that have been used in species distribution modelling. Variables that are very common relate to climate (for example, temperature, and rainfall), topography (for example, altitude, and aspect), substrate type and land cover. In all cases, variables tend to depict the abiotic environment, but there is also the possibility of involving biotic variables within the modelling (Pearson, 2007). Using many environmental variables as predictors may lead to overfitting, where the model fits the records very closely, at the cost of the capability to generalize (Newbold, 2009). Generally, the best way is to avoid environmental variables that have an indirect effect on distributions, because an indirect relationship may result in incorrect predictions when the model is used to forecast the distribution in new habitats, or under scenarios of climate change that involve novel conditions (Guisan and Thuiller, 2005). For instance, plants may stay alive when hot and dry conditions occur separately, but not when both occur together. In the same way, opportunistic animals that can utilize several kinds of resources, may switch to the commonest one, changing the determinants

of the distribution in different parts of the range (Hirzel and Le Lay, 2008).

Organisms do not respond to altitude directly, but more to changes in temperature and air pressure associated with altitude (Pearson, 2007).

In species distribution models the predictor variables which are used often fit into three different categories: environmental states that have an immediate impact on the ability of organisms to survive in an area; resources which are essential for species; and environmental states that have only an indirect influence through associations with other variables that have a direct impact (Newbold, 2009). It is very important to distinguish gradients of direct factors, which affect physiology directly (e.g. temperature, pH), from resource gradients which are spent or consumed (for example, foods, light, water, prey, appropriate nest sites). Gradients of indirect variables by definition have no direct impact on distributions or species richness: for example, elevation, latitude, longitude, slope angle and exposure. Direct factors and resource gradients are always useful as predictors in species distribution models (Franklin, 2009). When only indirect variables are available, it is even more essential not to extrapolate the model results outside the scope of the conditions used to create the model (Franklin, 2009). Theoretically there is no prior expectation of the form of the species response curve on a gradient of an indirect variable (Austin, 2007).

Environmental variables may include continuous and categorical variables. Continuous variables include many of the usual predictors: for example, temperature or rainfall. Categorical variables include variables such as soil type or land cover. Some of the common modelling algorithms cannot use categorical data. In these circumstances, generating continuous environmental variables from the categorical variables may be possible (Pearson, 2007). Some species distribution modellers use Principal Components Analysis to derive composite, uncorrelated climate predictors from the raw climate data, and then use these "factors" as new predictors in species distribution modelling (for more details, see (Hirzel and Le

Lay, 2008). Although this decreases model complexity, it comes at the cost of being more difficult to explain ecologically (Hirzel and Le Lay, 2008).

A very significant point in species distribution models is the selection and number of environmental variables. Grouping and putting all variables by subject (for example, climate, resources, disturbance) and checking each individually is always worth doing (Hirzel and Le Lay, 2008). A good number of predictors is from three to twelve, and is typically about 8-40 (Franklin, 2009); some studies obtained good predictive ability using 14 environmental variables), whilst others (e.g. Huntley et al., 1995) found the same with just three environmental factors (Pearson, 2007). Most of the methods try to use minimum combination of environmental predictors which drive the best fit to the data (Johnson *et al.*, 2006). Some variables should be rejected by applying collinearity criteria because they do not give useful extra information over and above that of other variables (e.g. Phillips et al., 2006; Dormann et al. 2013). In distribution modelling the selection of independent variables is often driven by the accessibility of environmental variables in a format fit for modelling. Consequently, in practice many distribution models have taken into consideration only factors describing the abiotic environment (e.g. climate, topography, and edaphic factors) or non-specific biotic factors (e.g. habitats, land cover, and plant productivity). Several of the variables that can be obtained in the form of maps are those that have only an indirect impact on the species (Austin, 2007).

1.5 Predictions of the effects of climate change

Climate change is one of the fundamental factors that has affected biodiversity in the past, is doing so in current environments, and is known to be capable of driving species to extinction (Alkemade *et al.*, 2011). The Intergovernmental Panel on Climate Change (IPCC) have documented that the world environment is warming, and noted that the temperature of the Earth's surface has increased by approximately 1 °C in the past and is probably to grow by

another 1.4 to 5.8 °C through the next century (Houghton *et al.*, 2001). The increased effect of global climate change on the environment is one of the greatest concerns of the 21 century (Smith *et al.*, 2009). Human intervention has led to a significant change in the global environment, altering biogeochemical cycles, converting land and enhancing the movement of biota. Over the past 300 years the concentration of carbon dioxide (CO₂) in the atmosphere has increased by 30%, more than 50% of this amount occurring in the last four decades. The concentration of methane has also more than doubled, and concentrations of other gases have increased, all of which have contributed to global warming (Chapin *et al.*, 2000).

Global warming is projected to grow rapidly during the twenty-first century (Morueta-Holme *et al.*, 2010), and affects the distribution, phenology, physiology and behaviour of organisms, effects which can build up through time (Walther *et al.*, 2002; Aublet *et al.*, 2009). There have been recent alterations in phenology, and altitudinal and latitudinal range (Morueta-Holme *et al.*, 2010). Thus it is very important to understand how species respond to expected future climate change in order to plan for biodiversity conservation and management (Hanna *et al.*, 2002). Understanding distribution responses to past climate changes can assist in predicting current patterns of distribution and genetic variation (Hijmans and Graham, 2006). Species distribution models use the current distribution of species in a geographical area to infer its environmental requirements, which are then used to predict the distribution under climate change (Hijmans and Graham, 2006; Araujo *et al.*, 2011). Decision makers in particular need models to assess the likely impacts of mitigation measures (Franklin *et al.*, 2014).

The great threatening feature of climate change affecting the conservation of biodiversity is the combination of climate change and habitat fragmentation (Hannah *et al.*, 2007; Hannah, 2011). When climate change takes place, the survival of populations will depend on whether the new ecological conditions match aspects of the organism's previous niche, or whether the populations have ability to

adapt when the new conditions are outside its usual niche (Martínez-Meyer, 2005). Likewise, the capacity to respond to global warming may be reliant on its capability of tracking climate changes across the landscape, colonising new locations and adapting its seasonal behaviour and physiology to new weather conditions (Thuiller, 2007).

Climate change plays an important role in shifts in species distributions over the large scale (Pearson *et al.*, 2002; Pearson and Dawson, 2003; Thomas *et al.*, 2004). Every change in temperature by one degree leads to shifts in suitable conditions on the Earth's surface of about 160 km; hence since the climate is predicted to warm by 4 °C over the next century, organisms in the Northern Hemisphere must either move large distances northward, or move up in altitude by about 500 m (Thuiller, 2007). Between 1970 and 1990, a large number of butterflies and birds in Europe have changed their distribution northwards by about 20 to 150 km (Parmesan *et al.*, 1999; Thomas and Lennon, 1999). These primary effects of climate changes may be mediated by impacts on synchrony with food and habitat resources (Bellard *et al.*, 2012). Climate change has the ability to change the flowering times of plants and the phenology of their insect pollinators, leading to mismatches and consequential linked losses, likely to shift the structure of plant-pollinator networks (Rafferty and Ives, 2011), and potentially producing dramatic changes to the structure of ecosystem services. Other estimates show that terrestrial plants and animals in the northern hemisphere have changed their distributions by about 6.1 km per decade northwards, and their phenologies by 2.3 - 5.1 days per decade, through the previous five decades. Significantly, all these shifts are correlated with changes in rainfall and temperature (Thuiller, 2007). Another study (Alkemade *et al.*, 2011) used a mixture of SDMs and environmental models for plant species in Europe to estimate shifts in the mean stable area of species and species turnover. The results show that with increasing temperature, species turnover will increase, and the mean stable area will decline in all biomes (Alkemade *et al.*, 2011). (Alkemade *et al.*, 2011) suggest that there will be

dramatic shifts in Northern Europe by 2100, in which more than 35% of species will be new for that location, and 25% of species in Southern Europe will be extinct.

There has been little research to predict the potential effect of climate change on Egyptian biodiversity using species distribution modelling, partly because of the lack of organized records of biodiversity in Egypt in the past, and partly because the modelling techniques are relatively new. The BioMAP project tried to collate all the records of the Egyptian fauna and flora, with the aim of stimulating more such studies. Already a number of studies of distributions (butterflies – Gilbert and Zalat 2008; mammals - Basuony *et al.* 2010, plants – Kaky and Gilbert (2016) and the effects of climate change (reptiles – El-Gabbas *et al.*, 2016; butterflies and mammals – Leach *et al.* 2013; plants – Kaky and Gilbert (2017)) has resulted from these databases. The most recent by Leach *et al.* (2013), El-Gabbas *et al.* (2016), and Kaky and Gilbert (2017) assessed the effect of future climate change on the distributions of butterflies and mammals, reptiles, and plants respectively, in Egypt's Protected Areas using an SDM technique (Maxent) and an area prioritization method (Zonation). They used two of the IPCC emission scenarios of climate change (A2a and B2a) of various Global Circulation Models, and then used Zonation to assess the effect of the Protected Area network in conserving biodiversity in Egypt under current and future climate change. The only other studies of Egyptian species that use SDMs are those of Sultana (2011) on the effect of climate change on the distribution of four Egyptian Bovidae, and El-Alqamy *et al.* (2010) on the Nubian Ibex *Capra nubiana*. As far as I know, there have been no similar studies of the distribution of Egypt's medicinal plants, apart from a couple of studies specific to South Sinai (Khafaga *et al.*, 2011; Khafagia *et al.*, 2012).

1.6 Applications of species distribution modelling

1.6.1 Managing biodiversity under climate future

Climate change appears an unprecedented challenge to the conservation of species and ecosystems, and therefore all agencies concerned with protecting the environment are looking for new ways to predict species distributions in the future under climate change in order to develop appropriate management strategies (Heller and Zavaleta, 2009; Sinclair *et al.*, 2010). It is essential that public policy responds effectively, with decisions taken at all levels to highlight the problem (Hannah *et al.*, 2002). With the trends observed recently, and as the fossil record shows, climate change can have a broad impact on the distribution of species (Davis and Shaw, 2001; Walther *et al.*, 2002), and therefore it will have a significant influence in the near future (Pearson and Dawson, 2003), increasing concerns about the efficiency of current strategies for the protection of biodiversity. Conservation of biological diversity is mostly based on stable networks of Protected Areas, involving many institutions and organisations all of which have similar goals and plans (Heller and Zavaleta, 2009). The crucial question that should be asked is: how can we protect species from extinction?

To react appropriately to climate change needs the development of regional official organisations that focus on the local predictions and associate climate-change scenarios with all of the planning and action processes, highlighting the drivers of multiple threats (Heller and Zavaleta, 2009). Increasing conservation planning capacity, improving management by design, and recruiting new Protected Areas are all essential elements in facing the impacts of climate change. Protected Areas have been shown to be vital in protecting biodiversity in present-day conditions (Newbold *et al.*, 2009) and under climate change (Araujo *et al.*, 2011).

A further issue is the inclusion of socioeconomic information in biodiversity conservation planning to make it more practical (Faleiro *et al.*, 2013), because this will reduce conflict between stakeholders, biologists, and decision makers in terms

of land use and human activities. Developments have made only slow progress in this area.

1.6.2 Predicting invasions

The issue of the spread of invasive species has become a major concern in various areas, for example, biodiversity, agriculture, and economics (Williamson and Fitter, 1996; Higgins *et al.*, 1999; Perrings *et al.*, 2002). Increasing human movement creates and increases opportunities for species to move, and thus help introduce them to new areas (Peterson, 2003). Invasive species change populations and communities across the world (Trethowan *et al.*, 2011), and it is important for land managers to understand the possibilities of their spread to be able to act preventatively. Modelling programs are a tool for everyone (land managers and researchers) to understand the potential magnitude of invasive species spread (Jarnevich and Reynolds, 2011) because one of the most important factors dictating the success of invasive species is the suitability of climatic conditions. Other factors are also important, however; for example, invasive species characteristics, human factors, and species composition in the region which has been invaded (Thuiller *et al.*, 2006; Ficetola *et al.*, 2009).

The negative effects of invasive species can be very large (Young and Larson, 2011). Pimentel *et al.* (2005) estimated the economic costs to be \$120 billion/year in the USA. South Africa is particularly vulnerable to invasive alien plants; for example, the composite Pompom weed (*Campuloclinum macrocephalum*) is believed to be one of the most harmful weeds (Richardson and Wilgen, 2004; Trethowan *et al.*, 2011). Alien plants have a negative impact on all components of biological diversity, including ecosystem processes to genes (Higgins *et al.*, 1999), changing the environment and decreasing the germination (Novoa *et al.*, 2013), growth (Fuentes-Ramírez *et al.*, 2011) and reproduction (Hata *et al.*, 2010; Loydi *et al.*, 2014) of native species.

Recently, SDM has been used to predict and manage invasive species, for example by determining containment boundaries, or for early identification for

likely invasion locations (Robinson *et al.*, 2010). Richardson and Thuiller (2007) modelled the distribution of South Africa biomes based on the current climate, and then recognised similar climate regions elsewhere, and hence identified potential source regions for invasive species. There are two basic approaches; first, one expects the distribution of an invasive species in a new location to depend on its habitat preferences in its native range; and second, one uses reliable information at the point of invasion to determine possible regions at risk (Franklin, 2009). Of course the models could be wrong for a number of reasons: invasive species can adapt rapidly to the new environmental conditions (Franklin, 2009); alien species typically violate a major assumption of distributions being in balance with climate (Robinson *et al.*, 2010); or poor predictions could be the result of differences in the realized vs. fundamental niche (Newbold, 2009).

Many studies have used SDMs to study invasive species (Peterson and Robins, 2003; Herborg *et al.*, 2007; Broennimann and Guisan, 2008). Ficetola *et al.* (2009) applied SDMs successfully to assess if climate change increases future fitness in slider turtles (*Trachemys scripta*). Trethowan *et al.* (2011) predicted the South African regions which are possibly suitable for pompom weed and the two biological control agents used to control it. Mestre *et al.* (2013) used both biotic and abiotic factors with SDMs to understand geographical barriers and the invasive range.

Maximum entropy (Maxent) is one of the methods suitable for modelling species with unbalanced distributions such as invasive species, because correct absence records may be problematic to obtain. If the species is absent from a place, there are two possibilities: either it did not invade this region (yet); or the region is inappropriate. Often these two options cannot be distinguished in invasive species (Jarnevich and Reynolds, 2011).

1.6.3 Biodiversity conservation

Biodiversity provides essential services upon which human society depends (Rands *et al.*, 2010). Systematic conservation planning (Margules and Pressey, 2000) is a

vital process to find, construct, implement and maintain regions for biodiversity to persist, with their associated ecosystem services (Pressey *et al.*, 2007). Many factors impact conservation planning and the management process: for example, human population (Rands *et al.*, 2010), climate change (Araujo *et al.*, 2004), urbanisation (Hamer and McDonnell, 2008) and invasive species (Thalmann *et al.*, 2015). To manage and conserve species we need to have essential monitoring on occurrence and how abundance changes with time: thus the goal of the monitoring is to define distributions in space and time (Rodríguez *et al.*, 2007).

The current rapid extinctions of species and habitat fragmentation requires significant protection against our incapability to preserve and inventory all species individually (Chefaoui, 2011). Protected Areas are considered the cornerstone of conservation, and so developing and supporting these areas is very important in arresting biodiversity loss. Protected Areas currently cover about 12% of terrestrial ecosystems (Seiferling *et al.*, 2012), and the target is to increase this to 17% (CBD). Recent studies have tried to assess the performance of Protected Areas in saving biodiversity. Some have found that biodiversity inside Protected Areas is greater than outside (Newbold *et al.*, 2009; Kaky and Gilbert, 2016), whilst others have found the opposite (Pawar *et al.*, 2007; Traba *et al.*, 2007). With climate change altering the spatial distribution of habitat suitability, it is possible that Protected Areas will remain more suitable than equivalent areas outside (Araujo *et al.*, 2011).

The International Union for Conservation of Nature (IUCN) produces the Red List of endangered species, by far the most important assessments of conservation status, used as a tool for conservation planning, monitoring and management (Rodrigues *et al.*, 2006). The IUCN Red List uses various criteria (e.g. population decline: (IUCN, 2012b) to assess species into one of nine categories (e.g. Critically Endangered: (IUCN, 2012b) to guide conservation planning (Cassini, 2011). However, applying these kind of assessments is time-consuming and often needs more or different data from those available at the time (Wulff *et al.*, 2013). In such

circumstances data from museums, herbaria and the literature may be useful sources (Newbold, 2010; Anderson, 2012), and international efforts are ongoing to create such global databases, such as Kew Botanical Garden and the Global Biodiversity Information Facility (GBIF). Caution is needed when using these kinds of data to avoid biases.

Stronger conservation and management decisions can be made using the predictions of SDMs, and new sites and species discovered (Guisan *et al.*, 2013). For example, on the basis of SDMs in Madagascar, Raxworthy *et al.* (2003) discovered seven new species of chameleon, and in Switzerland Guisan *et al.* (2006a) detected seven new populations of Alpine sea holly plants. Wulff *et al.* (2013) identified a range of areas and species important for conserving narrow-endemic New Caledonian plants. These examples constitute perhaps one of the best uses of SDMs, increasing our information and knowledge about distributions, which then leads to better conservation planning for decision makers. Many conservation organizations (e.g. the Darwin Initiative in Borneo, the Royal Society for the Protection of Birds in Britain, the BioMAP Project in Egypt, and the Commonwealth Scientific and Research Organization in Australia) are using SDMs in their research. They clearly have an important role in conservation and in adapting to climate change. Despite the burgeoning literature, there is a little direction on how SDMs can be used to support decision-making in conservation, and knowledge about them and experience in their use is still fairly rare. More practical training is needed because there is the urgent need to support the process of conservation by these models (Guisan *et al.*, 2013).

The associated techniques of spatial prioritization tools and software for conservation planning have only developed recently. For example, Zonation (Moilanen *et al.*, 2014), ResNet (Sarkar *et al.*, 2002), Marxan (Game and Grantham, 2008), ConsNet (Ciarleglio *et al.*, 2008), MultCSync (Moffett *et al.*, 2005) and WorldMap (Williams, 2001). All these tools and techniques use SDM predictions to design and assess Protected Areas in conservation planning. The

coordinated use of these two approaches appears to be very important to assess and analyse networks of Protected Areas within a reasonable time-frame (Leach *et al.*, 2013).

1.7 Medicinal plants

Plants are of course fundamental to all terrestrial ecosystems, and their loss will affect most animals and humans (Díaz *et al.*, 2006). As vital sources of herbal products and new drugs (Hamilton, 2004; Chen *et al.*, 2016), medicinal plants have important roles in health care, traditional cultures and local economic value especially in poor countries (Klein *et al.*, 2008; Okigbo *et al.*, 2008). The distribution and abundance of medicinal plants is affected by human activities, and this impacts on ecosystem services and human well-being (Klein *et al.*, 2008; Kaky and Gilbert, 2016). Currently the loss of plant species is occurring up to 100 times faster than the natural expectation of the extinction rate, which could imply the loss of at least one potential major drug every two years (Pimm *et al.*, 1995). According to the IUCN Red List and World Wildlife Fund, there are about 50,000 to 80,000 plant species used for medicinal purposes across the world (Chen *et al.*, 2016). Generally, overharvesting, the increasing human population, plant consumption and habitat destruction is leading to losses of around 20% of wild resources, and in addition 15,000 plant species are under threat of extinction (Ross, 2005; Chen *et al.*, 2016).

Because of the accelerated loss of medicinal plants and their habitats, conservation planning and protections of medicinal plants needs more action and effort. At present, there is no full assessment of the extinction rate of all plant species including medicinal plants (Brummitt *et al.*, 2015b). There is no distribution map for most plant species, and most countries do not have up-to-date checklists for their plant species (Kew, 2010). The distribution of medicinal plants is not uniform through the world (Huang, 2011; Rafieian-Kopae, 2012). For example, the highest number of medicinal plants are present in China and India with 11,145 and

7500 species respectively, followed by Colombia (see (Balunas and Kinghorn, 2005; Rafieian-Kopae, 2012; Srujana *et al.*, 2012)). The harvesting of medicinal plants is increasing especially from wild populations (Chen *et al.*, 2016), and the huge demand from Europe, North America, and Asia is enlarging by 8-15% per year (Ross, 2005; Chen *et al.*, 2016). Egyptian medicinal plants are under risk because of the large and rapacious pharmaceutical industry (GEF, 2000).

For all these reasons, the geographical distribution of medicinal plants should be better known in order to help conservation planning strategies, especially under climate change. I have taken advantage of the availability of a validated dataset of records of medicinal plants to analyse their distributions in Egypt, and their likely fates under climate change.

1.8 Thesis outline

The study starts by estimating the distributions of 114 Egyptian medicinal plants at the current time using SDM approaches implemented by *MaxEnt*, creating a distribution map for each species individually and then summing them all together to obtain a species richness map. Then I wanted to project the current distributions into different future times (2020, 2050, and 2080) using two emission scenarios (A2a and B2a) under two assumptions of dispersal (unlimited and no dispersal). Through this process I have estimated the predicted species gains, losses, and turnovers. The aim was to assess the effectiveness of Egypt's Protected Areas, and to predict to what extent the reserve network would function in the future under climate change.

The following gives the details of the thesis outline, with the important questions:

- Chapter 2 investigates how *MaxEnt* works by running different kinds of models using different criteria and setting options (e.g. feature classes, data partitioning, chosen background points, regularisation values, etc.). The aim was (a) to obtain the best settings for good model performance based on the area under the curve (AUC) values; and (b) to select suitable environmental variables that shape plant distributions, but then to remove high collinearity between them to avoid inaccurate model performance.
- Chapter 3 uses species distribution modelling to predict the distributions of Egyptian medicinal plants at the current time. It produces distribution map for each species individually, and then sums them all together to create a species richness map to identify hotspots of medicinal-plant richness across Egypt. It assesses the effectiveness of the Egyptian PAs at the current time by estimating species richness inside and outside the PAs. This chapter has been published as Kaky & Gilbert (2016) in the *Journal of Arid Environments*.

- Chapter 4 predicts the distribution of Egyptian medicinal plants under the effects of climate change. Through this chapter predictions of the current species distributions are projected into different future times (2020, 0250, and 2080) using two emission scenarios (A2a and B2a) and assuming unlimited dispersal and no dispersal, to figure out the predicted species distributions under climate change. It estimates the distributions of habitat suitability, and of species gains, losses and turnovers. Then it assesses the effectiveness of Egyptian PAs under climate change using predicted species richness inside and outside PAs under all assumption combinations. This process was helpful in identifying locations important for conservation in the future. A second revised version of this chapter has been resubmitted to *PLoS One*.
- Chapter 5 assessing the extinction risk of Egypt's medicinal plants now and under climate change using IUCN Red List categories and criteria as an example of a country with only sparse data available. For the current time, only preliminary assessments were possible because of the lack of information: all assessment used the B category. Under future climate change, assessments were completed using the A3 category, for two different timescales (the absolute gap between two different times, and scaled to the 10 years recommended by the IUCN). A revised version of this chapter has been resubmitted to *Conservation Biology*.
- Chapter 6 performs a gap analysis by exploring the efficiency of Egypt's PAs using the conservation planning software *Zonation*. *Zonation* implements spatial prioritization under various different options (e.g. rules for cell removal), and can include allowing for the effect of human activities. The chapter explores the impact on conservation prioritization of the human influence index and human population density as cost layers

under current and future emission scenarios. It finds out to what extent Egyptian PAs can conserve Egyptian plants under the impact of climate change, allowing for the effect of human activities. It highlights new locations that should be considered as additions to the PA network in the near future to mitigate biodiversity loss. This chapter has been submitted to *Landscape and Urban Planning*.

- Finally, Chapter 7 to brings all the threads of the project together, and discusses the general ideas and conclusions of the previous chapters in order to assess the value species distribution modelling as a conservation tool for biodiversity under effects of climate change.

2 Chapter Two: Using MaxEnt to select the best model compromise between complexity and performance

Abstract

Species distribution models (SDMs) are modern techniques that use species occurrence data with environmental predictors to build a model of the climate envelope that matches the species climate requirements. We used MaxEnt software to test and build different kinds of models, varying the feature class, background points, regularisation multiplier and threshold rules. We assessed the models based on the area under the curve (AUC). After exhaustive exploration of the various combinations, we chose a basic model for the rest of the thesis, which includes QPT feature class, 10000 background points, regularisation multiplier = 1, 10% training presences as threshold rule, 10-fold cross-validation partitioning and logistic output as standard. Such comparisons are an essential pre-amble to optimise predictions of species distributions.

2.1 Introduction

Species distribution models (SDMs) or ecological niche models, are a style of approach that use species location data in combination with environmental variables to create a model of the climate conditions that match the ecological requirements of a species, and hence predict the comparative appropriateness of habitat (Warren and Seifert, 2011). SDMs are used widely for different aims in ecology, conservation biology, and biogeography (Elith and Leathwick, 2009). Datasets of species records are gradually being made available through scientific institutions, museums, and herbaria, with free access to the data via the Global Biodiversity Information Facility (GBIF; www.gbif.org). Such data supply a huge treasure of information, but only about known presences rather than absences (Syfert *et al.*, 2013). In the last decade, numerous strategies and approaches for creating species distribution models have been invented and are now widespread in biogeography (Guisan and Thuiller, 2005; Peterson *et al.*, 2011). The techniques used to construct SDMs are growing quickly (Elith and Leathwick, 2009), and they have become a standard instrument for biologists and conservation biologists. Although current methods have their limitations, they are frequently the best accessible methods for deciding conservation issues in the absence of detailed biological and physiological information (Warren *et al.*, 2013). Their accuracy relies on the quality and amount of the input information, which varies from collations of accidentally collected occurrence records to more exact presence–absence information (Kramer-Schadt *et al.*, 2013). Users of SDMs are confronted with a great variety of options, and it is not generally evident whether selecting one choice over an alternative has a significant impact on model execution. Among all the possible methods, MaxEnt has become the standard and normal method of choice in many implementations (Phillips *et al.*, 2006; Elith *et al.*, 2011).

Species distribution models are constructed from two sets of input information: first, the known locations of the species; and second, environmental variables as raster GIS layers. Ecological variables are arranged in different ways, contingent upon their associations with, and impacts on, the geographic distribution

of species (Peterson *et al.*, 2011). Procedures have been created for selecting variables for incorporation in species distribution studies. A few specialists like to utilize a couple of preselected, generally uncorrelated variables that compare straightforwardly to known physiological effects, for example, temperature and precipitation (Peterson *et al.*, 2011). When no information exists with respect to the key components, extensive datasets (for example, 10 to 30 variables - some extremely intercorrelated) have been used (Stockwell, 2006). Despite the number and kind of environmental predictors picked, all variables need to meet certain standards to match the attributes of the occurrence information (Peterson *et al.*, 2011).

MaxEnt estimates connections between indicator variables in areas where an organism has been observed versus "background" areas in the study locale (Phillips *et al.*, 2006). The way these connections are modelled is controlled by choices about the form and complexity of the relationship (MaxEnt calls these 'feature classes'): permitting more feature classes empowers more adaptable, complex and better fits to the records, but risks model over-fitting (Peterson *et al.*, 2011). The default choice of MaxEnt permits the software to select the model that portrays the reactions of the species to ecological conditions, yet users can choose from a number of useful options (such as linear, quadratic, product, threshold, hinge, and categorical) and permit diverse structures for particular ecological variables. The MaxEnt default selects which feature classes to permit depending on the number of records in a dataset. Notwithstanding which classes are allowed in a model run, MaxEnt tries to protect against overfitting through 'regularisation', which punishes the use of extra parameters that result in practically no "gain" to the model (Warren and Seifert, 2011; Muscarella *et al.*, 2014). Users can select which feature classes to permit, and modify the level of regularisation through an individual regularisation multiplier (default = 1). On the basis of empirical tuning, Phillips and Dudik (2008) proposed that the default settings in MaxEnt are appropriate for most modelling endeavours (Warren and Seifert, 2011). Many studies have added to the scientific underpinnings of the MaxEnt method (Phillips *et al.*, 2006; Phillips and

Dudik, 2008; Elith *et al.*, 2011; Merow *et al.*, 2013; Yackulic *et al.*, 2013). Recent work has demonstrated that the default values of MaxEnt can result in poor models (Shcheglovitova and Anderson, 2013; Radosavljevic and Anderson, 2014).

Overfitting occurs when the model fits the calibration data too closely and hence is unsuccessful in predicting independent data. Underfitting happens when the model is not complex enough and fails to offer sufficient discrimination; in these cases predictions for new data are also not accurate (Radosavljevic and Anderson, 2014). Studies recommend that underfitting is less regularly an issue than overfitting, in any event for techniques such as MaxEnt that can fit complex relationships (Elith *et al.*, 2006; Anderson and Gonzalez, 2011; Warren and Seifert, 2011).

An increasing omission rate and differences between train and test AUCs are indicators of overfitting. Radosavljevic and Anderson (2014) found that the omission rate (false negative in confusion matrix: the model expects absence for species but the test data confirm presence) was low when they chose a '10% presence' threshold rule with random k-fold partitioning and masked geographically structured partitioning. However, random partitioning of the data achieves low omission rates regardless of the type of threshold rule (Radosavljevic and Anderson, 2014). In fact, low regularisation values (especially below the default setting) result in overfitting, while high regularisation values produce underfitting (Radosavljevic and Anderson, 2014).

Genuine assessment of environmental niche models and related geographic expectations relies on upon accurate and correct selection of appropriate occurrence dataset with which to estimate measure of performance and importance. There are some important issues should be taken into account: the extent to which there is independence between calibration and evaluation data in space and time; suitable techniques to split the occurrence data for calibration and evaluation; and whether occurrence points are spilt with respect to spatial site (Peterson *et al.*, 2011). Ideally, evaluation data will be completely autonomous from the calibration data, permitting genuine model validation (Araújo *et al.*, 2005).

Because there rarely are fully independent datasets, and it is difficult and costly to produce even relatively independent datasets, most evaluations depend on splitting one sample into data for calibration and evaluation. Several approaches are available to achieve this subdivision, but users always follow a simple random division of occurrence records without taking geography into account (Fielding and Bell, 1997). Such a simple method has weaknesses, and therefore there are different alternative ways for dividing the data, involving the use of spatially organized subdivisions: these may offer significance advantages (Peterson *et al.*, 2011).

One method that enhances the idea of a single random data partition is termed "K-fold cross-validation". Here, the researcher divides the number of occurrence points into calibration and assessment pools haphazardly. Instead of into two datasets, the occurrence records are divided to several (K) roughly equal-sized groups that represent calibration and evaluation datasets. One of the (K) groups is used to evaluate the model, and the rest (K-1 groups) are used for calibration, which together construct the building dataset for that step. Every group is utilised once as an evaluation dataset, and every occurrence point appears exactly once in an evaluation dataset (Peterson *et al.*, 2011).

Modifying SDMs results for species occurrence from probability to presence/absence requires specifying a particular threshold. There are several methods to choose thresholds, and studies to compare between threshold rules are few (Liu *et al.*, 2005). In ecological management practice and conservation, representing species as present/ absent is often much more useful than representing them in terms of habitat suitability or the probability of occurrence. Choosing a threshold rule is necessary to change the probability information to presence/absence data. Model evaluation in terms of performance uses tables derived from the confusion matrix, which also requires presence/ absence data (Liu *et al.*, 2005).

One major issue in creating species distribution models is the evaluation of predictive precision (Guisan and Thuiller, 2005; Barry and Elith, 2006). A quantitative evaluation of a model is vital in deciding its suitability for particular

applications, and helps to distinguish those parts that need change or development (Barry and Elith, 2006; Guisan *et al.*, 2006b). Evaluation can help explore how distinctive properties of the data and/or the species influence the quality of prediction maps created by the model (Allouche *et al.*, 2006). Evaluation has been carried out in two ways: the first depends on describing receiver operating characteristic (ROC) plots using the AUC criterion (area under the curve); and the second uses presence/absence data in criteria such as kappa or the 'true skill statistic' TSS (Baldwin, 2009). The AUC is produced from a ROC plot to compare model performance against random expectation (Phillips *et al.*, 2006). Standardly model assessment corresponds to particular threshold values of AUC (for example, $AUC < 0.7$ = poor; $AUC > 0.7-0.9$ = good; and $AUC > 0.9$ = very good) (Baldwin, 2009; Franklin, 2009). Kappa (Liu *et al.*, 2005; Pearson, 2007) and jackknife (Pearson, 2007) measurements are additionally used to assess models. Kappa is a chance-adjusted measure of accuracy usually used in environmental studies that have presence/absence data (Baldwin, 2009). Another comparable method called the 'true skill statistic' is not reliant on prevalence, and hence may be more appropriate than kappa (Allouche *et al.*, 2006). The jackknife depends on the "leave-one-out" procedure, where one area is deleted from the sample pool (n) and a model is built with the residual areas ($n-1$). This process is repeated n times, successively leaving out each area (or variable). Model evaluation depends on its performance in predicting each region left out (Baldwin, 2009).

Most model assessments test predictions against random expectation, but give little indication about selecting the best model out of a subset of potential models (i.e., model selection). Such assessments are essential in selecting a minimal model that best predicts species distribution and environment use, since simpler models are preferred to give conservation practitioners a reasonable set of habitat elements that can be monitored for wildlife (Peterson *et al.*, 2011). In this chapter I use MaxEnt to test different kinds of model complexity (from feature combination, regularisation multiplier, and different background points), choose suitable environmental variables, and choose threshold rules to select the best

model. I then assess the models using the AUC score and the true skill statistic (TSS).

2.2 Methods

In this research, Maxent (maximum entropy: Phillips et al. 2006; Phillips and Dudík, 2008) was chosen as the modelling method because it has great efficiency in generating predictions based on presence data only, and has been used extensively for species distribution modelling (Elith *et al.*, 2011; Slater and Michael, 2012; Leach *et al.*, 2013; de Araújo *et al.*, 2014). In predicting the (unknown) likely distribution defining the distribution of species throughout region of study, Maxent makes relatively few assumptions; derived from machine learning approaches, it is hard to explain exactly how it works, so much so that special descriptions are needed for ecologists (Elith *et al.*, 2011). Maxent needs only presence data, taking a sample of 10000 pixels from the area of study to use in model calibration to characterise the background of environmental variables available to the species (Anderson and Gonzalez, 2011).

Maxent version 3.3.3k was used to run the models in this study (downloaded from: <http://www.cs.princeton.edu/~schapire/maxent/>). Initial models assessed how data partitioning, threshold rules, number of background points, number of iterations, and the combinations of feature types affect model accuracy and AUC values. As a result of these tests I chose one 'best' set of model assumptions to run Maxent for all the plant species in my subsequent work.

Each model was run by choosing cross-validation with ten replications for every species (with the exception of species with fewer than 10 unique pixels at the resolution of 2.5 arc minutes: in these cases the number of replicates was set routinely to the number of unique records). I divided the records randomly in two ways. The first used 70% and 90% of the data for model calibration (training), leaving 30% and 10% of the data for model evaluation (testing). The second method was K-fold division, where the data are divided into K equal parts randomly ($K > 2$), and then every partition is utilised as a test set and the rest used for model

building (Pearson, 2007). All continuous and categorical predictors were used (Table 2.1), and the Variance Inflation Factor (VIF) used to decrease the negative effect of correlation among the variables then remove the predictors which they have high correlation.

The default settings in Maxent have proven ability to achieve good performance (Phillips and Dudik, 2008), and so were used here with some exceptions described below to see how Maxent options affect model accuracy (as indexed by the AUC value). The most significant variable was determined as the predictor with the highest mean permutation importance through all model runs. To determine the most important variables across all species, the mean contribution of every predictor across all species was calculated.

The relationship between environmental predictors and the probability of occurrence can take a variety of forms. In Maxent there are six ways to model these, known as "feature types": linear (L), quadratic (Q), threshold (T), product (P), hinge (H), and the 'auto' feature (Phillips and Dudik, 2008). Environmental predictors can be continuous (for example, precipitation, temperature and altitude) or categorical (such as vegetation, habitat and soil types). Linear, quadratic, product, threshold, and hinge are applicable to continuous predictors. In this study, I used all these features to compare between them. Maxent gives options to permit different feature types to be utilised for diverse ecological variables. "Auto feature" is the default setting, which uses an algorithm to indicate the most appropriate combination depending on the number of occurrence records utilising for model training; to include all feature types under the "Auto feature" setting needs at least 80 occurrence records in the training data. I examined the degree to which allowing Maxent to utilise diverse feature types affected the predictive precision of the ensuing models (Syfert *et al.*, 2013). The following are the feature type combinations which I examined: L, Q, H, T, LQ, LQP, LQPH, LQHPT, LQPT, PTH, QPT, QPTH, HT, LHT and Auto.

I chose a continuous logistic output format, i.e. a value between 0 and 1 that is relative habitat suitability, related to the likelihood of occurrence (see

Guillera-Arroita et al. 2014). Ten raster ASCII files resulted from the cross-validation runs for each species, and were averaged to produce the mean probability distribution.

To reduce the risk of overfitting, MaxEnt uses a process called 'regularisation', which represents a balance between fitting the data closely and overfitting (Dudík *et al.*, 2004). The default regularisation value was chosen empirically using a range of taxonomic groups (Phillips and Dudik, 2008), and may be valuable when building models for several species at the same time, when species-specific tuning is impractical (Merow *et al.*, 2013). Many studies are carried out on one or a small number of species, and therefore the default regularisation value might not be suitable for every system (Phillips and Dudik, 2008; Elith *et al.*, 2010; Warren *et al.*, 2013).

Overfitting is one of the important issues in species distribution model, and to measure it I used two ways, threshold-independent and threshold-dependent. In the former case, AUC was the measure. In MaxEnt output there are two AUCs scores, the train AUC and test AUC. The Train AUC is the fit of the model to the calibration data, while the test AUC is the fit of the model to the evaluation data (Phillips *et al.*, 2006). The difference (AUC_{Diff}) between the mean train and test AUCs is a measure of overfitting, with decreasing differences indicating that the model avoids overfitting (Warren and Seifert, 2011). For threshold-dependent we used one of MaxEnt's threshold rules (i.e. 10% training presence) which measures the omission rate. With 10% training presence rule, I expect there to be 10 percent omission: omission rates more than this means there is overfitting and vice versa.

Binary maps (suitable/non-suitable, or present/absent) can be created in Maxent from these probabilities of habitat suitability by choosing one type of threshold rule. There are many methods to select from for the threshold rule: Liu *et al.* (2005) evaluated more than ten threshold criteria, and recommended five of them as better than the others. These were prevalence, average probability/suitability, sensitivity-specificity sum maximisation, sensitivity-specificity equality, and ROC plots. Several are implemented in the MaxEnt software (see (Fielding and Bell, 1997;

Liu *et al.*, 2005; Phillips *et al.*, 2006; Pearson *et al.*, 2007; Freeman and Moisen, 2008; Jarnevich and Reynolds, 2011)).

In this study, for every species, thresholded distribution maps were made from the ten replicates of each of the two data partitions (70%, 90% and k-fold), choosing one of two of the rules in MaxEnt:

- i) 10th percentile training presence; this expects that 10% of the training records have errors (incorrect georeferencing, records are immigrants, or transients: Morueta-Holme *et al.* (2010)).
- ii) Minimum training presence; this is the minimum threshold that results in the inclusion of all the training presences in the set of predicted presences (Pearson *et al.*, 2007).

Maxent does not naturally give an average binary map over all the replicates, and so this was made manually by allotting 'presence' to a pixel that had presence values in more than 50% of the model runs (i.e. >5 replicates). The process was carried out using the Raster Calculator of Arcmap10.

The following models describe the variations that I explored between the MaxEnt default settings and particular aspects of the settings:

A) Basic model

I used 70% of data for (training) model calibration, with the remaining 30% of the data for evaluating the model (testing) without replication in the first step, and then I used K-fold cross-validation partitioning, dividing the data 10-fold randomly. I set the number of iterations to 1000 to be sure that MaxEnt had enough time to converge (Phillips *et al.*, 2006). All combinations of the feature types listed above were used for each species to see which gave the best AUC value. The threshold used in this model was 10% training presences, with cross validation and logistic output.

B) Increasing the data partition for training to 90%

This model was similar to (A) except that the data partitioning was 90% for training and the remaining 10% for testing; again I used 10-fold partitioning with this model.

C) Same as B but reducing the number of iterations

In this model I also used 90% of the data for training and the rest for testing, but the iteration number was the default setting of 500: 10-fold partitioning was used, with ten replications for each species. All combinations of feature types were used, with cross validation and the minimum training presence as the threshold rule.

D) Same as C but reducing the proportion of the data to 70% used for training and remaining 30% for testing, with 10-fold partitioning used with ten replications for each species.

E) Changing the number of background points

In this model, 70% of the data was for training and 30% for testing, with 1000 iterations. I changed the background number of points in different ways, using 100, 1000, 5000, 25000, 50000, and 100000 points instead of the 10000 points in the default setting. I found that that 100 background points was the worst, giving the smallest values for AUC. Therefore, at the end we chose the default setting (10000 background points) based on two reasons first, AUC values; seconded recommended by (Phillips *et al.* 2006; Phillips and Dudik, 2008).

F) Altering the regularisation multiplier

In this study, I produced a set of models to determine the best value of regularisation β for each species. In each model I used the same set of variables, and changed the β values from 0 to 10 in increments of 0.5. The data were partitioned 10-fold randomly. All combinations of feature types were used. Iteration was set at 1000, with 10 replications per run. The 10th percentile training presence threshold rule was chosen, and the model was run with cross validation and logistic output.

In its default setting, models of Maxent assume that all sites on the landscape are equally likely to be sampled. In reality, occurrence datasets normally show some sampling bias, where some sites (e.g. close to roads, towns, etc.) are more heavily sampled than others, especially when the records come from museum samples (Phillips *et al.*, 2009). When there are biases in the samples, it is not easy to differentiate whether the species is detected in particular environments because those sites are better or because they have been sampled more (Phillips *et al.*, 2009; Wisz and Guisan, 2009; Newbold *et al.*, 2010).

Usually, users of MaxEnt assume explicitly or implicitly that the chance of detection and sampling are constant through space, and therefore that the data do not contain any sampling bias. For presence-only data, one must expressly demonstrate the likelihood of sampling an area in light of the fact that no absence records exist to determine which areas were sampled. Models for discovery likelihood can be built from recurrent sampling from similar regions (Merow *et al.*, 2013). This enables MaxEnt to choose background points to reflect the bias in sampling, and hence adjust for it. However, to find out whether sampling bias exists is tricky: the easiest way is to compare the locations of the sampled distribution relative to background locations in environment space. When these distributions are the same, then the bias is insignificant for this choice of background (Merow *et al.*, 2013). The process of producing a bias file is difficult and is itself subject to bias. Much of the plant data I am using come from recent systematic surveys (of Sinai in particular) where bias is small. For these reasons, in this study I have not used a bias file.

2.3 Results

To assess model performance, I ran MaxEnt varying six different parameters (A to F, below). Overall the AUC values were good (>0.80) for most models.

A) Basic models

The mean AUC values for all combinations of feature types ranged from 0.890 to 0.933. The highest and lowest mean AUC values were for QPT (0.933) and Q features (0.890) respectively (Table 2.2): these results were with 10-fold partitioning. However, in single partitioning with all combinations, the highest and lowest mean AUC values were recorded for LQPTH (0.963) and LQPT (0.855) respectively (Table 2.3).

B) Increasing the data partition for training to 90%

The mean AUC values with 10-fold partitioning for the feature type combinations varied from 0.890 to 0.930. Auto feature and LQPT recorded the highest AUC values (0.930) and the L feature the lowest (0.890) (see Table 2.4). The highest and lowest mean AUC values were recorded for QPTH (0.975) and H (0.860) respectively (Table 2.5).

C) Same as B but reducing the number of iterations

The mean AUC values were not very different from (A): the AUC for feature-type combinations ranged from 0.888 to 0.929. The highest and the lowest values were recorded for QPT/LHT combinations (0.929) and L and Q (0.888), respectively (see Table 2.6). However, with single partitioning the highest and lowest mean AUC values were recorded for LQPTH (0.977) and LQ (0.849) respectively (Table 2.7).

D) Same as A but reducing the number of iterations

The AUC values for all combinations ranged from 0.887 (Q) to 0.928 (QPT, T) with 10-fold partitioning (see Table 2.8), but with single partitioning the highest

and lowest mean AUC values were recorded for H (0.966) and LQ (0.860) respectively (Table 2.9).

E) Changing the number of background points

These runs were different from the others above in that here I compared the effect of the number of background points on the AUC values with just one feature type combination (LQP). Table 2.10 shows that the lowest mean AUC value (0.700) was recorded with 100 background points and the highest mean AUC value (0.909) with 100000 background points.

F) Altering the regularisation multiplier

Finally, I ran a much more complex set of models by varying the regularisation multiplier from 0 to 10 in increments of 0.5 across all feature-type combinations (315 models in total): all models were better than random in terms of AUC scores. The results shows that mean AUC scores for most feature-class combinations were slightly decreased by increasing the values of the regularisation multiplier. The default setting (when the regularisation value is 1) gave both the best AUC value (0.933) in combination with the QPT combination, and the lowest value (0.891) with the Q feature. Overall the lowest AUC values were recorded for the Q feature across all regularisation values except when regularisation = 10 (LHT) (see Table 2.11).

There were slight differences between the effects of single partitioning and 10-fold partitioning on the differences between AUC values for training and test and omission rates with all feature-class combinations. In single partitioning the highest AUC was recorded for LQPHT (0.963), with the lowest omission rate (0.055), and the difference between train and test AUCs was 0. The lowest test AUC was recorded for L and LQ (0.858), with high omission rates (0.194, 0.250 respectively), and the highest difference between train and test AUCs (0.067 and 0.082 respectively) (Table 2.12). In 10-fold partitioning, the highest test AUC was recorded for QPT (0.933), with an omission rate of 0.135, and differences between

train and test AUC of 0.028. However, the lowest test AUC was noted for Q (0.889), with omission rate of 0.120, and train and test AUC difference of 0.014 (see Table 2.12 for more details).

Table 2.13 shows that difference between train and test AUCs and the omission rates are not very large for the QPT model with default regularisation except when the regularisation multiplier was between 0 and 1. With increases in the regularisation multiplier, the mean AUC clearly decreased but the omission rate and the difference between train and test mean AUC drop also, both indicators of overfitting. The highest omission rate was recorded with a regularisation multiplier of 0, and the lowest with regularisation multipliers 7 and 8. In terms of the differences between train and test AUCs, the highest recorded difference was for a regularisation multiplier of 0, and the lowest for regularisation multipliers of 9.5 (see Table 2.13 for more details).

Most important environmental variables

There were 11 environmental variables used to run MaxEnt (Table 2.1). Across all models the most significant variables which gave the highest contribution in term of permutation importance for each combination of feature types were Bio4 (temperature seasonality), Bio8 (Mean Temperature of Wettest Quarter), and altitude. The variables which have the lowest contribution in the final models were Bio3 (Isothermality BIO2/BIO7), Bio13 (Precipitation of Wettest Month), Bio9 (mean temperature of driest quarter), Bio6 (minimum temperature of coldest month), Bio15 (Precipitation Seasonality), and ndvi-Max (the maximum value of the vegetation index). The relative contributions for each environmental variable changed slightly from model to model. For example, in all models Bio4 was the most significant variable in all feature combinations, but in some models with a few feature-type combinations sometimes Bio8 or altitude, and in one case in model D Bio13, was the most important variable.

Table 2.1. Environmental variables used to build the models (The highlighted one thrown), after applying Variance Inflation Factor (VIF) to reduce the collinearity.

BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (* 100)
BIO4	Temperature Seasonality (standard deviation *100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter
Altitude	Altitude
Habitat	Habitat
NDVI_Max	NDVI maximum value
NDVI_Difference	Absolute difference between the highest and lowest NDVI values

Table 2.2. Mean and SD of AUC values for each feature type (model A with 10-fold partitioning).

No.	Features	AUC values	Influential variables	Standard deviation
1	L	0.892	Bio8	0.061
2	H	0.917	Bio4	0.045
3	T	0.925	Bio4	0.021
4	Q	0.89	Bio8	0.05
5	LQ	0.899	Bio8	0.056
6	LQP	0.908	Altitude	0.057
7	LQPT	0.916	Bio4	0.045
8	LQPTH	0.931	Bio4	0.031
9	PTH	0.927	Altitude	0.051
10	LQPH	0.923	Bio4	0.035
11	QPT	0.933	Bio4	0.038
12	QPTH	0.926	Bio4	0.032
13	TH	0.925	Bio4	0.042
14	LTH	0.924	Bio4	0.043
15	Auto features	0.929	Altitude	0.034

Table 2.3. AUC values and standard deviation with all feature combinations for model A with single partitioning, 70% for model building and 30% for model testing.

No.	Features	AUC values	Influential Variable	Standard deviation
1	L	0.859	bio8	0.043
2	H	0.941	bio8	0.015
3	T	0.936	bio4	0.022
4	Q	0.862	bio8	0.046
5	LQ	0.859	bio8	0.043
6	LQP	0.898	bio8	0.037
7	LQPT	0.855	altitude	0.047
8	LQPTH	0.963	bio4	0.012
9	PTH	0.952	altitude	0.015
10	LQPH	0.888	bio13	0.036
11	QPT	0.941	bio13	0.018
12	QPTH	0.926	bio8	0.035
13	TH	0.925	bio4	0.025
14	LTH	0.921	bio8	0.02
15	Auto features	0.924	bio4	0.02

Table 2.4. Mean and SD of AUC values for each feature type (model B with 10-fold partitioning).

No.	Features	AUC values	Influential Variable	Standard deviation
1	L	0.89	Bio8	0.052
2	H	0.917	Bio4	0.048
3	T	0.925	Bio4	0.039
4	Q	0.892	Bio8	0.048
5	LQ	0.897	Bio8	0.049
6	LQP	0.9	Bio8	0.054
7	LQPT	0.93	Altitude	0.035
8	LQPTH	0.923	Bio4	0.036
9	PTH	0.925	Altitude	0.053
10	LQPH	0.915	Bio4	0.048
11	QPT	0.925	Bio4	0.038
12	QPTH	0.921	Bio4	0.037
13	TH	0.926	Bio4	0.032
14	LTH	0.922	Bio4	0.054
15	Auto features	0.93	Bio4	0.028

Table 2.5. AUC values and standard deviation for model B with single partitioning, 90% for model building and 10% for model testing.

No.	Features	AUC values	Influential Variable	Standard deviation
1	L	0.907	bio8	0.043
2	H	0.860	bio8	0.074
3	T	0.888	bio4	0.044
4	Q	0.942	bio8	0.032
5	LQ	0.875	Bio8	0.042
6	LQP	0.928	bio8	0.047
7	LQPT	0.954	bio4	0.023
8	LQPTH	0.951	Bio4	0.032
9	PTH	0.898	bio13	0.048
10	LQPH	0.972	bio4	0.009
11	QPT	0.955	bio4	0.025
12	QPTH	0.975	bio4	0.012
13	TH	0.902	bio4	0.059
14	LTH	0.954	Bio8	0.020
15	Auto features	0.931	altitude	0.029

Table 2.6. Mean and SD of AUC values for each feature type (model C with 10-fold partitioning).

No.	Features	AUC values	Influential Variable	Standard deviation
1	L	0.888	Bio8	0.075
2	H	0.921	Bio4	0.055
3	T	0.925	Bio4	0.053
4	Q	0.888	Bio8	0.036
5	LQ	0.898	Bio8	0.042
6	LQP	0.902	Bio8	0.081
7	LQPT	0.927	Bio4	0.041
8	LQPTH	0.921	Bio4	0.044
9	PTH	0.927	Bio4	0.056
10	LQPH	0.922	Bio4	0.039
11	QPT	0.929	Bio4	0.056
12	QPTH	0.918	Bio4	0.047
13	TH	0.922	Bio4	0.053
14	LTH	0.929	Bio4	0.025
15	Auto features	0.927	Bio4	0.047

Table 2.7. AUC values and standard deviation for model C with single partitioning, 90% for model building and 10% for model testing.

No.	Features	AUC values	Influential Variable	Standard deviation
1	L	0.941	Bio8	0.030
2	H	0.955	Bio4	0.030
3	T	0.881	Bio4	0.054
4	Q	0.965	Bio8	0.011
5	LQ	0.849	Bio8	0.062
6	LQP	0.898	Bio8	0.057
7	LQPT	0.959	altitude	0.017
8	LQPTH	0.977	Bio4	0.005
9	PTH	0.878	Bio4	0.074
10	LQPH	0.948	Bio4	0.027
11	QPT	0.954	Bio4	0.024
12	QPTH	0.964	altitude	0.019
13	TH	0.907	Bio4	0.047
14	LTH	0.937	Bio8	0.023
15	Auto features	0.909	Bio4	0.074

Table 2.8. Mean and SD of AUC values for each feature type (model D with 10-fold partitioning).

No.	Features	AUC values	Influential Variable	Standard deviation
1	L	0.891	Bio13	0.044
2	H	0.915	Bio4	0.042
3	T	0.928	Bio4	0.042
4	Q	0.887	Bio8	0.056
5	LQ	0.899	Bio8	0.059
6	LQP	0.898	Bio8	0.043
7	LQPT	0.92	Bio4	0.057
8	LQPTH	0.926	Bio4	0.044
9	PTH	0.925	Bio4	0.048
10	LQPH	0.92	Altitude	0.045
11	QPT	0.928	Bio4	0.039
12	QPTH	0.924	Bio4	0.051
13	TH	0.922	Bio4	0.044
14	LTH	0.927	Bio4	0.055
15	Auto features	0.921	Bio4	0.063

Table 2.9. AUC values and standard deviation for model D with single partitioning, 70% for model building and 30% for model testing.

No.	Features	AUC values	Influential Variable	Standard deviation
1	L	0.865	bio13	0.041
2	H	0.965	Bio4	0.010
3	T	0.966	Bio4	0.011
4	Q	0.923	Bio8	0.028
5	LQ	0.860	bio8	0.042
6	LQP	0.870	bio8	0.042
7	LQPT	0.933	bio4	0.026
8	LQPTH	0.918	Bio13	0.028
9	PTH	0.952	bio8	0.016
10	LQPH	0.897	bio4	0.038
11	QPT	0.954	Bio8	0.013
12	QPTH	0.885	Bio3	0.034
13	TH	0.959	Bio4	0.013
14	LTH	0.924	bio4	0.027
15	Auto features	0.898	bio4	0.030

Table 2.10. Mean and SD of AUC values for varying numbers of background points (model E).

No.	Background points	AUC values	Influential Variable	Standard deviation
1	100	0.7	Bio8	0.049
2	1000	0.869	Bio8	0.037
3	5000	0.896	Bio8	0.049
4	10000	0.902	Bio8	0.074
5	25000	0.903	Bio8	0.056
6	50000	0.903	Bio8	0.084
7	100000	0.909	Bio8	0.042

Table 2.11. Mean and SD of AUC values for each feature type with varying values of the regularisation multiplier (model F).

Feature	Regularisation multiples													
	0		0.5		1		1.5		2		2.5		3	
	AUC	SD	AUC	SD	AUC	SD	AUC	SD	AUC	SD	AUC	SD	AUC	SD
L	0.902	0.049	0.9	0.059	0.892	0.061	0.894	0.057	0.895	0.042	0.898	0.052	0.897	0.038
H	0.918	0.049	0.924	0.035	0.917	0.045	0.914	0.031	0.914	0.071	0.916	0.039	0.91	0.056
T	0.924	0.056	0.931	0.028	0.925	0.021	0.925	0.04	0.922	0.05	0.921	0.038	0.921	0.023
Q	0.892	0.066	0.891	0.049	0.89	0.05	0.889	0.052	0.888	0.081	0.892	0.034	0.883	0.097
LQ	0.904	0.026	0.903	0.054	0.899	0.056	0.896	0.066	0.896	0.074	0.903	0.043	0.9	0.036
LQP	0.91	0.036	0.902	0.046	0.918	0.057	0.905	0.041	0.897	0.063	0.904	0.042	0.901	0.053
LQPT	0.924	0.05	0.929	0.03	0.916	0.045	0.926	0.036	0.919	0.028	0.914	0.049	0.918	0.061
LQPTH	0.917	0.051	0.93	0.054	0.931	0.031	0.921	0.039	0.918	0.053	0.90913	0.042	0.912	0.044
PTH	0.927	0.029	0.931	0.044	0.927	0.051	0.923	0.031	0.922	0.043	0.914	0.038	0.914	0.034
LQPH	0.916	0.059	0.918	0.052	0.923	0.035	0.911	0.048	0.909	0.051	0.908	0.061	0.908	0.041
QPT	0.926	0.053	0.927	0.051	0.933	0.038	0.923	0.048	0.926	0.036	0.915	0.031	0.916	0.03
QPTH	0.919	0.028	0.929	0.056	0.926	0.032	0.923	0.03	0.921	0.031	0.916	0.048	0.913	0.054
TH	0.924	0.032	0.932	0.046	0.925	0.042	0.923	0.046	0.917	0.061	0.917	0.053	0.918	0.029
LTH	0.916	0.028	0.926	0.059	0.924	0.043	0.923	0.032	0.915	0.043	0.91	0.045	0.913	0.041
Auto features	0.918	0.05	0.926	0.05	0.929	0.034	0.918	0.036	0.917	0.045	0.914	0.055	0.91	0.066

Feature	Regularisation multiples													
	3.5		4		4.5		5		5.5		6		6.5	
	AUC	SD	AUC	SD	AUC	SD	AUC	SD	AUC	SD	AUC	SD	AUC	SD
L	0.89	0.064	0.894	0.062	0.899	0.053	0.901	0.072	0.899	0.043	0.897	0.036	0.898	0.046
H	0.909	0.053	0.91	0.048	0.912	0.039	0.909	0.042	0.906	0.054	0.907	0.027	0.901	0.082
T	0.926	0.036	0.921	0.041	0.917	0.043	0.92	0.031	0.92	0.031	0.916	0.21	0.913	0.051
Q	0.89	0.056	0.894	0.077	0.895	0.047	0.895	0.07	0.889	0.043	0.893	0.046	0.89	0.056
LQ	0.902	0.041	0.904	0.049	0.899	0.048	0.898	0.085	0.902	0.04	0.9	0.054	0.901	0.042
LQP	0.902	0.066	0.904	0.054	0.904	0.031	0.9	0.052	0.903	0.049	0.906	0.04	0.907	0.041
LQPT	0.909	0.053	0.906	0.06	0.906	0.044	0.899	0.099	0.906	0.033	0.903	0.4	0.903	0.039
LQPTH	0.916	0.046	0.911	0.055	0.904	0.042	0.908	0.037	0.908	0.064	0.902	0.052	0.906	0.068
PTH	0.912	0.049	0.904	0.034	0.908	0.034	0.906	0.061	0.896	0.061	0.908	0.041	0.908	0.034
LQPH	0.909	0.033	0.908	0.061	0.907	0.05	0.902	0.039	0.905	0.055	0.897	0.067	0.903	0.049
QPT	0.911	0.046	0.908	0.037	0.906	0.047	0.904	0.067	0.905	0.034	0.9	0.054	0.903	0.058
QPTH	0.902	0.044	0.904	0.058	0.911	0.046	0.908	0.042	0.899	0.069	0.903	0.043	0.904	0.058
TH	0.918	0.035	0.919	0.027	0.913	0.041	0.912	0.039	0.911	0.035	0.91	0.07	0.911	0.043
LTH	0.906	0.042	0.906	0.031	0.903	0.062	0.898	0.058	0.902	0.03	0.903	0.041	0.903	0.045
Auto features	0.91	0.064	0.902	0.078	0.903	0.069	0.904	0.06	0.91	0.036	0.904	0.05	0.908	0.036

Feature	Regularisation multiples													
	7		7.5		8		8.5		9		9.5		10	
	AUC	SD	AUC	SD	AUC	SD	AUC	SD	AUC	SD	AUC	SD	AUC	SD
L	0.899	0.061	0.901	0.036	0.898	0.054	0.899	0.03	0.901	0.067	0.899	0.036	0.9	0.073
H	0.904	0.047	0.907	0.037	0.904	0.028	0.906	0.046	0.903	0.049	0.906	0.036	0.9	0.066
T	0.912	0.038	0.913	0.028	0.911	0.023	0.914	0.028	0.908	0.038	0.908	0.027	0.9	0.027
Q	0.898	0.052	0.885	0.076	0.895	0.048	0.895	0.08	0.898	0.057	0.895	0.054	0.895	0.053
LQ	0.901	0.041	0.905	0.051	0.901	0.057	0.902	0.039	0.902	0.035	0.903	0.043	0.902	0.05
LQP	0.907	0.056	0.903	0.05	0.904	0.046	0.905	0.052	0.9	0.052	0.904	0.04	0.907	0.049
LQPT	0.902	0.053	0.904	0.052	0.91	0.039	0.906	0.047	0.903	0.046	0.906	0.043	0.905	0.064
LQPTH	0.901	0.046	0.898	0.057	0.906	0.069	0.907	0.054	0.903	0.043	0.904	0.04	0.905	0.023
PTH	0.905	0.05	0.899	0.058	0.903	0.042	0.909	0.038	0.904	0.06	0.902	0.054	0.9	0.073
LQPH	0.908	0.041	0.906	0.061	0.908	0.053	0.902	0.052	0.903	0.045	0.906	0.045	0.905	0.063
QPT	0.906	0.029	0.905	0.045	0.905	0.032	0.905	0.052	0.906	0.067	0.906	0.047	0.902	0.041
QPTH	0.906	0.032	0.908	0.049	0.908	0.029	0.9	0.053	0.907	0.043	0.899	0.04	0.903	0.036
TH	0.907	0.031	0.905	0.048	0.905	0.043	0.905	0.054	0.904	0.037	0.907	0.034	0.908	0.033
LTH	0.902	0.061	0.9	0.026	0.902	0.057	0.899	0.046	0.9	0.049	0.901	0.047	0.893	0.043
Auto features	0.901	0.059	0.906	0.049	0.903	0.031	0.907	0.058	0.903	0.043	0.905	0.048	0.904	0.058

Table 2.12. Effect of single partitioning and 10 K-fold partitioning on the omission rate and the difference between train and test AUCs (model A).

Features	Single partitioning				K-fold partitioning			
	AUC train	AUC test	Train - Test	Omission rate	AUC train	AUC test	Train - Test	Omission rate
L	0.925	0.858	0.067	0.194	0.908	0.891	0.017	0.119
H	0.948	0.941	0.007	0.111	0.943	0.916	0.027	0.146
T	0.959	0.936	0.023	0.111	0.959	0.925	0.034	0.186
Q	0.914	0.861	0.014	0.166	0.903	0.889	0.014	0.12
LQ	0.94	0.858	0.082	0.25	0.915	0.898	0.017	0.096
LQP	0.94	0.897	0.043	0.111	0.936	0.907	0.029	0.12
LQPT	0.963	0.885	0.078	0.277	0.959	0.916	0.043	0.16
LQPTH	0.947	0.962	0	0.055	0.959	0.931	0.028	0.153
PTH	0.951	0.951	0	0.083	0.959	0.926	0.033	0.164
LQPH	0.953	0.887	0.066	0.194	0.946	0.923	0.023	0.112
QPT	0.948	0.941	0.007	0.138	0.961	0.933	0.028	0.135
QPT mean 10 r.	0.955	0.929	0.026	0.118	0.961	0.933	0.028	0.135
QPTH	0.958	0.926	0.022	0.055	0.959	0.926	0.033	0.176
TH	0.962	0.924	0.038	0.138	0.957	0.924	0.033	0.15
LTH	0.953	0.921	0.032	0.222	0.957	0.923	0.034	0.069
Auto features	0.956	0.923	0.033	0.166	0.959	0.928	0.031	0.153

Table 2.13. Omission rate and the difference between mean train and test AUC values with varying regularisation multipliers (QPT model only, with default setting 1).

Regularisation multiplier	Train AUC	Test AUC	Diff.	Omission rate
0	0.992	0.925	0.067	0.760
0.5	0.974	0.926	0.048	0.282
1	0.961	0.933	0.028	0.135
1.5	0.950	0.923	0.027	0.114
2	0.945	0.926	0.019	0.128
2.5	0.940	0.914	0.026	0.128
3	0.937	0.915	0.022	0.130
3.5	0.933	0.910	0.023	0.121
4	0.931	0.907	0.024	0.128
4.5	0.926	0.906	0.020	0.114
5	0.926	0.904	0.022	0.130
5.5	0.924	0.905	0.019	0.112
6	0.924	0.900	0.024	0.112
6.5	0.922	0.902	0.020	0.112
7	0.922	0.905	0.017	0.105
7.5	0.920	0.905	0.015	0.113
8	0.919	0.904	0.015	0.105
8.5	0.919	0.905	0.014	0.114
9	0.944	0.905	0.039	0.119
9.5	0.917	0.905	0.012	0.113
10	0.916	0.901	0.015	0.121

2.4 Discussion

Users of species distribution model programs are confronted with a mixed bag of alternative options, and it is not generally evident how selecting one alternative over another will influence model performance (Syfert *et al.*, 2013). In term of AUC values, all the models show good performance that is greatly better than random. Most models with different feature-class combinations achieved a mean AUC score better than 0.8, confirming that the overall models show good performance. Approximately 86% of the models had a mean AUC score of 0.9 or above, indicating very good performance capability (Pearson, 2007).

For the different models created with different settings in Maxent, in general for all models the simple feature classes gave relatively low AUC values. More complex models with different feature classes gave slightly better AUC scores, but the differences were not large among all the models. Therefore, my chosen combination gave a high value for the mean AUC (QPT) combined with the basic model (model A) with 10-fold partitioning, for the simple reason of saving time and space. This combination runs quickly, produces excellent performance, and because it is not more complex than the 'auto' feature, the response curves are not very complex, neither are the overly simple, resulting in an easier interpretation than the more complex models.

According to the results, the different feature-class combinations do not have a great effect on the AUC values and hence they do not affect model prediction performance very much. Syfert *et al.* (2013) also found that the selection of different feature classes had insignificant impact on prediction performance. MaxEnt may have the capacity to create models with comparable levels of performance with mixes of much less complex feature classes (Syfert *et al.*, 2013). It is important to remove highly correlated environmental variables in advance because if not, then more complex features are known to affect prediction performance (Merow *et al.*, 2013).

Through selecting models the data partition is one of the important steps, because there are different strategies to divide the occurrence data for calibration

(building) and evaluation (testing) of species distribution models. Maxent allow the use of different ways for data partitioning through its settings. In general studies use K-fold partitioning more often than single partitioning (e.g. (Phillips and Dudik, 2008; Elith *et al.*, 2011; Warren *et al.*, 2013; Radosavljevic and Anderson, 2014)). I used the AUC as an indicator to see the impact of data partitioning methods on model performance, because this is independent of any thresholding technique. In general, both approaches of data partitioning achieved good performance, much better than random. In some models, K-fold was better than single partitioning, and vice versa. I conclude, however, that K-fold partitioning is more suitable than dividing the data into a single partition for a number of reasons. First, in K-fold partitioning, every record appears in the evaluation, enabling the maximum ability of the model to forecast the entire suitable habitat for the species, while in the single-sample partitioning each record may not be included in the evaluation dataset (Peterson *et al.*, 2011). Second, model results with K-fold partitioning indicate the sensitivity of the modelling method to arbitrary differences in the occurrence data. Additionally, models with K-fold partitioning can be averaged to produce more reliable predictions of the niche and distribution, more resistant to the vagaries of partitioning records into calibration and evaluation sets. The assessment statistics from the K-fold method can therefore provide good measures of model performance, significance and uncertainty (Peterson *et al.*, 2011).

Single partitioning sometimes leads to over- or under-fitting more often than K-fold partitioning. For example, in the basic model (model A) (Table 2.11) the highest differences between train and test AUC values, and omission rates were recorded with single partitioning, indicating overfitting. In this model the threshold rule was 10% training presence, implying that the omission rate should be 10% or 0.1; when the results indicate an omission rate of 10%, this means there is no overfitting and indicate the accuracy of the model (Radosavljevic and Anderson, 2014). Additionally, in most feature combinations models the differences between train and test AUC values in K-fold partitioning were lower than single partitioning except in a few cases of overfitting and underfitting.

MaxEnt compares a set of chosen background points against presences whenever absences are not surveyed (Phillips and Dudik, 2008), called pseudoabsences (Phillips *et al.*, 2009). In MaxEnt there is flexibility to choose the number of background points according to the purpose of the study. My results demonstrate that by increasing the number of background points the mean AUC values gradually rose, particularly when >5000 background points were used. Phillips and Dudik (2008) also explored this question, and found that AUC scores improved with increasing numbers, and the highest AUC values were achieved when >8000 background points were used. They suggested that more background points were appropriate when the number of records used for modelling was large (Phillips and Dudik, 2008). Table 9 shows there were no large differences between the default setting of MaxEnt and other choices of the background number, and so I chose to use the default setting (10000) for my models. MaxEnt has flexibility in specifying precisely which locations to use as background, selecting both their total number and spatial range. For instance, if the study aims to describe the best area for conservation for a particular species, selected background points should be drawn according to the range of this species only, while if the study aims to know which climate locations were susceptible to invasion in the absence of dispersal limitation, the background should be selected from these suitable territories worldwide (Merow *et al.*, 2013).

The process which Maxent models avoid over-fitting is called regularisation. I produced 315 models using different feature-class combinations and regularisation multipliers (Table 2.10) to show how changing regularisation values affect the AUC scores. With increasing regularisation values the AUC score slightly decreased for all feature combinations, and hence for the rest of this study I chose the default setting together with the QPT combination since this achieved the highest mean AUC value. In this project I will use 115 plant species, and it seems clear that the default settings achieve very good performance when the number of species is high, when species-specific settings are unfeasible (Merow *et al.*, 2013), and across different taxonomic groups (Phillips and Dudik, 2008). The default

regularisation value may not be optimal when the study is focussed on just one or a few species (Elith *et al.*, 2010; Anderson and Gonzalez, 2011), and when it is feasible to produce models with different optimised regularisation values.

3 Chapter Three: Using species distribution models to assess the importance of Egypt's Protected Areas for the conservation of medicinal plants

Abstract

Human activities affect the distribution and abundance of plants, with impacts on ecosystem services and human well-being; it is thus vital that a network of Protected Areas is capable of conserving plants that are useful. Using the species distribution (SDM) model algorithm MaxEnt, we tested whether Egypt's network of Protected Areas performs well in conserving the region's important medicinal plant species. We constructed individual SDMs for each species, and then combined the models into a single 'species-richness' layer, which we then compared to the distribution of the existing Protected Areas. Temperature was the most important of eleven predictor variables used to build the SDMs. Assuming the SDM's prediction of suitable habitat was accurate and corresponded to the occurrence each of the medicinal plant species, then on average species richness was significantly higher within than outside the Protected Areas. Based on our findings, Egypt's Protected Areas are effective at conserving its medicinal plants.

3.1 Introduction

Human activities are having a strong impact on plant abundance and distribution, with consequent effects on ecosystem services and human well-being (Klein *et al.*, 2008). This growing effect of human activities on biodiversity (Chapin *et al.*, 2000) creates an urgent need to understand the elements that determine the distribution and abundance of plant in order to enhance their conservation (Dubuis *et al.*, 2011). The identification of species-rich regions and those where geographically limited species co-occur can optimise the creation of Protected Areas (Bojórquez-Tapia *et al.*, 1995).

Medicinal plants are one of the most important elements of biodiversity around the world (Klein *et al.*, 2008; Okigbo *et al.*, 2008) because of their role in ecosystem services such as healthcare, cultural value and heritage, local economics and human well-being, especially in poor areas (Klein *et al.*, 2008; Okigbo *et al.*, 2008). Conserving and protecting these kinds of species is vital, including improving knowledge about the important ecological requirements of medicinal plants, and raising awareness among all stakeholders to protect this heritage. Consequently, conservation planning and effective management is important in protecting the most threatened species in order to avoid declines in the diversity of medicinal plants.

Species distribution models (SDMs) can be used to predict the geographic distribution of individual species using locality data and ecological variables as predictors (Franklin, 2009). While occurrence records can be harvested from museums/herbaria, published reports, and original fieldwork, accurately identifying whether a species is truly absent is exceedingly difficult. To address this challenge, several SDM algorithms have been designed to employ only positive presence data (Phillips *et al.*, 2006). One such SDM algorithm, MaxEnt, has been shown to be one of the most effective tools for accurately predicting species distributions (Elith *et al.*, 2006). SDMs using MaxEnt offer a valuable tool for creating general patterns of species richness without needing to analyse the specific quality or precision of the

predictions for every individual species (Pineda and Lobo, 2009). Several studies have added together the models for individual species to create maps of species richness, the approach we adopt here. For example, Ortega-Huerta and Peterson (2004) added the individual maps of 285 bird and 114 mammal species of part of Mexico to create a map of species richness; Newbold *et al.* (2009) and Pineda and Lobo (2009) used the same approach for Egyptian mammals and butterflies, and Mexican amphibians respectively, as did de Pous *et al.* (2011) on Moroccan reptiles. It is exciting that the same approach can be used to project into the future under climate change (Distler *et al.*, 2015), as we have also done (Kaky & Gilbert, 2017). Ideally the maps of predicted species richness should be validated using independent data (Pineda and Lobo, 2009). Such species-richness maps make it possible to distinguish hotspots of species richness (Newbold *et al.*, 2010), and hence to select feasible regions for conservation relatively objectively (Pressey *et al.*, 1993). This is a powerful tool to help build conservation efforts or anticipate the future of biodiversity under worldwide climate change (Algar *et al.*, 2009).

The climatic predictors used in our SDMs should be very suitable for plants. The physiological toleration hypothesis suggests that plant species richness is most elevated in warm and/or wet environments because a more extensive range of functions can persevere under such circumstances (Spasojevic *et al.*, 2014). For instance, Hawkins *et al.* (2003) found that a measure of the balance between energy and water nearly always described spatial difference in species richness better than other environmental variables. In warm regions of the tropics and subtropics, the most robust predictors are typically water variables, while water/energy variables (for plants) or energy predictors (for animals) predominate in high latitudes (Hawkins *et al.*, 2003).

Protected Areas currently cover about 12% of the terrestrial surface of the earth (Seiferling *et al.*, 2012), while those that have been declared in Egypt cover 15% of the total land area (El-Gabbas *et al.*, 2016). The 30 Egyptian Protected Areas were all established since 1983, based on the recommendations of experts

familiar with Egyptian biodiversity (Newbold *et al.*, 2009). An obvious issue is the extent to which these Protected Areas are capable of conserving Egypt's fauna and flora: a basic requirement is that they contain a high proportion of the biodiversity of the country. Thus ideally there should be higher species richness within the Protected Areas than outside them. Several studies have measured this: for example, Sciberras *et al.* (2013) showed that the density and biomass of fish and invertebrates inside partially protected areas was higher than in unprotected areas; Newbold *et al.* (2009) and Lee *et al.* (2007) found that species richness inside Protected Areas was higher than outside, but others found the reverse (Pawar *et al.*, 2007; Traba *et al.*, 2007). Human activities are one of the main reasons for declines both inside and especially outside Protected Areas: thus forest cover decreased between 1980 and 2001 in areas surrounding most tropical Protected Areas (DeFries *et al.*, 2005), and one might anticipate similar declines in the fauna. The active management of Protected Areas needs many more such comparisons to guide management decisions (Linkie *et al.*, 2006).

Our objective is therefore to assess the role of the network of Egyptian Protected Areas in conserving medicinal plants by comparing their diversity within and just outside each Protected Area, averaging this difference across all the Protected Areas. We did this by predicting the distribution of each species using SDMs, and summing together all the SDMs to create two kinds of species-richness maps (by either using or not using thresholds to binarize the predicted habitat suitabilities). We then use these maps to assess the predicted species richness inside and outside Egypt's Protected Areas.

3.2 Methods

We used data for 121 medicinal plant species of the Egyptian flora. The occurrence data for these species were collated by the BioMAP project (<http://www.biomapegypt.org/>), a project run from Cairo in 2004–2008 and funded by Italian Debt Swap. The data are presence-only records collected from different

sources (i.e. literature, herbarium, and field work). To avoid inaccurate predictions, we deleted species with fewer than ten records to avoid overfitting (Baldwin, 2009), species with more than ten but spatially very restricted records, and the one species whose SDM had a mean AUC less than 0.7 (Franklin, 2009). We ended up with 114 species of Egyptian medicinal plants, with 14396 point records.

The environmental variables used in this study were 23 predictors, 19 of them (Bio layers) downloaded from the WorldClim v1.4 dataset at resolution of 2.5 arc-minutes (<http://www.worldclim.org/bioclim>) (Hijmans *et al.*, 2005) (chapter two Table 2.1). Normalized Difference Vegetation Index (NDVI) data for seven years (2004 to 2010) were downloaded from the Spot Vegetation website (<http://free.vgt.vito.be/>) and used to create two layers: maximum NDVI (Max_NDVI), and the difference between the Minimum and Maximum NDVI values (NDVI_differences). A further environment layer was a habitat layer, derived from the Biomap project, which divided Egypt's terrain into eleven classes ("sea, littoral coastal land, cultivated land, sand dune, wadi, metamorphic rock, igneous rock, gravels,serir sand sheets, sabkhas and sedimentary rocks") (for more detail, see (Newbold *et al.*, 2009). Altitude data were downloaded from <http://www.cgiar-csi.org/data/elevation> and the resolution rescaled from 90 m to be 2.5 arc-minutes (see (El-Gabbas *et al.*, 2016). Eleven of the 23 environmental variables (see chapter two Table 2.1) remained for use after 12 were removed based on collinearity analysis using the Variance Inflation Factor, implemented in R v2.15 (the 'car' package: R Development Core Team 2012).

We used Maximum Entropy (MaxEnt) version 3.3.3k (Phillips *et al.*, 2006) (downloaded from: <http://www.cs.princeton.edu/~schapire/maxent/>) to run the models, choosing a set of options (i.e. feature classes QPT, 10000 background points, 1000 iterations, cross-validation with 10 replications, 10% training presence threshold, and logistic output format) to create both 'probability' (i.e. raw values of habitat suitability) and 'binary' (predicted 'suitable'/'unsuitable' via thresholding) maps. MaxEnt performance is good with presence-only data and small numbers of

records (Elith *et al.*, 2006; Franklin, 2009) , and its performance is good in comparison with other algorithms (Elith *et al.*, 2006). The options were chosen after exhaustive runs with different option combinations (of feature classes, number of background points, number of iterations and regularization values) to obtain the best models. Two statistics were used to evaluate the accuracy of each model, the AUC, and the true skill statistic (TSS) (Allouche *et al.*, 2006). TSS values lie between -1 and +1: close to +1 indicates perfect performance, while close to zero or less than zero point to model performance no better than random (details, see Allouche *et al.* 2006). (For details of each SDM, see Table 3.1)

The relative importance of the environmental predictors can be determined in three ways by Maxent (percent contribution, permutation importance, jackknife: (Phillips *et al.*, 2006)). Care is needed when there are high correlations between variables, but pre-screening variables for collinearity (as we have done) minimises this problem (Dormann *et al.*, 2013). Here we used permutation importance to determine the importance of the environmental predictors, calculated by permuting the values of each predictor and calculating the resulting reduction in the training AUC: a large reduction shows that the model is influenced by that predictor. The values are standardized to a percentage (Phillips *et al.*, 2006).

We created two kinds of maps of the distribution of species richness. The first was the 'probability' map, made manually by obtaining the average of the replicate ascii files obtained from Maxent for each species, and then adding all the species layers together using the 'raster calculator' of ArcGIS10.2.2. This map was then rescaled to fit the same range as the second type, the 'binary' map, which is the product of adding together the binary maps for each species. The binary map converts each pixel value of the MaxEnt output (a continuous value between 0 and 1) into binary data (predicted suitable/ unsuitable) by choosing a threshold rule (see (Liu *et al.*, 2005)). We chose the "10% training presence" as our threshold rule (El-Gabbas *et al.*, 2016), which produced a binary map for each of the 10 replicates for each species. Subsequently we produced a single consensus binary

map for each species by allocating 'suitable' to a pixel that had 'suitable' values in more than 50% of the model runs (i.e. >5 replicates). Then we added together all the species maps to create the 'binary map' for species richness.

Finally we compared the species richness inside and outside Protected Areas. First we chose at random 2000 pixels from the map. A 50-km buffer zone was created around each Protected Area, and the random pixels that lay within each Protected Area and within each buffer zone identified. The mean species richness for the random pixels within each Protected Area ('within') and within its buffer zone ('outside') created paired values inside and outside each Protected Area. We then compared the average difference (within - outside) using a paired t-test.

3.3 Results

In terms of mean AUC values, all models showed good performance (range 0.802 to 0.989) (mean = 0.901 ± 0.0036), as do the TSS scores (mean TSS across all species 0.63 ± 0.01). The lowest mean AUC value was recorded for *Pluchea dioscoridis* and the highest for *Solanum elaeagnifolium* (for more details see Table 3.1). High mean AUC values were not just limited to species with few records, since there were several species with large numbers of records which achieved very good performance. There were 12 species with mean AUC values of 0.80 – 0.85, 38 species between 0.85 – 0.90, 55 species between 0.90 – 0.95, and 10 with very high AUC between 0.95 – 1 (Figure 3.1). There was no significant correlation between the mean AUC and the number of records used in the model ($n=114$, $r=-0.052$, $P>0.05$). In general, for the 10 replicates for each species there were not big differences between the AUC values for each run. The standard deviations ranged between 0.011 and 0.291, the smallest for *Lavandula pubescens* and the highest for *Herniaria hirsuta*. There were five species with a standard deviation between 0.2 – 0.3, 14 species between 0.1 – 0.2, and the rest (96 species) less than 0.1 (Table 3.1).

Environmental predictors that achieved highest permutation importance through all the modelled species, and the maximum contribution to the final models, were Bio6 (the minimum temperature of the coldest month), altitude, Bio3 (isothermality, the ratio of the mean monthly temperature range [max – min] and the maximum annual temperature range), Bio8 (the mean temperature of the wettest quarter), and Bio4 (temperature seasonality, the SD of monthly temperature). There were six variables with low permutation importance: Bio13 (precipitation of the wettest month) Bio15 (precipitation seasonality, the CV of monthly precipitation), habitat, Bio9 (mean temperature of the driest quarter), differences between maximum and minimum NDVI, and maximum NDVI (Figure 3.2). Across all species, Bio6 was the highest for 36 species, followed by altitude (highest for 19 species), Bio3 and Bio8 (16 species) and Bio4 (see Figure 3.3). Sometimes Bio15, Bio13, habitat and Bio9 achieved the highest mean permutation importance, but clearly these were not normally the most influential predictor.

In general, the occurrence locations (Figure 3.4) match well with both types of species richness maps (Figure 3.5 A & B). Species richness is highest from the southwest to the northeast, especially North and South Sinai, along the Mediterranean coast, and scattered areas of the Nile Delta. The probability species richness map (Figure 3.5 A) shows that the highest predicted species richness is situated in south Sinai, especially the area around St Katherine to Sharm El-Sheikh, to the Aqaba Gulf from Sharm El-Sheikh through Dahab to Taba, around El-Tur, some scattered locations between Abu Zneima to Suez, some scattered locations in North Sinai around Gebel Yillaq, El-Hassana, Gebel El-Hallal, Gebel El-Maghara, and some small areas on the border between Egypt and Israel, especially east of Gebel El-Hallal. All locations along the Mediterranean Sea coast from Rafah to Port Said are also suggested to have high species richness, especially from around Lake Bardawil to Mersa Martruh, and inland from Alexandria to Wadi El-Natron (Appendix 1).

In the binary richness map (Fig. 5B) the highest species richness is predicted to be located in north-eastern Egypt, especially in Sinai from the north to the mountain areas of the south, in the north particularly at Gebel Yillaq, El-Hassana, Gebel El-Hallal, Gebel El-Maghara, all the border between Egypt and Israel, the coastal regions of the Mediterranean Sea from Rafah to Port Said, and south of Gebel Yillaq and El-Hassana. In the south the highest predicted species richness is the area from St Katherine to Sharm El-Sheikh, then the entire border along the Aqaba Gulf and along the other side from St Katherine to El-Tur, and to Suez along the Red Sea. The highest predicted species richness is north of Suez to Ismailia, east and west of Ismailia, Greater Cairo, the Mediterranean Sea coast from Lake Manzala to Sallum, north of Wadi El-Natrun, Ain Sukhna, Gebel El-Gallala El-Bahariya, and from Ras Zaafarana south to Ras Gharib, then from Ras Gharib to Hurghada, with some scattered locations at Gebel El-Gallala El-Qibliya. There are also some scattered areas between Mersa Alam to Berenice, and south of Halayeb (Appendix 1).

The predicted species richness was significantly higher inside Protected Areas than outside for both the binary map (paired $t = 14.8$, $df = 24$, $p < 0.001$) (Figure 3.6 A) and for the probability map (paired $t = 9.9$, $df = 24$, $p < 0.001$) (Figure 3.6 B).

Table 3.1. The plant species used for species distribution models, showing the model fit in terms of the mean and standard deviation of the AUC values of the 10 replicates.

Species	Mean AUC	AUC SD	Number of records	Mean TSS
<i>Acacia pachyceras</i>	0.982	0.018	11	0.7433
<i>Acacia tortilis</i>	0.89	0.031	242	0.6255
<i>Achillea fragrantissima</i>	0.926	0.035	239	0.7558
<i>Achillea santolina</i>	0.98	0.029	13	0.5901
<i>Adonis dentata</i>	0.972	0.035	33	0.7648
<i>Aerva javanica</i>	0.911	0.026	175	0.6425
<i>Agathophora alopecuroides</i>	0.891	0.074	26	0.4993
<i>Alhagi graecorum</i>	0.806	0.067	100	0.4384
<i>Anabasis articulata</i>	0.924	0.032	126	0.7171
<i>Anagallis arvensis</i>	0.889	0.084	119	0.6548
<i>Anastatica hierochuntica</i>	0.841	0.13	31	0.5556
<i>Andrachne aspera</i>	0.941	0.049	31	0.6533
<i>Artemisia judaica</i>	0.93	0.031	684	0.7617
<i>Artemisia monosperma</i>	0.946	0.025	115	0.7516
<i>Asclepias sinaica</i>	0.973	0.044	31	0.5421
<i>Asparagus stipularis</i>	0.987	0.016	20	0.8527
<i>Atriplex halimus</i>	0.898	0.055	125	0.6311
<i>Avena barbata</i>	0.914	0.112	22	0.614
<i>Ballota undulata</i>	0.929	0.061	124	0.7757
<i>Bassia muricata</i>	0.853	0.074	83	0.4282
<i>Calendula arvensis</i>	0.895	0.052	66	0.5986
<i>Calotropis procera</i>	0.858	0.065	228	0.5769
<i>Capparis spinosa</i>	0.859	0.065	241	0.5982
<i>Chenopodium album</i>	0.926	0.027	166	0.6583
<i>Chenopodium murale</i>	0.88	0.027	319	0.6219
<i>Chiliadenus montanus</i>	0.91	0.081	88	0.7248
<i>Citrullus colocynthis</i>	0.879	0.047	168	0.6261
<i>Cleome amblyocarpa</i>	0.916	0.044	71	0.6467
<i>Colutea istria</i>	0.91	0.107	24	0.6265
<i>Cornulaca monacantha</i>	0.914	0.053	93	0.6469
<i>Cymbopogon schoenanthus</i>	0.835	0.291	15	0.6702
<i>Cynodon dactylon</i>	0.88	0.045	240	0.6023
<i>Deverra tortuosa</i>	0.94	0.021	141	0.7197
<i>Deverra triradiata</i>	0.832	0.096	64	0.5348
<i>Diploaxis acris</i>	0.916	0.05	60	0.5567
<i>Diploaxis eruroides</i>	0.898	0.061	12	0.4236
<i>Diploaxis harra</i>	0.911	0.039	147	0.6993
<i>Echinops spinosus</i>	0.915	0.024	213	0.6633
<i>Ephedra alata</i>	0.85	0.087	46	0.5024

<i>Eruca sativa</i>	0.938	0.038	96	0.7137
<i>Euphorbia peplis</i>	0.96	0.049	13	0.2698
<i>Euphorbia retusa</i>	0.885	0.059	114	0.5865
<i>Fagonia arabica</i>	0.91	0.025	294	0.7153
<i>Fagonia glutinosa</i>	0.902	0.077	125	0.6877
<i>Fagonia mollis</i>	0.924	0.062	698	0.7687
<i>Farsetia aegyptia</i>	0.906	0.043	114	0.6469
<i>Globularia arabica</i>	0.923	0.063	51	0.6803
<i>Gypsophila capillaris</i>	0.885	0.067	59	0.5575
<i>Halocnemum strobilaceum</i>	0.897	0.134	53	0.7111
<i>Haloxylon salicornicum</i>	0.943	0.026	242	0.7134
<i>Haloxylon scoparium</i>	0.882	0.172	36	0.5885
<i>Haplophyllum tuberculatum</i>	0.889	0.046	73	0.5624
<i>Heliotropium arbainese</i>	0.877	0.05	146	0.6176
<i>Herniaria hirsuta</i>	0.846	0.287	13	0.4588
<i>Hyoscyamus muticus</i>	0.877	0.043	143	0.5604
<i>Imperata cylindrica</i>	0.835	0.054	109	0.4851
<i>Iphiona mucronata</i>	0.904	0.089	53	0.691
<i>Juncus rigidus</i>	0.855	0.042	235	0.6189
<i>Lavandula pubescens</i>	0.986	0.011	15	0.6827
<i>Lycium shawii</i>	0.905	0.04	161	0.6773
<i>Malva parviflora</i>	0.866	0.053	165	0.6021
<i>Melilotus indicus</i>	0.906	0.04	239	0.6941
<i>Mesembryanthemum crystallinum</i>	0.934	0.091	38	0.7484
<i>Mesembryanthemum forsskaolii</i>	0.833	0.246	13	0.4882
<i>Mesembryanthemum nodiflorum</i>	0.912	0.059	79	0.6469
<i>Moltkiopsis ciliata</i>	0.931	0.03	181	0.7196
<i>Nitraria retusa</i>	0.92	0.045	100	0.6799
<i>Noaea mucronata</i>	0.86	0.149	47	0.6708
<i>Ochradenus baccatus</i>	0.898	0.045	137	0.7031
<i>Orobancha cernua</i>	0.909	0.086	42	0.6759
<i>Pancratium sickenbergeri</i>	0.93	0.144	42	0.7258
<i>Panicum turgidum</i>	0.906	0.048	164	0.6076
<i>Paronychia arabica</i>	0.888	0.058	169	0.5699
<i>Paronychia argentea</i>	0.867	0.215	17	0.6129
<i>Peganum harmala</i>	0.913	0.055	138	0.7301
<i>Pergularia tomentosa</i>	0.85	0.053	362	0.5225
<i>Phoenix dactylifera</i>	0.826	0.078	64	0.4957
<i>Phragmites australis</i>	0.858	0.061	128	0.5755
<i>Plantago afra</i>	0.908	0.081	43	0.5387
<i>Plantago ovata</i>	0.904	0.043	36	0.5251
<i>Pluchea dioscoridis</i>	0.802	0.145	62	0.4685
<i>Polycarpaea repens</i>	0.895	0.04	172	0.6532

<i>Polycarpon succulentum</i>	0.908	0.099	94	0.6654
<i>Pulicaria undulata</i>	0.89	0.035	271	0.5856
<i>Reaumuria hirtella</i>	0.948	0.023	109	0.6699
<i>Reichardia tingitana</i>	0.902	0.044	120	0.5946
<i>Retama raetam</i>	0.915	0.037	261	0.7296
<i>Salvia aegyptiaca</i>	0.911	0.058	69	0.6422
<i>Salvia lanigera</i>	0.877	0.107	44	0.5316
<i>Senecio glaucus</i>	0.914	0.05	159	0.6424
<i>Seriphidium herba-album</i>	0.94	0.045	267	0.8026
<i>Silene succulenta</i>	0.857	0.202	25	0.5365
<i>Silene villosa</i>	0.908	0.14	51	0.6186
<i>Sisymbrium irio</i>	0.88	0.05	56	0.5751
<i>Solanum elaeagnifolium</i>	0.989	0.014	24	0.7357
<i>Solanum nigrum</i>	0.883	0.041	199	0.604
<i>Stachys aegyptiaca</i>	0.95	0.022	168	0.6911
<i>Stipagrostis scoparia</i>	0.93	0.061	49	0.6533
<i>Tamarix aphylla</i>	0.823	0.122	86	0.5691
<i>Tamarix nilotica</i>	0.853	0.025	332	0.5859
<i>Tephrosia purpurea</i>	0.881	0.068	78	0.5825
<i>Teucrium leucocladum</i>	0.943	0.071	66	0.8113
<i>Teucrium polium</i>	0.868	0.13	133	0.6113
<i>Thymelaea hirsuta</i>	0.92	0.092	61	0.746
<i>Tribulus terrestris</i>	0.869	0.067	65	0.5519
<i>Trifolium resupinatum</i>	0.93	0.043	126	0.7076
<i>Trigonella stellata</i>	0.922	0.031	62	0.5318
<i>Urginea maritima</i>	0.918	0.185	24	0.69
<i>Urtica urens</i>	0.919	0.092	34	0.5589
<i>Vicia sativa</i>	0.851	0.121	68	0.5381
<i>Zilla spinosa</i>	0.919	0.036	632	0.7028
<i>Zygophyllum album</i>	0.92	0.034	115	0.6487
<i>Zygophyllum coccineum</i>	0.87	0.039	488	0.6131
<i>Zygophyllum dumosum</i>	0.971	0.019	27	0.7678

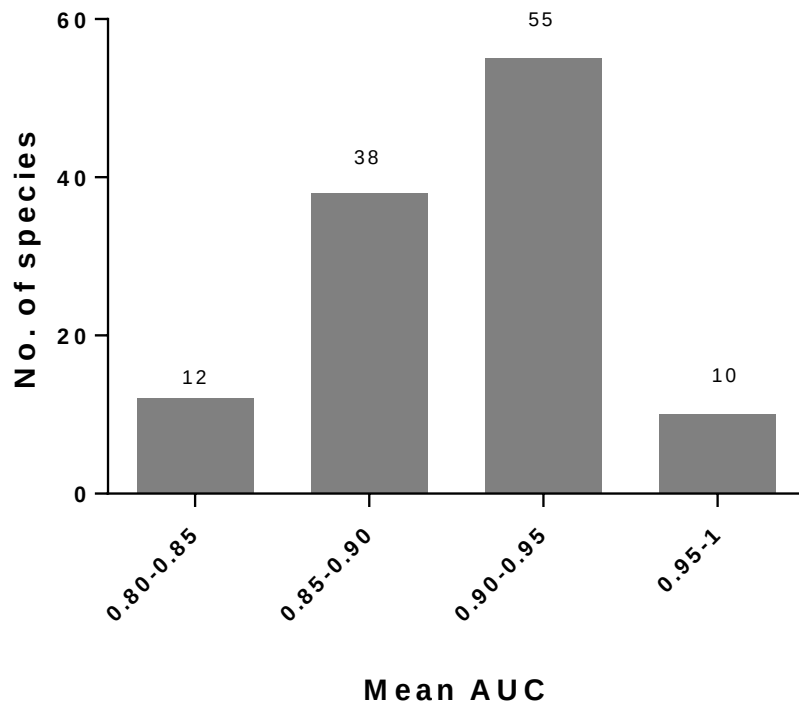


Figure 3.1. Frequency distribution of the mean AUC values achieved in the distribution models of plant species.

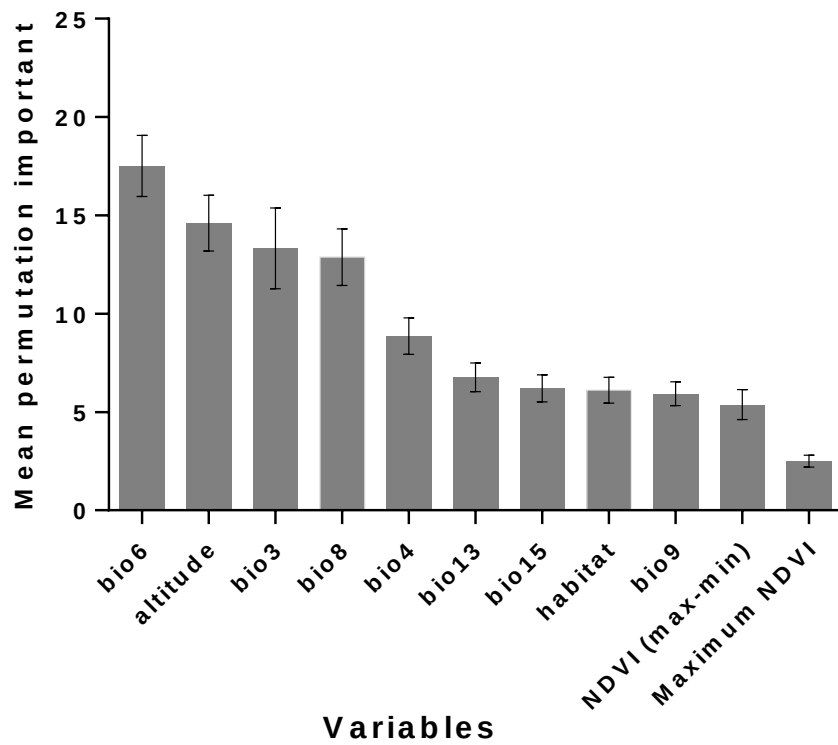


Figure 3.2. Contribution to the final species distribution models made by each environmental predictor, illustrated by the mean permutation importance.

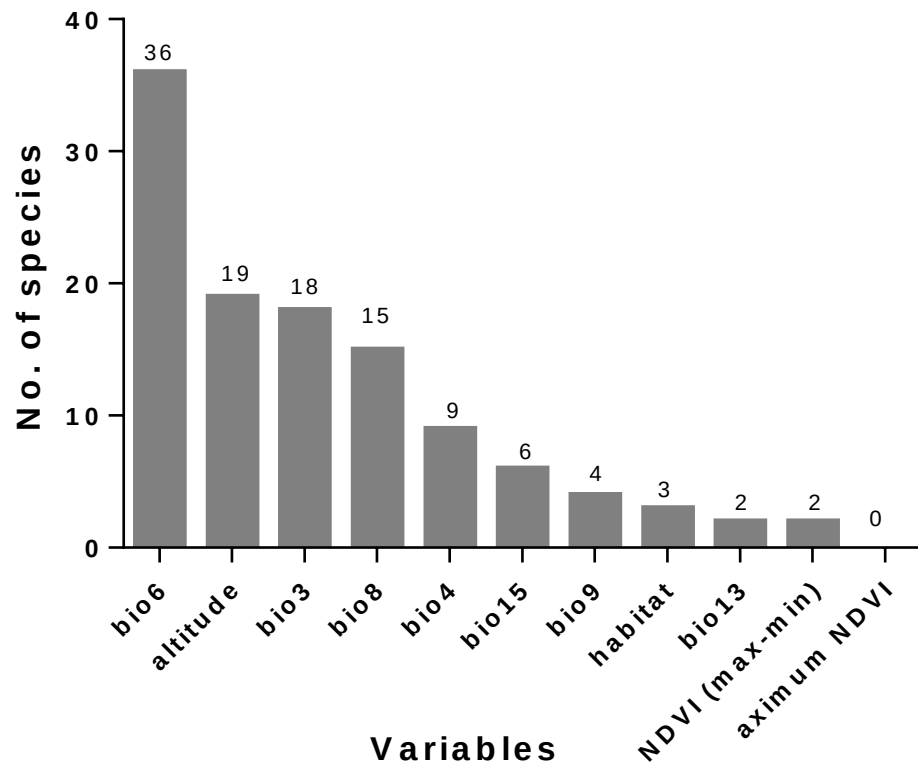


Figure 3.3. Numbers of species where particular variables were the best predictor in species distribution models. One of the variables (ndvi_max) included in modelling was never the best predictor.

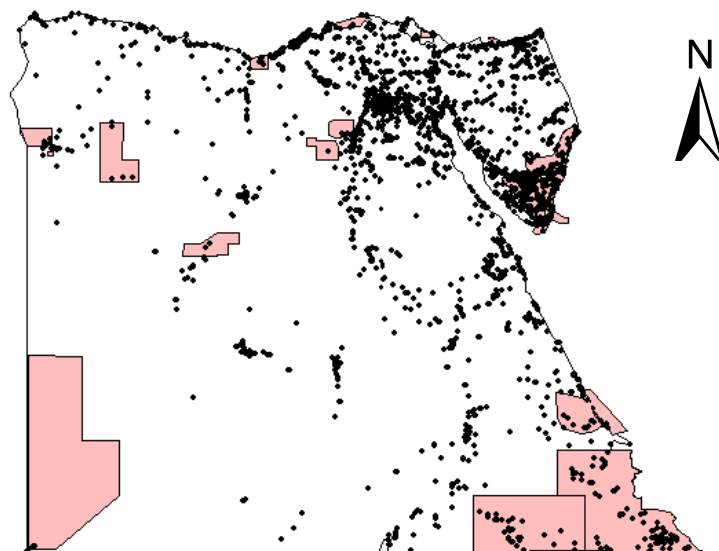


Figure 3.4. Locations which Egyptian plants were sampled (square circle), and protected areas of Egypt (pink shading).

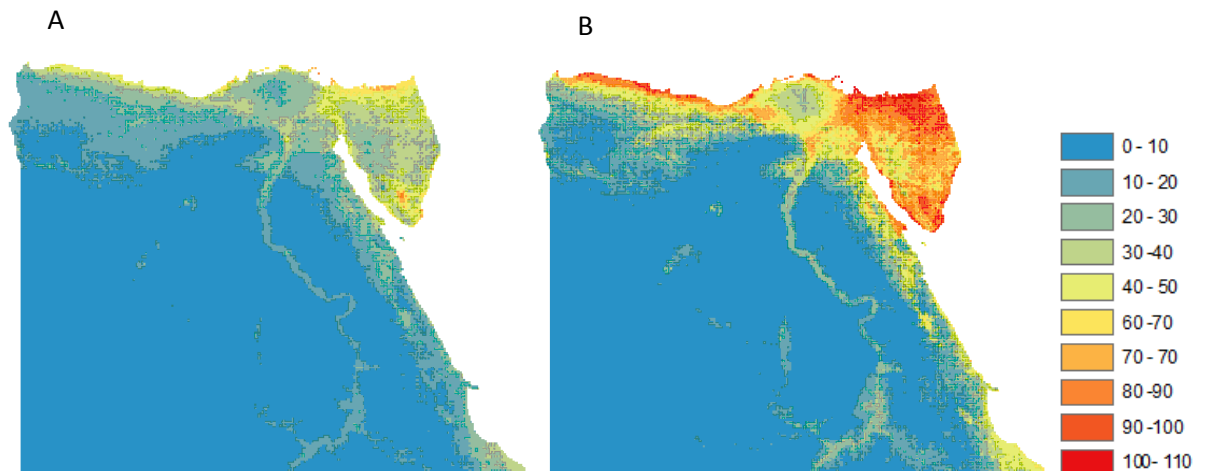


Figure 3.5. Species richness for predicting current distributions: (A) probability richness map resulting from summing all individual species probability maps then rescaled to the same range as that of the binary map; (B) binary richness map, produced from adding all individual species thresholded maps. The colours ranged from blue to red, which blue indicate for low species richness and red indicated for high species richness.

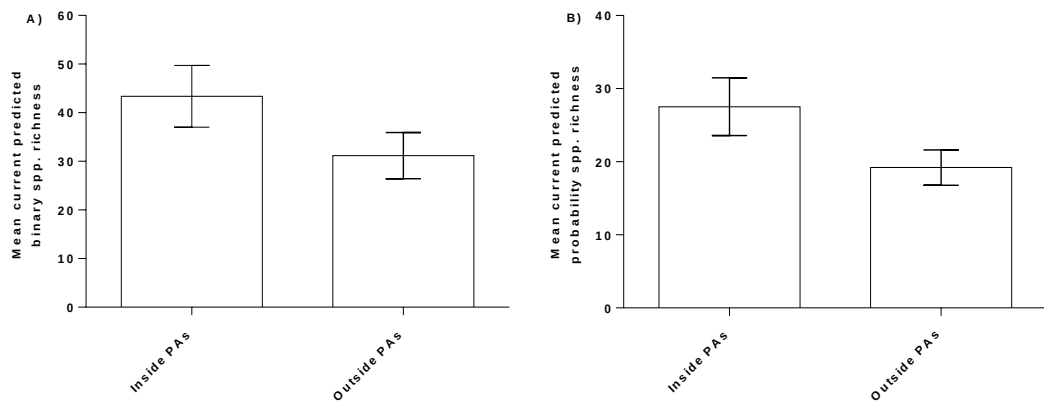


Figure 3.6. A) Comparison of binary predicted species richness (mean $\pm$ SE) between inside and outside protected areas, expected by adding all individual species distribution models; B) Comparison of probability predicted species richness (mean $\pm$ SE) between inside and outside protected areas.

3.4 Discussion

The most important result of this study was that the predicted species richness of medicinal plants was higher inside Egypt's Protected Areas than outside, implying that the Protected Areas have been well located to implement the conservation of these important deliverers of a valuable ecosystem service.

Overall model performances were good in terms of the mean AUC scores. There are some studies which have recently criticized the use of AUC as an indicator for model accuracy (Austin, 2007; Lobo *et al.*, 2008), because of its bias caused by species with narrow ranges (Lobo *et al.*, 2008). Getting high AUC values it is easy when there are relatively few records (Jiménez-Valverde *et al.*, 2008; Lobo *et al.*, 2008), and therefore it is worth using other criteria such as the True Skill Statistic, although many recent studies still use AUC alone e.g. (Warren and Seifert, 2011; Beauregard and de Blois, 2014). When there is agreement between both validation methods, then we can assume good model performance (Beauregard and de Blois, 2014). In our data there was no significant correlation between the mean AUC values and the number of records, and hence we believe that sample size did not affect model performance (Elith *et al.*, 2006; de Pous *et al.*, 2011). Some other studies have achieved good model performance with large sample sizes (Kadmon *et al.*, 2003; Hernandez *et al.*, 2006), as we did.

In SDM studies, selecting appropriate environmental variables is very important because climate predictors are assumed to determine the distribution of species; a current topic of research is the extent to which biotic interactions affect distributions, but there is no consensus about how to allow for this (Wisz *et al.*, 2013). Robust models are produced by choosing the right predictors and modelling approach (Elith and Leathwick, 2009), which are then useful in conservation analysis (Austin, 2007; Araújo and Peterson, 2012). The most significant environmental variables in our study were the minimum temperature of the coldest month, followed by altitude; these make ecological sense in that temperature and elevation should predict much of the distribution of plant species in Egypt. (Newbold *et al.*, 2009) found that

temperature was the major predictor of the distributions of Egyptian butterflies, again making perfect ecological sense. Some variables did not have much of an effect on species distributions (e.g. habitat, and NDVI): neither of the NDVI predictors provided useful information on Egyptian plant distributions. Some studies have found NDVI important (Anderson *et al.*, 2006), while some have not (El-Gabbas *et al.*, 2016). Most of Egypt is hyper-arid with extremely low NDVI values, so it is not surprising that NDVI is poor as a predictor. Habitat was not a powerful predictor either, perhaps related to its correlation with other predictors (e.g. altitude).

The predictions showed that the main hotspots of plant species richness are found in South Sinai, extending around the northern part of Egypt: this pattern occurs in both probability and binary species-richness maps. Similar studies on Egyptian animal taxa (Gilbert and Zalat, 2008; Basuony *et al.*, 2010; Leach *et al.*, 2013; El-Gabbas *et al.*, 2016) found high levels of predicted species richness around greater Cairo. This may be the result of spatial bias in the records, particularly of mammals. In the plant dataset, recent more systematic collecting has been undertaken in Sinai, and hence there is a different spatial bias in the data. However, the gradient from south-west to north-east in plant species richness is undoubtedly correct. The physiologically optimal temperature for most plants is between 10-35 °C (Berry and Bjorkman, 1980), much more present in the north than in the south, although desert plants live in much higher temperature (Berry and Bjorkman, 1980) and most Egyptian habitats are deserts of one kind or another (90% of the land). Most areas in Egypt receive very much less than 80 mm precipitation annually, while the northern coastal areas can receive the highest recorded levels of up to 180-200 mm (El-Nahrawy, 2011) (albeit meagre by world standards).

Plant species richness for both the probability and binary maps was significantly higher inside Protected Areas than outside, as Newbold *et al.* (2009) found for Egyptian butterflies and mammals. Thus despite their relatively recent establishment, the locations of Egypt's Protected Areas were well chosen. Sciberras *et al.* (2013) for marine reserves and Lee *et al.* (2007) for Sulawesi also found higher

biomass inside Protected Areas than outside, but other studies on Indian herpetofauna (Pawar *et al.*, 2007; Traba *et al.*, 2007) have found the converse, and some have found no differences (e.g. Joppa *et al.* (2008) showed that the vegetation inside and outside Protected Areas in both the Amazon and Congo was very similar). Obviously Protected Areas are generally established in places known to have high biodiversity, and the Egyptian Protected Areas, although relatively new, were chosen carefully with expert knowledge (Newbold *et al.*, 2009). Alternatively, for older reserves, effective ecosystem management inside Protected Areas could be one of the reasons for their high biodiversity (Thomas and Gillingham, 2015).

About 12% of global terrestrial habitat is covered by Protected Areas, but many of them fail to protect biodiversity and ecological processes (Seiferling *et al.*, 2012). One of the main reasons for that failure is human activity changing the vegetation inside Protected Areas and the areas around them (DeFries *et al.*, 2005). It is important to sustain habitat heterogeneity within Protected Areas and the surrounding areas to enable good management (Oliver *et al.*, 2010). There is clear evidence that forest cover has decreased from 1980 to 2001 in the areas neighbouring Protected Areas in tropical regions. High human population densities and land-use isolate Protected Areas from their surroundings (Joppa *et al.*, 2009).

In conclusion, the positions of Egypt's Protected Areas appear to have been well chosen to maximise their potential effectiveness in conserving plant diversity, and their potential ability to preserve at least one important ecosystem service, that deriving from medicinal plants. A second conclusion we can draw is that species distribution modelling is an appropriate approach to measuring patterns of species richness in countries where information is sparse, and records may be the only available data. The models can predict new suitable locations for species that have not been surveyed very well (Franklin, 2009) , helping to save time and costs. Thus SDMs represent a very useful tool to help plan the conservation process and suggest the locations of new Protected Areas in such countries.

4 Chapter Four: Plant distributions, climate change and Protected Areas in data-sparse countries

Abstract

Climate change is one of our most difficult challenges, with a major impact on the distributions of organisms. Species distribution modelling is a modern approach to assess the potential effects of climate change on biodiversity, with the great advantage of being robust to small amounts of data. Can suitable predictions be made for data-sparse countries? We use Egypt as a test case, and identify hotspots of plant diversity now and in the future by predicting the effect of climate change on the pattern of species richness using species distribution modelling. Then we assess how Egypt's current Protected Area network is likely to perform in protecting plants under climate change. The patterns of species richness, losses and gains were described under the various combinations of scenarios and assumptions; in most cases the A2a scenario was more harmful than B2a. Potential species richness inside Protected Areas was always predicted to be significantly higher than outside. We conclude that species distribution models are effective in allowing data-sparse regions to take a more rational and evidence-based approach to conservation planning.

4.1 Introduction

Climate is one of the main elements used to describe plant niches, and climate change is considered the major threat to biodiversity (Hannah, 2011). Climate variables (mainly temperature and precipitation) together can be used to predict where plants can develop or where animals can survive (Hannah, 2011). One of the main challenges today is how the various climate-change scenarios might affect species in the future (Regos *et al.*, 2015). There is much evidence to show that climate change causes shifts in species distributions (Parmesan and Yohe, 2003), and can lead to extinction (Thomas *et al.*, 2004). Each species probably reacts in an individual way to changes in the different environmental variables, and hence biological communities may fall apart as individual species change their ranges in diverse directions (Thuiller, 2004).

Global warming is mostly caused by increases in carbon dioxide (Thuiller, 2007), in large part anthropogenic, which particularly affects vulnerable ecosystems such as polar or mountain areas (Walther *et al.*, 2002; Root *et al.*, 2003). The capacity of a species to react will depend on its ability to track climate change, colonize new habitat and adjust its behaviour and physiology to acclimate to new climate circumstances (Thuiller, 2007). To reduce the effects of climate change on biodiversity, we should be taking precautionary measures, in the long term to reduce emission gases, and in the short term to design appropriate Protected Areas (PAs) for conservation (Botkin *et al.*, 2007).

Thus being able to predict distributions under climate change is fundamental to our ability to plan for conservation in the future. Recently species distribution models (SDMs) have been used to estimate the potential effect of future climate change on biodiversity. They create a model of the relationship between distribution and climate, which can then be projected under different climate scenarios (Thomas *et al.*, 2004; Araújo *et al.*, 2005; McClean *et al.*, 2005). Modelling techniques rather than field data are more effective in evaluating the spatial reaction to climate drivers over large spatial and temporal scales (Thuiller, 2007). There are many different SDM approaches with differing abilities in predicting current distributions

(Elith *et al.*, 2006) and potential future changes (Pearson *et al.*, 2006). A major reason to develop SDMs is to estimate the impact of climate changes on biodiversity, and hence to develop mitigation strategies (Bellard *et al.*, 2012). SDMs have become important in conservation, biogeography and ecological change (Pearson, 2007; Franklin, 2009). They use species records and environmental variables to predict suitable future habitat, enabling the management of species most under threat, by finding new pathways for dispersal, new habitat areas for re-introduction and new locations to protect (Thuiller, 2007).

The complexity of ecosystems shows the fundamental limits to modelling approaches, because extrapolation uncertainties are unavoidable, but SDM techniques for particular species at particular scales can be useful (Pearson and Dawson, 2003). Predictions should therefore be interpreted with caution, as initial estimates of potential impacts, instead of precise descriptions of future biodiversity distribution (Pearson and Dawson, 2003). SDMs are associated with many uncertainties, and modellers should be particularly careful when predicting species distributions at different scales (see (Thuiller, 2004; Araújo and Guisan, 2006). However, one great advantage of some SDM methods is their ability to produce reasonable models with sparse data (Elith *et al.* 2006). Sometimes SDMs can be a good technique to disclose more threatened species (Fois *et al.*, 2015). The majority of countries find themselves in the position of having to make decision about conservation in the face of climate change, but few data to guide them. Here we take advantage of a validated datasets on the Egyptian medicinal plants to test whether reasonable evidence-based guidance can be made.

SDMs use the emission scenarios of climate models to estimate the effects of mitigation strategies (Beaumont *et al.*, 2008). According to Intergovernmental Panel on Climate Change (IPCC), future concentrations are based on scenario groups (categorized A1, A2, B1, and B2: (Nakicenovic *et al.*, 2000). Each group contains feasible scenarios for future developments in the human population, the politico-economic system, social relations and future technologies (Arnell *et al.*, 2004). In this study we used one of the main global circulation models (HadCM3,

generated by the UK Hadley Centre, UK) for different future times (2020, 2050, and 2080) under two emission scenarios (A2a and B2a). Many studies have used these models and scenarios to evaluate the impact of climate change on biodiversity, including likely shifts in distribution, habitat change, gains and losses, turnover and extinction (Peterson *et al.*, 2002; Thuiller *et al.*, 2005). Species gains occur when species occupy new areas, while losses can occur when the habitat suitability is reduced for that area in the future. Species turnover is the differences between the current and future species composition of the same location, used as an indicator at large or regional scales (Thuiller, 2004).

SDMs are also used to assess the likely future value of PAs, important fundamental units in conservation which cover about 12% of the entire land area of the world (Chape *et al.*, 2005). There is a big effort to enlarge the coverage of PAs to 17% by 2020 (CBD). The important question is to what extent these PAs can preserve species under climate change, recognising that many species will shift their distributions. Current PAs might still achieve significant roles if they provide suitable areas for species to disperse into new districts (Thomas *et al.*, 2012). The best strategy to preserve biodiversity is to recognise and protect the best locations (Pressey *et al.*, 1993) - but are PAs in the "best" locations? There are several studies that measure current species richness inside and outside PAs: some found that species richness is higher inside (Newbold *et al.*, 2009; Leach *et al.*, 2013; Kaky and Gilbert, 2016), while others found the opposite (Pawar *et al.*, 2007; Traba *et al.*, 2007).

Here, the pattern of species richness is evaluated for 114 Egyptian medicinal plants in the future. First, MaxEnt models of current distributions were projected into future times and scenarios. The predicted distributions were either left as habitat suitability (= 'probability' map) or converted to predicted presence/absence (really, suitable/unsuitable) data using a threshold (= 'binary' map) under two assumptions of dispersal (unlimited and no-dispersal). Second, we calculated the gains and losses for the binary distributions: gains were calculated only for unlimited dispersal, while losses could happen under either dispersal assumption.

Third, species turnover was calculated under both dispersal assumptions. Finally, we asked whether Egypt's PAs provide and will provide suitable plant habitat compared with outside the PAs. There are about 30 PAs in Egypt covering approximately 15% of Egypt's land area (El-Gabbas *et al.*, 2016). According to Chape *et al.* (2005), PAs are imperfect in their coverage of biodiversity, but Egyptian PAs at least in theory protect biodiversity much better than the PAs of many other countries (Newbold *et al.*, 2009). In all this work, "species richness" is understood to mean a quantitative estimate of the collective habitat suitability of all the 114 species combined, since that is what MaxEnt output actually means.

4.2 Methods

We had data for 121 species of Egyptian medicinal flora, but removed species with fewer than ten spatially separate records, and those where the records were spatially very close together and with mean AUC of the models less than 0.5 (all to avoid overfitting: (Baldwin, 2009)). We eventually used 114 species consisting of 14396 point records. The data were collated by the BioMAP project in Cairo between 2004–2008, funded by Italian Debt Swap (see Leach *et al.*, 2013); the data are presence-only, collected from different sources (i.e. literature, herbarium, and field work), but mainly recent fieldwork especially in Sinai. There are virtually no available validated records of these species from surrounding countries, so we were unable to model the entire range of non-endemic species: this will often be the case for developing countries.

The environmental variables were 23 predictors, 19 of them (Bio-layers) downloaded from the WorldClim v1.4 dataset at a resolution of 2.5 arc-minutes (<http://www.worldclim.org/bioclim>) (Hijmans *et al.*, 2005) (see chapter two Table 2.1). The Normalized Difference Vegetation Index (NDVI) data for seven years (2004 to 2010) were downloaded from the website of Spot Vegetation (<http://free.vgt.vito.be/>) and used to create two predictors - maximum NDVI value (Max_NDVI) and the difference between the Minimum and Maximum NDVI value

(NDVI_differences). The predictor 'habitat' was created by BioMAP (see (Newbold *et al.*, 2009), dividing Egypt into eleven classes (sea, littoral coast, cultivation, sand dune, wadi, metamorphic rock, igneous rock, gravels,serir sand sheets, sabkhas and sedimentary rocks). Altitude data were downloaded and rescaled to a pixel size of 2.5 arc-minutes (see (El-Gabbas *et al.*, 2016). Eleven of these 23 predictors (chapter two Table 2.1) were eventually used after removing collinearity (Dormann *et al.* 2013) by applying the Variance Inflation Factor using R v2.15 (the 'car' package: R Development Core Team 2012).

Models for the current distribution of each species were projected into the future at the standard three different time slices (2020, 2050, and 2080) using predicted future climates from the IPCC's 4th assessment (IPCC 2007) taken from the International Centre for Tropical Agriculture website (see <http://www.ccafs-climate.org/>), selecting two HadCM3 scenarios (A2a and B2a). Such Global Circulation Models are widely used in SDMs to explore the effect of climate change on biodiversity (Thuiller, 2004; Araújo *et al.*, 2006; Hamann and Aitken, 2013). We chose to use the IPCC 4th assessment, rather than the latest 5th assessment and its very different scenarios, for continuity with previous work (e.g. El-Gabbas *et al.*, 2016) and because the differences in SDMs are slight (Wright *et al.*, 2016).

The A2 and B2 scenarios (see IPCC 2007) are regularly used in climate-change assessments (Hannah, 2011). Both scenarios have different assumptions about the levels of CO₂ emissions. The A2 scenario expects this level to increase without barriers because of high growth rate in human population, not much technological development, expanded land-use change, and less environmental awareness. The B2 scenario expects the level not to change much because human population growth will be slower, with fewer changes in land-use, people are more environmentally conscious, and there is increasing technological invention (Nakicenovic *et al.*, 2000; Saupe *et al.*, 2011). In this study, we do not take into account any phenological and/or evolutionary reactions to climate change, and hence we assume that species will attempt to find their climatically suitable habitat

dependent on their dispersal capability. We are forced to make the assumption that some predictors (e.g. habitat, NDVI) do not change because there is no information on how they might change; others (e.g. altitude) will clearly not change. These unchanging predictors were included because we sought the best model in each case.

Maximum Entropy (MaxEnt) version 3.3.3k (Phillips *et al.*, 2006) was used to run the models, choosing the options that created the best models (i.e. feature classes QPT, 10000 background points, 1000 iterations, cross-validation [k=10] with 10 replicates [for estimating prediction errors], 10% training presence threshold, and logistic output format), and creating both 'probability' (i.e. raw values of habitat suitability) and 'binary' (via thresholding) maps. MaxEnt performance is good with presence-only data and relatively few records (Elith *et al.*, 2006; Franklin, 2009). The option set was chosen after extensive tests to maximise the AUC and TSS, the standard measures of goodness-of-fit for SDMs (Allouche *et al.*, 2006). The one species with a mean AUC score less than 0.7 was removed from the analysis, as recommended by Pearce and Ferrier (2000). Following (Pearson *et al.*, 2007) and Liu *et al.* (2005), we chose the "10% training presence" threshold rule to give a binary map for each of the 10 replicates for each species.

The resulting maps were analysed under the two extreme dispersal assumptions (unlimited and no-dispersal) usually applied in such studies (for example, (Peterson *et al.*, 2002; Thuiller *et al.*, 2005; Broennimann *et al.*, 2006). Both assumptions have been criticized for not involving the impact of biotic interactions on species distributions (Araújo and Peterson, 2012), but there is no practical way of incorporating any putative interactions for Egyptian species.

MaxEnt does not automatically produce a consensus binary (presence/absence) map from the 10 replicate runs, and hence this was made manually using the Raster Calculator and Reclassify tools in ArcGIS 10.2.2 (ESRI, USA). For unlimited dispersal, the consensus map allotted a 'presence' to a pixel that had presence values in more than 50% of the model runs (i.e. >5 replicates). Under the no-dispersal assumption, the consensus binary maps for two time periods (e.g.

'current' and '2020') were compared so as to allocate a pixel to be a 'presence' in the event that it was a 'presence' in both maps.

Maps for the distribution of species richness for current and future times were produced in two ways. First, by summing all predicted mean probability distribution maps for the individual species together (supposing unlimited dispersal in the future); and secondly, by summing all predicted consensus binary distribution maps for the individual species together (assuming either unlimited or no-dispersal in the future). Thus maps were produced for probability and binary species richness for future times (2020, 2050, and 2080) under both scenarios (A2 and B2) for both unlimited and no-dispersal (binary only) assumptions, a total of 18 species-richness maps. Change maps produced by subtracting one map from another aided interpretation.

We compared the species richness inside and outside PAs to see to what extent they protect Egyptian plants now, and in the future, using the oldest and largest 25 PAs, excluding just the most recent and smallest. We chose 2000 pixels at random, and then created a 50-km buffer around each PA. The mean species richness was then calculated for the random pixels lying within each PA, and lying outside but within the appropriate buffer zone of each PA, creating paired values inside and outside of each PA. In case of very small PAs which are smaller than one pixel (whose side is 4.64 km), species richness was taken to be the value for the pixel containing the PA. The mean values of species richness for the areas inside and outside each PA were obtained from each combination of distribution (probability, binary), scenario (A2, B2), year (current, 2020, 2050, 2080) and dispersal assumption (unlimited, no-dispersal). The paired difference inside-outside was calculated for each PA, and the difference became the response variable of a GLM with normal errors.

To estimate how much each species loses or gains in habitat suitability, the number of pixels gained and lost for each species was calculated (see Figure 4.1 for an example), and the gain maps (future times × scenarios emissions) were summed together across species to produce a "gain in suitability" map to

demonstrate which locations are projected to gain more species in the future (under the assumption of unlimited dispersal); such sites may constitute potential new PAs in the future. A loss map shows locations predicted to lose suitability for species in the future (assuming either unlimited and no-dispersal).

Species turnover is defined as the number of species changes in specific locations (Peterson *et al.* 2002; Thuiller 2004; Broenimann *et al.* 2006), used as a suitable measure of change in species composition to evaluate the effect of climate change on biodiversity from regional to continental levels (Peterson *et al.* 2002; Thuiller 2004; Broenimann *et al.* 2006). It is calculated as the differences between present-day and future species composition (Thuiller 2004). Locations with small turnover are predicted to remain suitable in the future, whereas locations with higher turnover indicate less stable habitat suitability with time. Species turnover for unlimited dispersal was calculated (following Thuiller 2004; Thuiller *et al.* 2005; Broennimann *et al.* 2006) as $SG + SL$, where SG is the number of species gained, and SL is the number of species lost (see Figure 4.1 for details). The equation normally expresses turnover as a proportion of the species richness of each pixel, but this was unsuitable in the case of Egyptian plants because of the very low richness in areas of the Western desert, which made some of the proportional turnover values unreasonably large. Species turnover for no-dispersal is just equal to species losses because there can be no gains.

All mean values are given $\pm$ one SE. Plant nomenclature follows (Boulos, 1999-2005). Appendix 1 gives all the locations and areas names mentioned in the text.

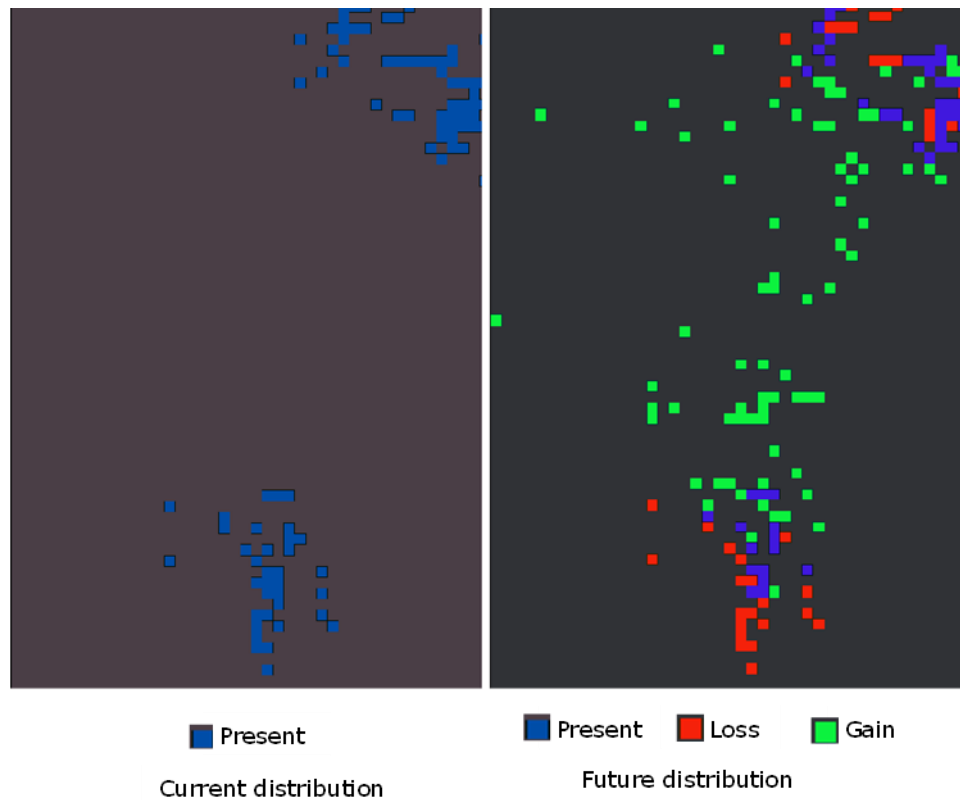


Figure 4.1. An example to show predicted gain and loss areas in the future distribution of one species.

4.3 Results

The performance of the models was good in term of AUC (0.90 ± 0.004 , 0.80 to 0.98) and TSS scores (0.63 ± 0.01). Temperature had the most important effect on distributions (see chapter two Table 2.1 for details) and Bio 6 was more important variable (see Figure 4.17).

The pattern of species richness (Figure 4.2) increased toward the north and east of Egypt, especially the Mediterranean coast and Sinai. With unlimited dispersal, both probability (Figure 4.2) and binary (Figure 4.4) species richness was predicted to increase for all future times (2020, 2050, and 2080) and both scenarios (A2 and B2). For probability distributions, the predictions show that species richness is predicted to increase by 2020 under the A2 scenario (Figures 4.2 & 4.3) along the Red Sea, in Sinai and along the Mediterranean coast, and decrease in a few scattered areas. The increases are predicted to become more marked by 2050 and very marked by 2080, especially along the Mediterranean coast,

scattered patches in Sinai, and along the Red Sea coast. There were clear differences under the B2 scenario (Figures 4.2 & 4.3). By 2020 there were generally lower predicted increases, and some strong predicted declines along both sides of the Suez Gulf and further south along the Red Sea coast. By 2050, species richness is predicted to recover and increase along the Mediterranean coast, in Sinai and along the Red Sea coast, becoming more marked (but still modest) by 2080.

Using binary distributions, the pattern of species richness was predicted under both dispersal assumptions. For unlimited dispersal, by 2020 under the A2 scenario (Figures 4.4 & 4.5) species richness is predicted to increase along the Mediterranean coast and in the Qattara Depression, and in scattered areas on both sides of the Suez Gulf, the Red Sea coast, and Sinai. These predicted increases become more obvious by 2050 and very marked by 2080. Decreases in species richness are predicted to occur in small scattered areas, similar in all future time periods. There were clear differences under the B2 scenario (Figures 4.4 & 4.5): by 2020 the predicted increases are lower, and include some strong predicted declines along both sides of the Suez Gulf and further south along the Red Sea coast. By 2050 species richness is predicted to increase generally, eliminating the previous declines. By 2080 the increases are predicted to be more marked in the same areas. Assuming no-dispersal, the predicted pattern under the A2 scenario (Figures 4.6 & 4.7) shows no change or slight declines by 2020, more marked on both sides of Suez Gulf, along the Red Sea coast, and some scattered areas around greater Cairo. By 2050, these predicted declines are less except for areas around greater Cairo. By 2080, predicted species richness declines are only marked on both sides of the Suez Gulf, the Red Sea coast, and in central Sinai and greater Cairo. Under the B2 scenario, the predicted pattern of decline is similar but the magnitudes are greater except for 2080 (Figures 4.6 & 4.7).

The overall average predicted mean species richness for both the probability and binary distributions, assuming unlimited dispersal (Figure 4.8), gradually increase for future times (2020, 2050, and 2080) under both A2 and B2 scenarios

compared to the present day, while assuming no-dispersal results in predicted declines for both scenarios (Figure 4.9).

The predicted species richness is significantly higher inside PAs than outside in all combinations of assumptions (overall mean excess is 10.2 ± 0.6 , $t_{498} = 17.5$, $p < 0.001$: see Figure 4.10). None of the predictors affected the difference in species richness (inside - outside), although the AIC-based *step* function for reducing model complexity in R did retain just one predictor, the type of distribution (binary or probability: Figure 4.10). For unlimited dispersal, the mean predicted species-richness excess inside relative to outside PAs declines slightly with time for binary distributions, but increases slightly (2020, 2050) and then declines (2080) for probability distributions (Figure 4.11). With no dispersal (binary distributions), this predicted excess inside relative to outside declines slightly under both scenarios (Figure 4.12).

Species gains and losses were only predicted for binary distributions. With unlimited dispersal, under the A2 scenario the maximum species gain by 2020 (Figure 4.13) is predicted to be at the Mediterranean coast, along both sides of the Suez Gulf, along the Red Sea coast further to the south, and some scattered patches in Sinai. By 2050, the highest predicted gains appear along the Mediterranean coast and the Qattara Depression, scattered places on both sides of the Suez Gulf and the Red Sea coast. By 2080, the highest species gains are predicted to be along the Mediterranean coast, the Qattara Depression to Wadi El-Natrun, small areas around greater Cairo, and scattered areas along the Red Sea coast. There were no big differences in predicted gains under the B2 scenario (Figure 4.13), although the magnitudes were lower.

For unlimited dispersal, under the A2 scenario the maximum species losses by 2020 (Figure 4.14) are predicted to be on both sides of the Suez Gulf, along the Red Sea coast, and some small scattered areas in Sinai, east of Cairo and around Ismailia. By 2050, they are predicted to be along the Red Sea coast and areas around greater Cairo, and by 2080, along the Mediterranean coast, north and south Sinai, some scattered areas on both sides of the Suez Gulf, and along the Red Sea

coast. Under the B2 scenario, predicted losses are higher but similar in pattern (Figure 4.14).

For the no-dispersal assumption, under both scenarios the pattern of predicted losses does not differ much from those for unlimited dispersal. Differences are only apparent in the magnitudes, which are less under the no-dispersal assumption (Figure 4.15).

Species turnover was only predicted for binary distributions. For unlimited dispersal, under the A2 scenario by 2020 the highest turnover (Figure 4.16) is predicted to occur along the Red Sea coast, in Sinai, along the Mediterranean coast, and along both sides of the Suez Gulf. By 2050 the pattern is similar but the magnitude is lower. By 2080, the highest predicted species turnover is along the Mediterranean coast, greater Cairo southwards, scattered areas both sides of the Suez Gulf, and some scattered areas along the Red Sea coast. Under the B2 scenario, the pattern of turnover is very similar (Figure 4.16), with some differences in magnitude. Under the no-dispersal assumption, turnover for both scenarios and all times are also similar to the pattern of losses under the no-dispersal assumption (see Figure 4.15).

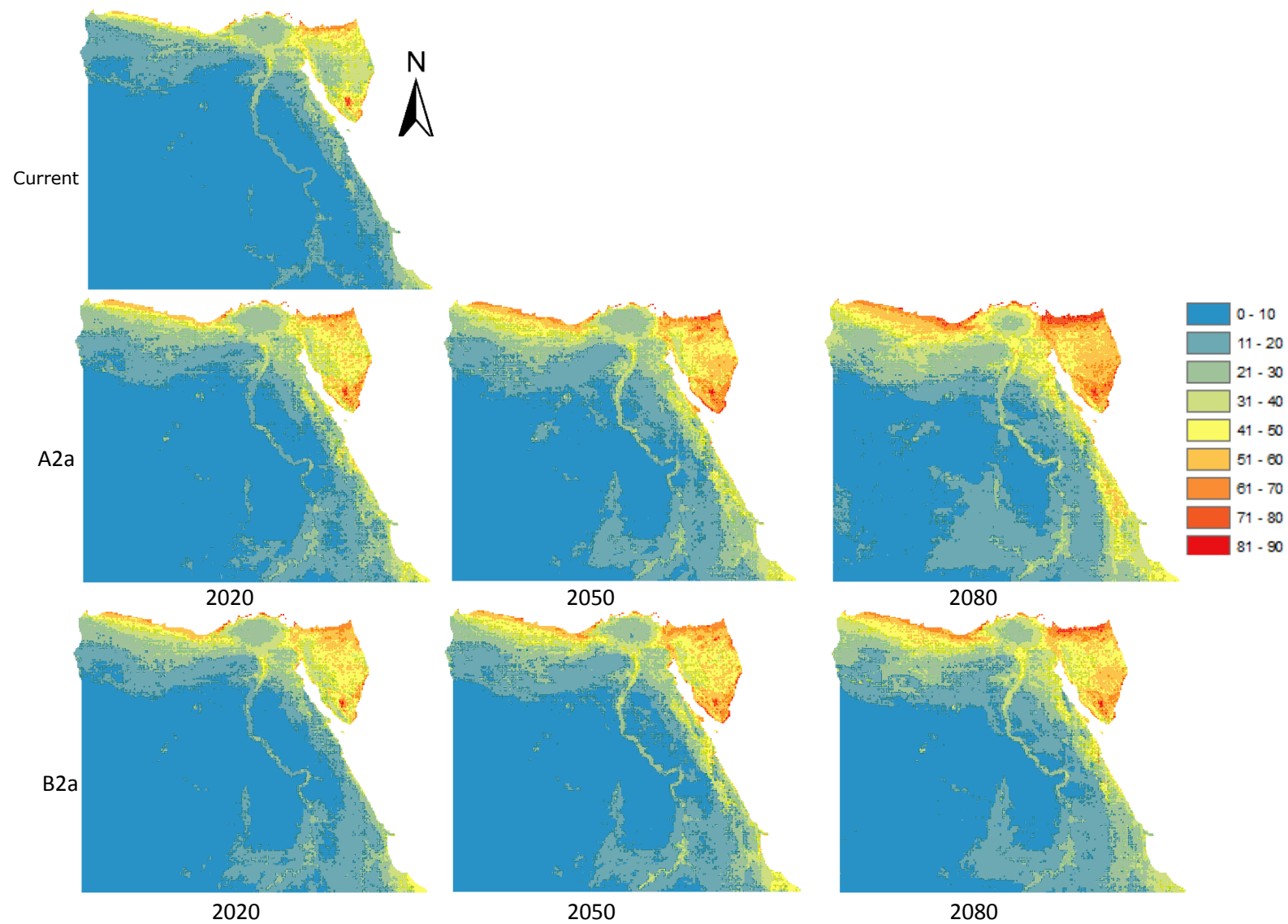


Figure 4.2. Predicted patterns of species richness using probability distributions for the present-day ('current') and into the future (2020, 2050, 2080) under two climate-change scenarios (A2a and B2a), created by adding together the maps of all 114 species and assuming unlimited dispersal. The colours indicate predicted species richness ranging between dark red (high) and blue (low).

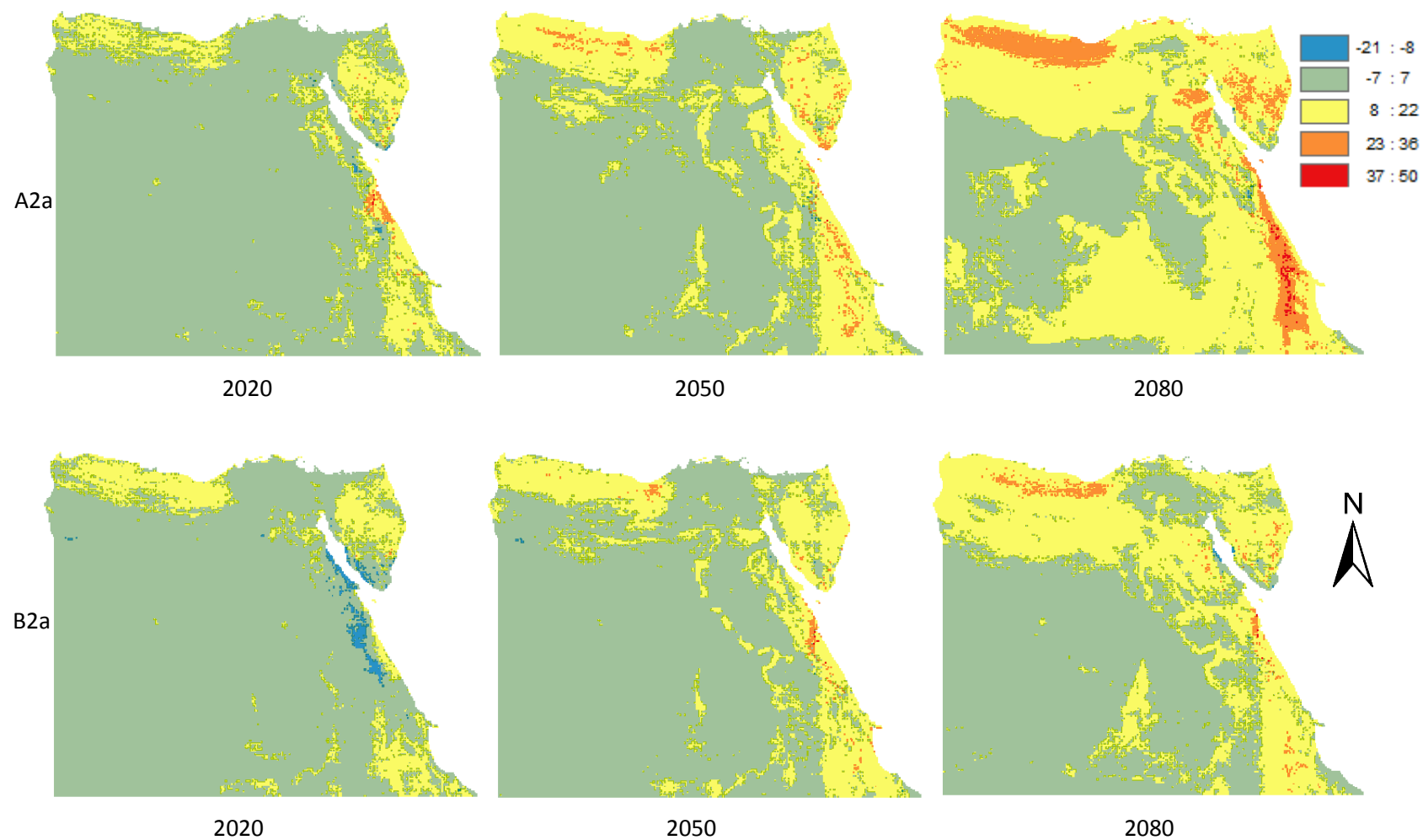


Figure 4.3. Potential effect of different climate-change scenarios (A2a and B2a) on changes in future species richness (using probability species distributions and assuming unlimited dispersal); maps created as differences between future and current species richness maps (presented in Fig. 2). Red means increasing future species richness, and blue means declining future species richness.

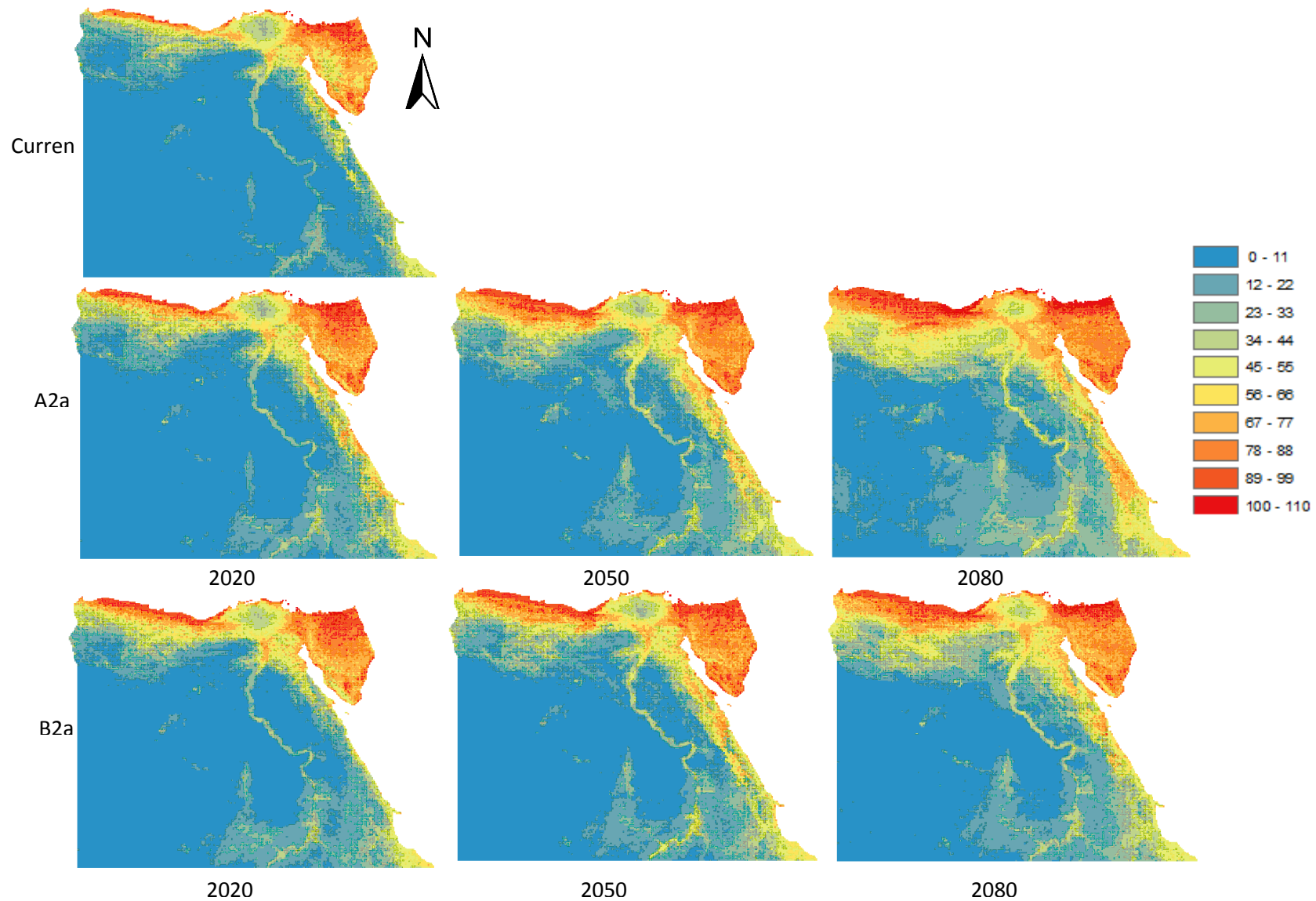


Figure 4.4. Predicted patterns of species richness using binary distributions for the present-day ('current') and into the future (2020, 2050, 2080) under two climate-change scenarios (A2a and B2a), created by adding together the maps of all 114 species and assuming unlimited dispersal. The colours indicate predicted species richness ranging between dark red (high) and blue (low).

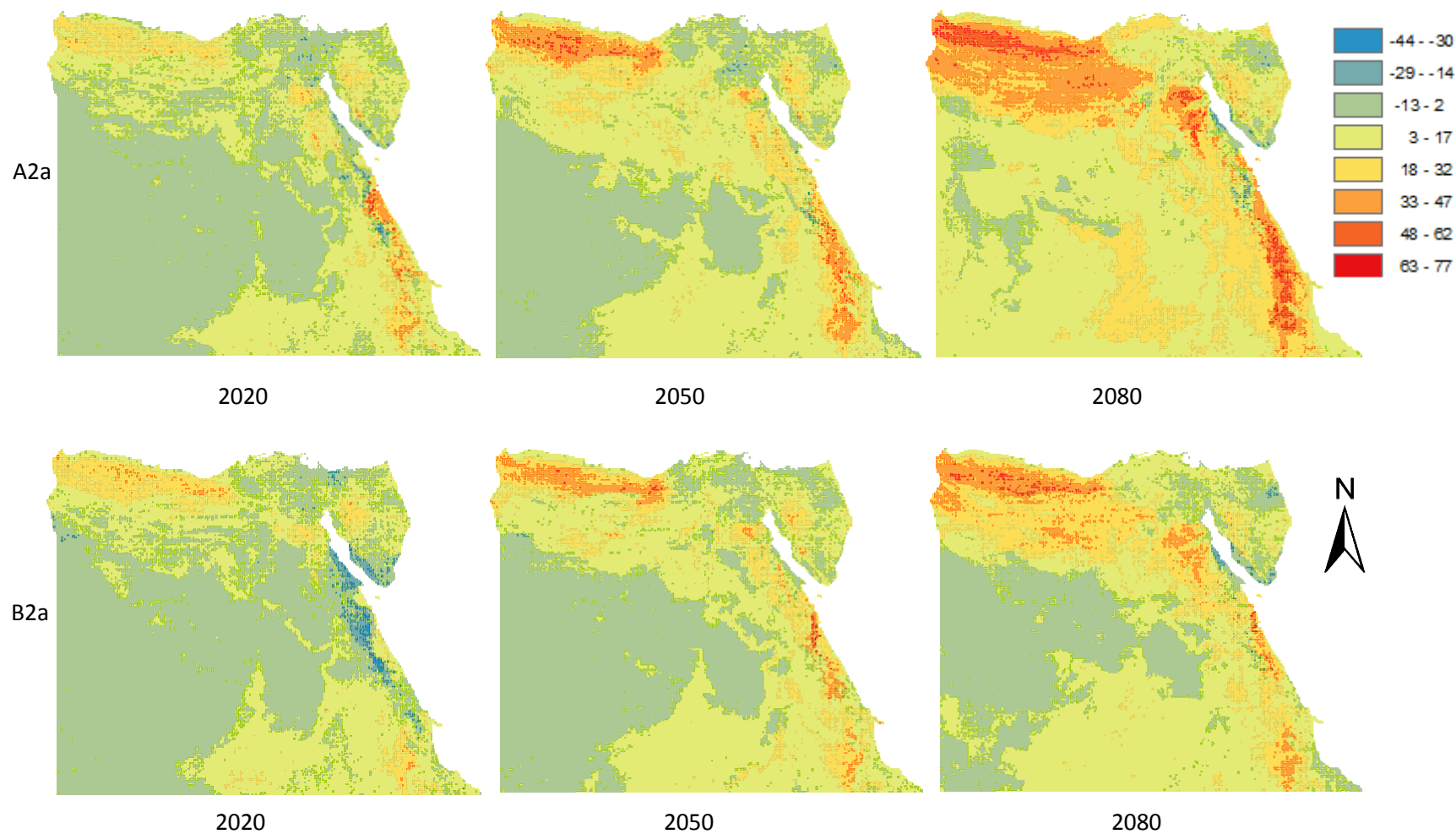


Figure 4.5. Potential effect of different climate change scenarios (A2a and B2a) on changes in future species richness (using binary species distributions and assuming unlimited dispersal); maps created as differences between future and current species richness maps (presented in Fig 3). Red means increasing future species richness, and blue means declining future species richness.

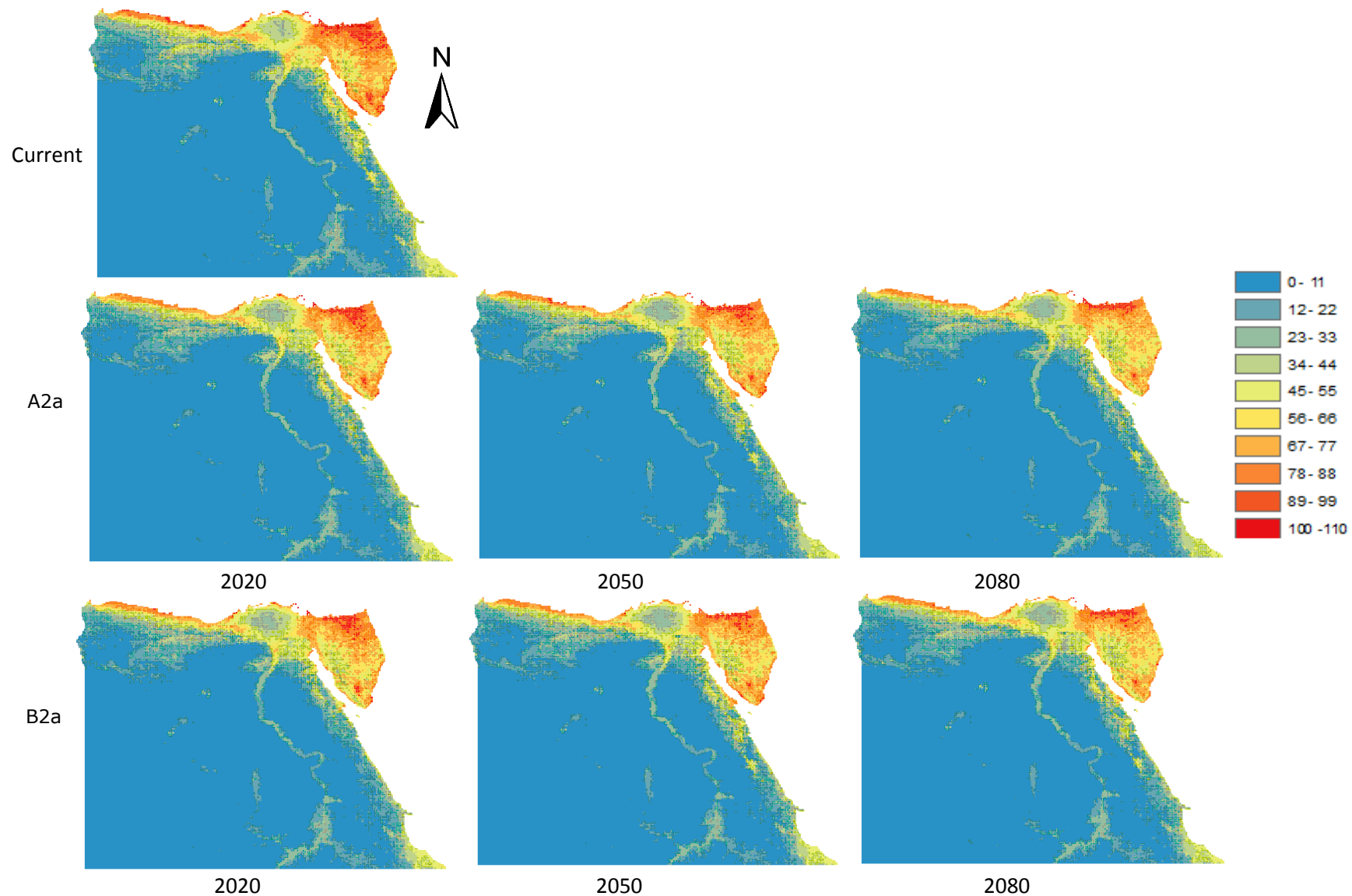


Figure 4.6. Predicted patterns of species richness using binary distributions for the present-day ('current') and into the future (2020, 2050, 2080) under two climate-change scenarios (A2a and B2a), created by adding together the maps of all 114 species and assuming no-dispersal. The colours indicate predicted species richness ranging between dark red (high) and blue (low).

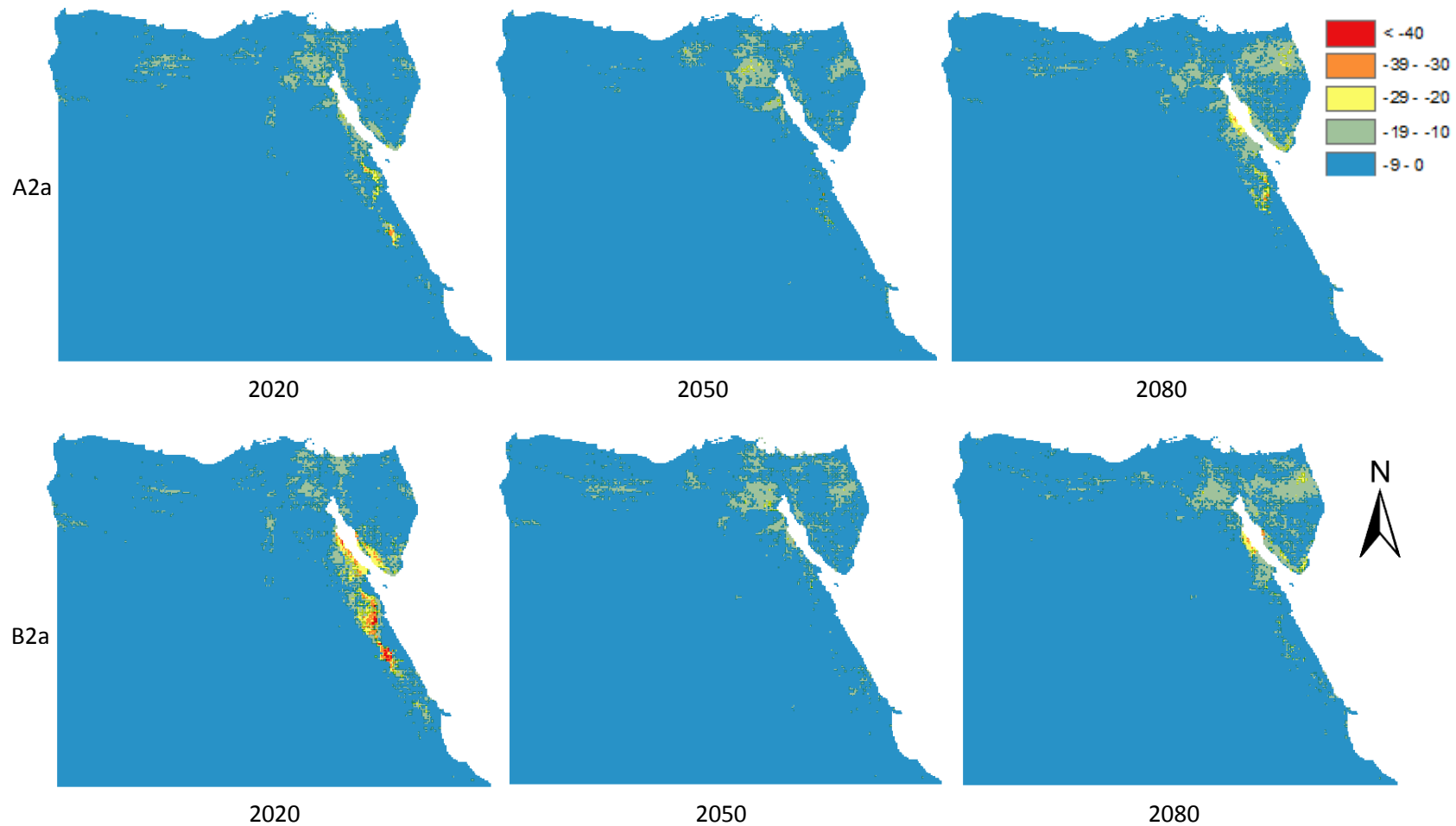


Figure 4.7. Potential effect of different climate change scenarios (A2a and B2a) on changes in future species richness (using binary species distribution and assuming no-dispersal); maps created as differences between future and current species richness maps (presented in Fig 4). Red means decline future species richness, and blue means increasing future species richness.

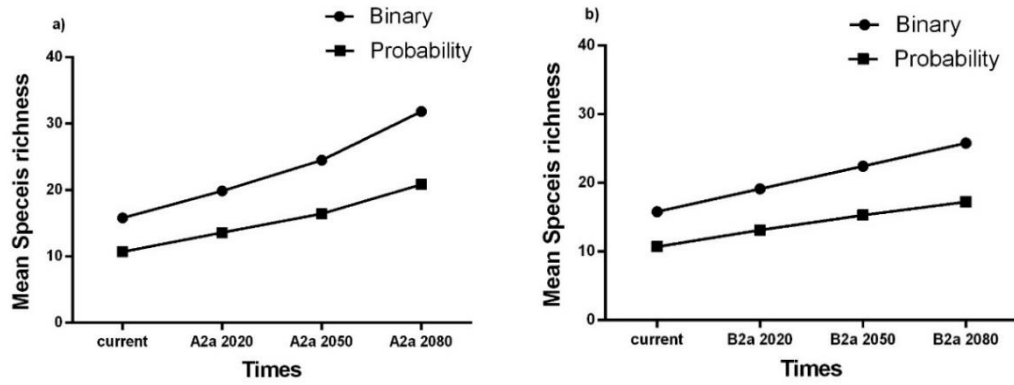


Figure 4.8. Average predicted mean species richness assuming unlimited dispersal for binary and probability distributions, A): Current and future times with the A2a scenario; B): current and future times with the B2a scenario.

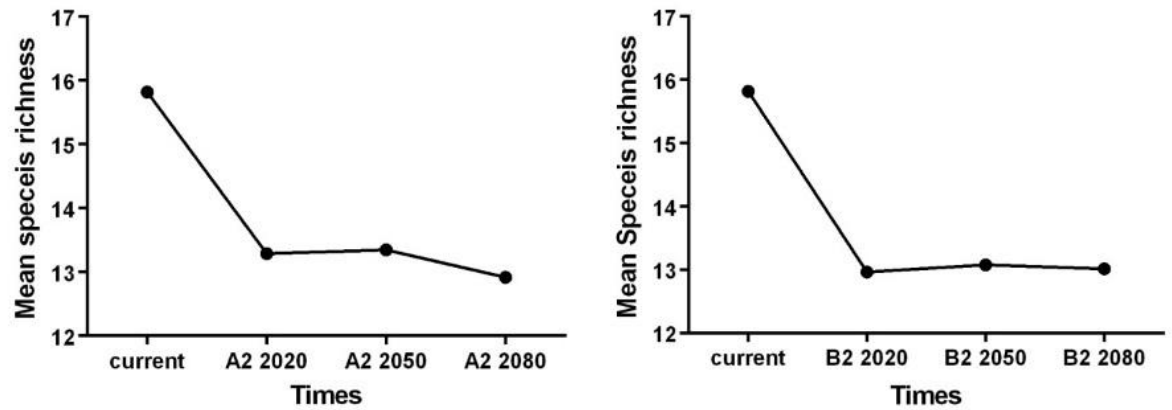


Figure 4.9. Predicted mean species richness assuming no-limited dispersal for binary distributions for the two scenarios A2a (left) and B2a (right).

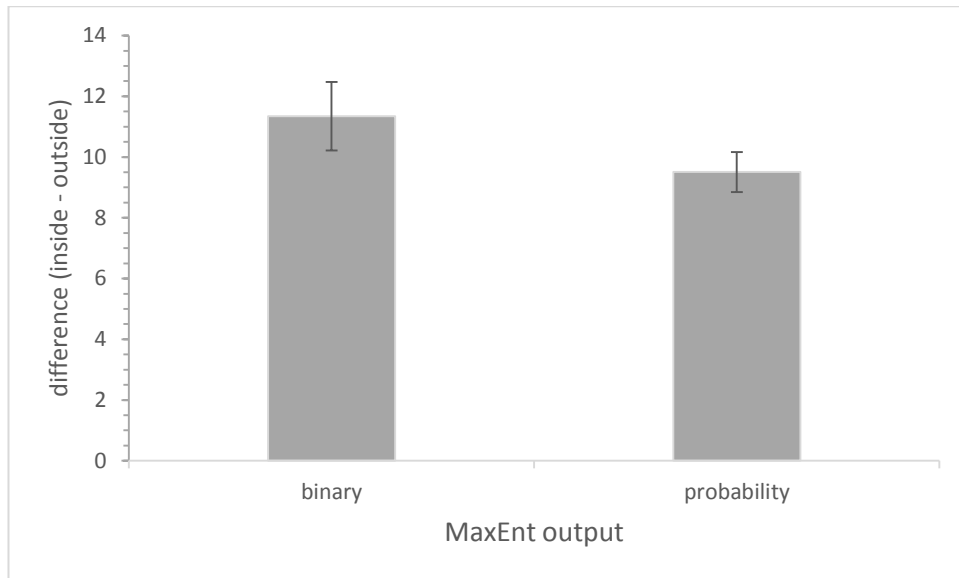


Figure 4.10. Mean of the difference in predicted species richness between inside and outside each of the Egyptian PAs for both probability and binary distributions. Only this predictor was retained in the GLM model (scenario, time, and dispersal were not significant). Note that the mean differences are both highly significantly different from zero, implying that species richness is higher inside than outside PAs.

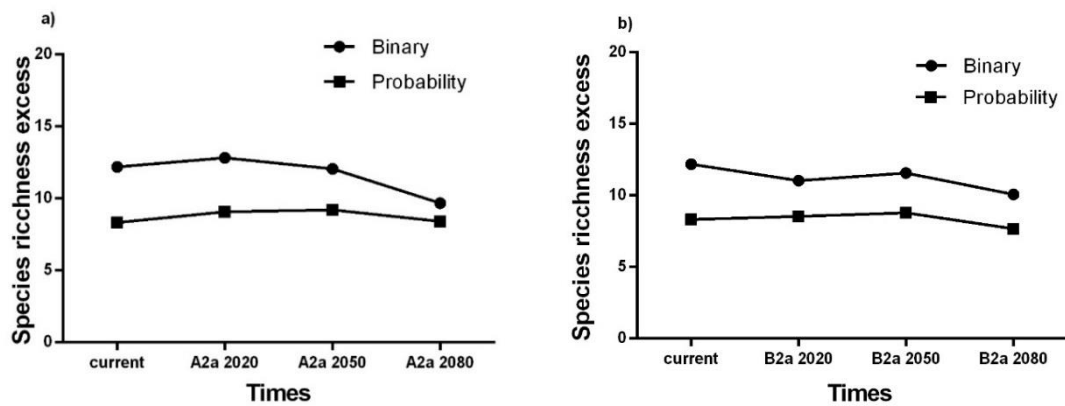


Figure 4.11. Species richness excess inside relative to outside PAs through time, using probability and binary distributions (both assuming unlimited dispersal). A): A2a scenario; B): B2a scenario.

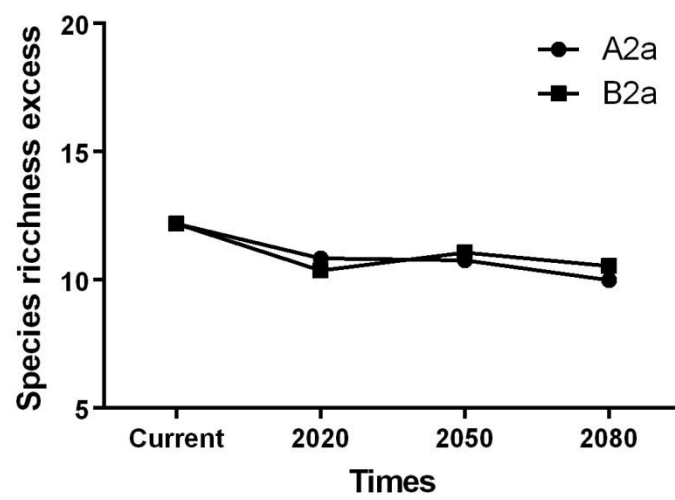


Figure 4.12. Species richness excess inside relative to outside PAs using binary distribution (assuming no dispersal).

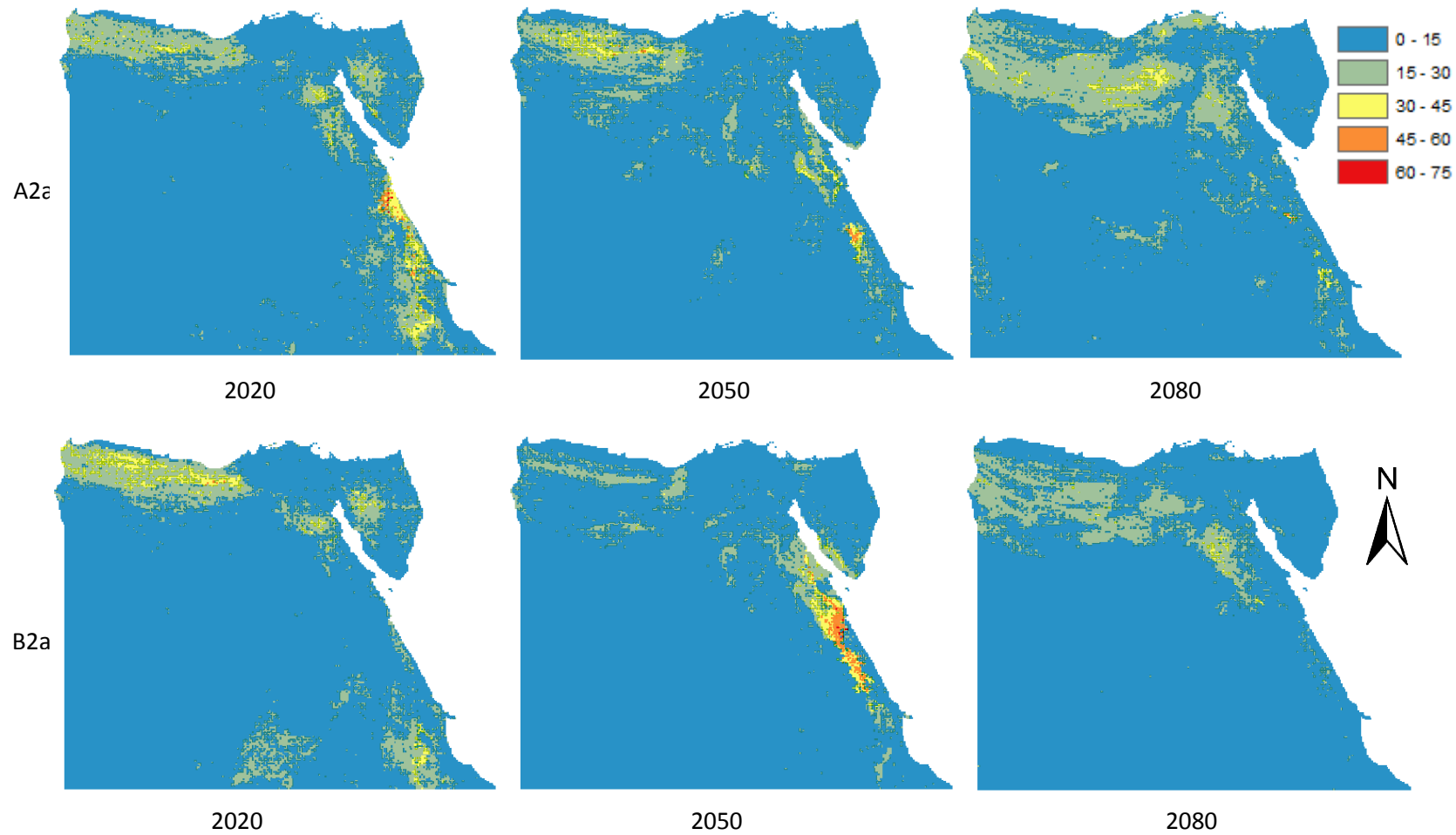


Figure 4.13. Spatial pattern of the number of species gained under climate change in the future (assuming unlimited dispersal). Colours indicate few (blue) to many (red) species gained.

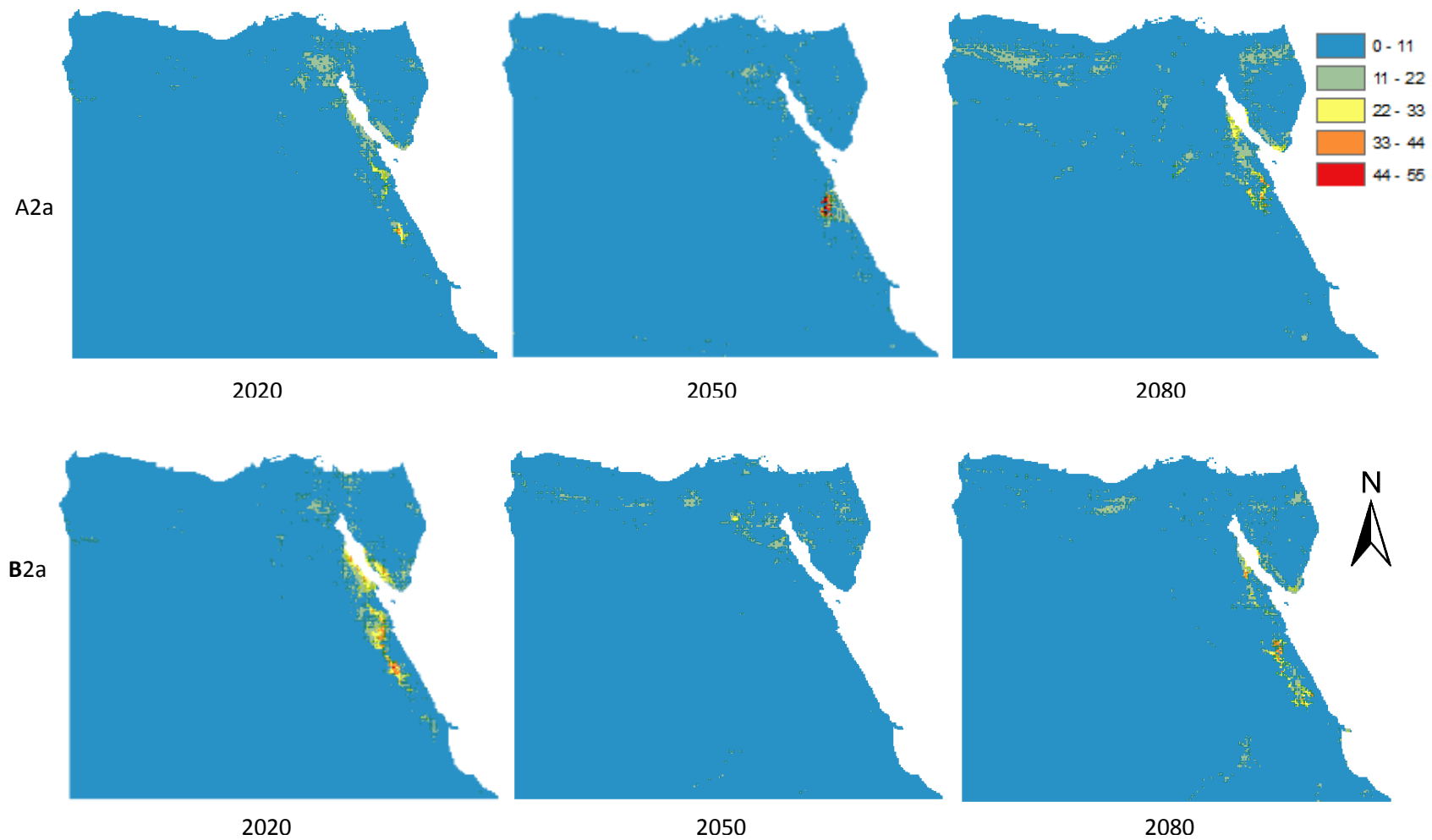


Figure 4.14. Spatial pattern of the number of species lost under climate change in the future (assuming unlimited dispersal). Colours indicate few (blue) to many (red) species lost.

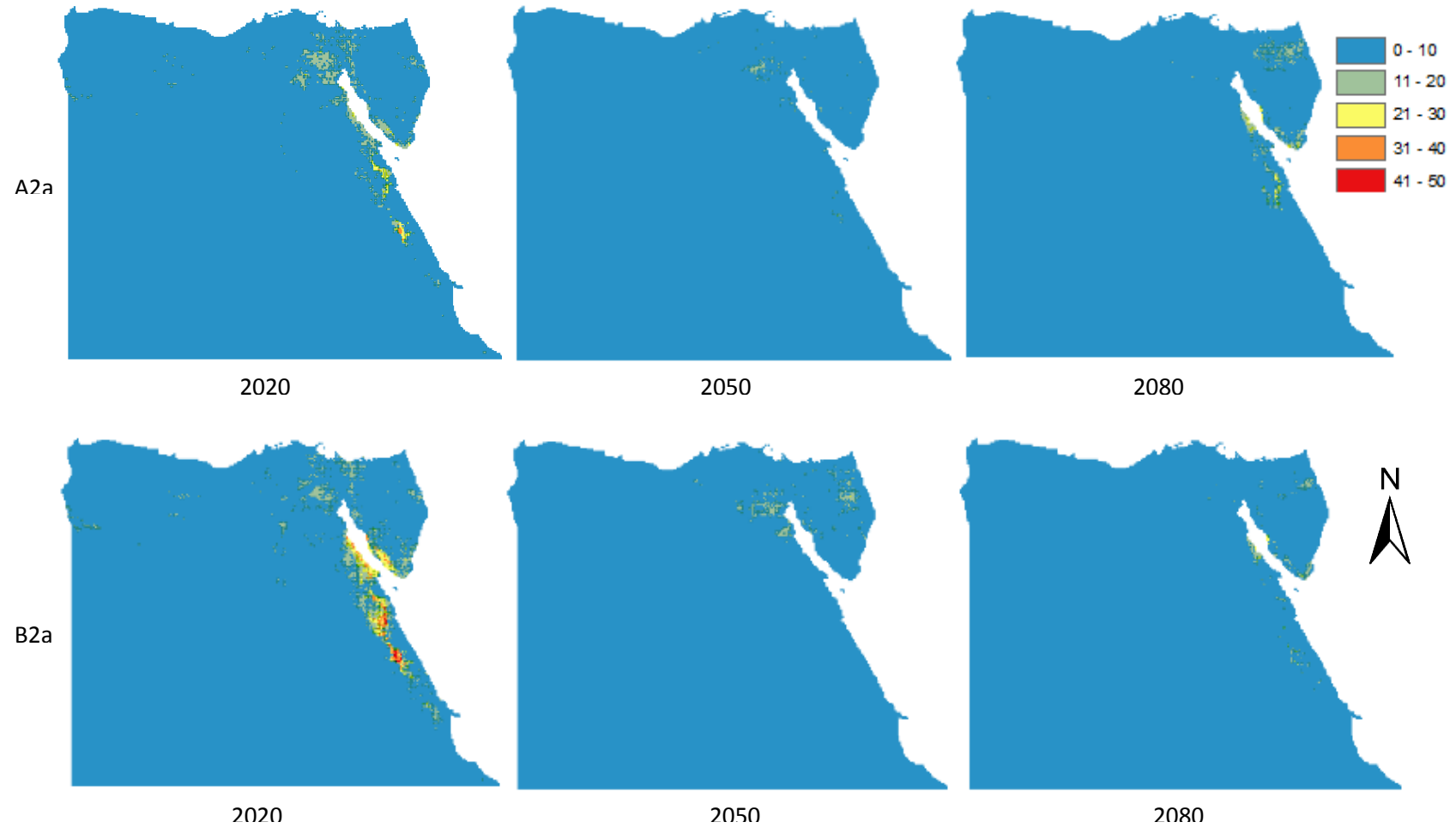


Figure 4.15. Spatial pattern of the number of species lost under climate change in the future (assuming no dispersal). Colours indicate few (blue) to many (red) species lost.

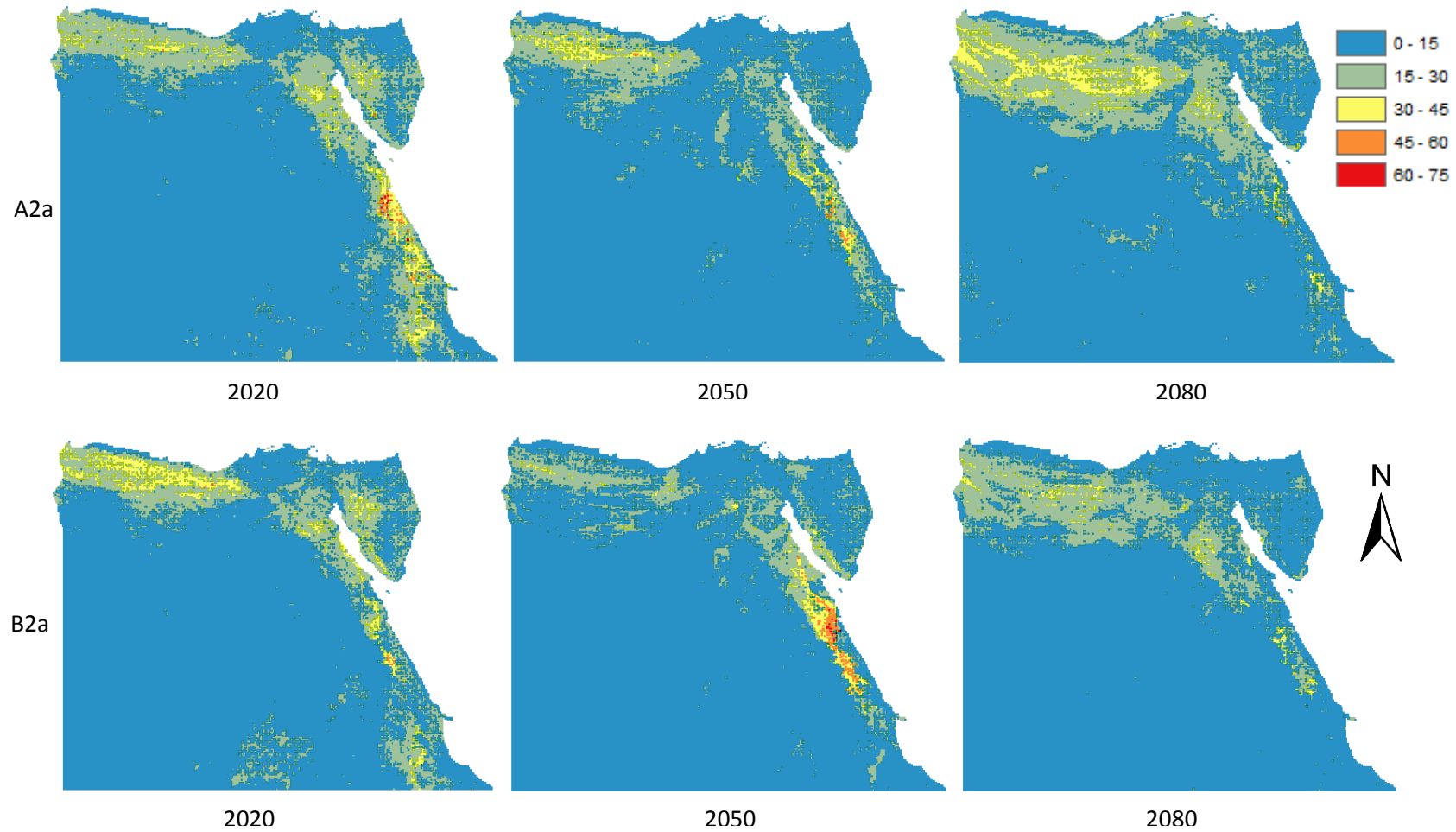


Figure 4.16. Predicted future species turnover (change in species composition), assuming unlimited dispersal. The colours indicate ranges, from low (blue) to high (red) change in species composition).

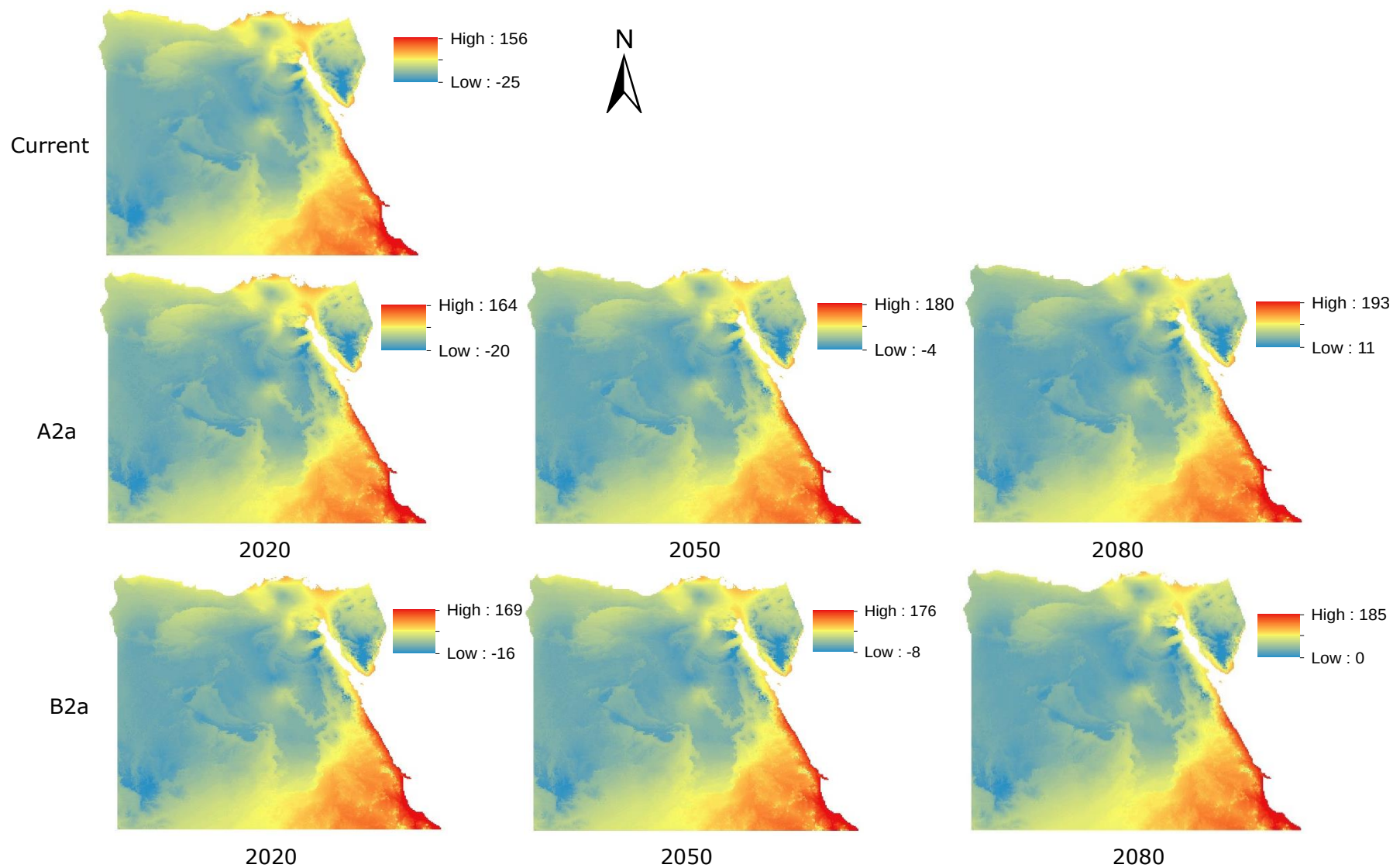


Figure 4.17. Predicted patterns of temperature distributions (Bio 6) across Egypt for the present-day ('current') and into the future (2020, 2050, 2080) under two climate-change scenarios (A2a and B2a). The colours indicate predicted temperature ranging between dark red (high) and blue (low).

4.4 Discussion

The predicted patterns of species richness of Egyptian plants under climate change and a variety of assumptions showed obvious shifts towards the north and north-east of Egypt, along the Mediterranean coast, Sinai Peninsula, Red Sea coast, and both sides of the Suez Gulf. There are several studies elsewhere demonstrating that species tend to shift poleward in latitude and upwards in elevation (Parmesan and Yohe, 2003; Root *et al.*, 2003), and the most important drivers for these changes are temperature and rainfall (Thuiller, 2007). For example, meta-analysis shows that terrestrial species distributions have shifted about 11 m per decade to higher altitudes, and about 17 km per decade towards higher latitudes, depending on the ability of species to track suitable climate change (Chen *et al.*, 2011). The MaxEnt models in this study show, perhaps unsurprisingly, that Egyptian plants respond to temperature and precipitation more than to other environmental variables for example see Bio 6 (Figure 14.7) which represent one of the important factor how changed under climate change scenarios. The predicted species richness gradually increased over time under different scenarios compared with the present day when unlimited dispersal is assumed, because species can then track their habitat under climate change and find suitable environments. Temperatures at the Mediterranean coast, Sinai, the Red Sea coast, and both sides of the Suez Gulf are lower, and rainfall is higher, than in the Western and Eastern deserts and the southern parts of Egypt: these factors create suitable habitat. However, habitat suitability generally declined for future times and climate scenarios compared with current conditions, when no-dispersal was assumed, because species were then not able to track the changing environment. The pattern of species richness appeared to increase more under the A2 scenario than the B2 scenario, as (Ihlow *et al.*, 2012) also found.

Notably, Egypt has a hyper-arid environment and enormous desert spaces in the western, eastern and southern regions. Visually there is agreement between plots of the actual records and predictions of species richness under current conditions. There are very few records found in either desert or southern areas of Egypt, and hence greater species richness northward, and in Sinai and the Red Sea

coast. The main reasons behind this low species richness in much of Egypt lies in the extreme climatic and environmental conditions which are not suitable for most plants.

There is no previous map, atlas or study about Egyptian plant distributions under climate change with which to compare, but our results are similar to other studies recently conducted for Egyptian mammals, butterflies and reptiles (Gilbert and Zalat, 2008; Newbold *et al.*, 2009; El-Gabbas *et al.*, 2016). These all used a similar approach with species distribution modelling, finding that the pattern of species richness increased towards the north and east, with the highest species richness along the Red Sea coast down to Gebel Elba, Sinai, and from the Delta stretching along the Mediterranean coast. Butterflies are good indicators of general biodiversity (Gilbert and Zalat, 2008), since they depend on plants throughout their life cycle. The pattern of our results is certainly in agreement with their findings. For mammals Basuony *et al.* (2010), there is an even greater concentration of species in these places. All these studies taken together indicate that there will be increases in habitat suitability in the northern and eastern coastal areas of Egypt under climate change, while declines occur in the deserts and southern areas of Egypt. Furthermore, this study agrees with previous studies about Egypt that there will be many areas across Egypt that will become more suitable for survival and for protecting biodiversity, especially for plants. The climate (temperature and rainfall) will become more suitable in northern and eastern coastal areas of Egypt for plant growth (for more details see El-Nahrawy, 2011).

There were differences between the A2 and B2 scenarios in species gains, losses, and turnover for different future times. Mean species gains under the A2 scenario assuming unlimited dispersal increased more than under the B2 scenario, but the gains decline from 2020 to 2050 and then increase again between 2050 and 2080 for both scenarios. Under the B2 scenario in 2050 (Figure 4.12), it looks as if more species will be gained than at 2080, but in reality the mean species gain at 2080 is slightly more (see Table 4.3). The A2 scenario appears less harmful than the B2 scenario for species gains, while more harmful for mean species losses

(Figure 4.13, Table 4.3). Under the no-dispersal assumption, A2 appears more harmful than B2 for species loss. Thuiller (2004) also suggested that the A2 scenario in some cases might be less harmful than the B2 scenario. Most of our findings agree with the IPCC special report (Nakicenovic et al. 2000) on emission scenarios, under which the B2 scenario is said to be less harmful.

Similarly, the A2 scenario was more harmful than B2 scenario for species turnover; under both scenarios there was a decline in species turnover between 2020 and 2050, and then an increase again from 2050 to 2080. In general the species losses, gains, and turnover happen along the Mediterranean coast, both sides of the Suez Gulf, the Red Sea coast, Qattara Depression, Siwa Oasis, some patches around greater Cairo and Sinai. According to the Nakicenovic *et al.* (2000) special report on emission scenarios, under the A2 scenario there is more climate change related to CO₂, N₂O, methane, and other gases than the B2 scenario. All these gases increase gradually in both scenarios until 2100, and then some decline afterwards but mostly they remain steady. Under the A2 scenario more of these gases are released than under the B2 scenario, implying that A2 should be more destructive (see Tables 4.1 & 4.2: for more details see (Nakicenovic *et al.*, 2000). Thus in some cases our results agree with Thuiller (2004) that the A2 scenario is less harmful, and in other cases more harmful.

A possible reason is that the main SDM predictors are temperature and precipitation. All environmental variables related to temperature (Table 4.4) increase gradually with time under both scenarios, but by 2050 A2 predicts wetter conditions than B2: Table S5 is thus consistent with (Nakicenovic *et al.*, 2000) on emission scenarios. Thuiller (2004) mentioned that CO₂ and NO₂ emissions under the A2 scenario between 2020 to 2050 are less than those of the B2 scenario, but this directly disagrees with what Nakicenovic *et al.* (2000) mentioned in the IPCC report. We have not found any recent studies that touch upon these issues of the emission scenarios, and which scenario is predicted to be more harmful. There is an important question here, as to why the A2 scenario in some cases is predicted to be less harmful than the B2 scenario.

Other studies from different continents are relevant here. Under the effects of climate change, 2-40% of woody plants in Yunnan Province (China) are predicted to become seriously endangered or disappear by 2080 under the two assumptions of dispersal (Zhang *et al.*, 2014). The current distribution of most chelonians is predicted to alter in the future Ihlow *et al.* (2012), perhaps leading to a decline in abundance and species richness, linked to temperature change as the main driver. Two-thirds of plant species are predicted to decline, and between 5 and 25% to lose their range completely by 2080 in southwestern Australia (Fitzpatrick *et al.*, 2008). Thuiller *et al.* (2005) predicted that more than 50% of 1350 European plants would be under threat by 2080. Golicher *et al.* (2012) suggested that predicted increases in temperature of 3°C and decreases in precipitation by about 20% would cause a decline of about 15% in the species richness of the tropical forests of Mesoamerica. Thus most studies predict much more change, and more particularly serious losses, than we do for Egypt.

Protected areas are important strategic elements of conservation planning. Compared with other countries, the proportion of Egypt's land surface represented by PAs (about 15%) is good, but as elsewhere, there was no consideration of the potential effects of climate change when these PAs were selected (Araujo *et al.*, 2011). With the first being established in 1983, Egyptian PAs are all relatively new, but they were chosen under scientific supervision and using expert knowledge about Egyptian biodiversity (Newbold *et al.*, 2009). The likely future plant species richness inside PAs is significantly higher than outside for all combinations of assumptions. These results suggest that Egyptian PAs are placed appropriately for plants, because they provide suitable environments for Egyptian plants to flourish under climate change, and also effectively represent the plant diversity of the country.

However, there are many locations outside PAs that have high species richness, and hence this needs more effort and management to provide suitable habitat to avoid losing particular species in the future. This is particularly true of

areas along the Red Sea coast, some locations around the Suez Gulf, and areas around the Qattara Depression. This result concurs with other studies conducted on other Egyptian taxonomic groups (Gilbert and Zalat, 2008; Newbold *et al.*, 2009). Leach *et al.* (2013) found that the present-day species richness of butterflies and mammals was higher inside than outside PAs, while in the future this difference will not be stable, as in other taxonomic groups in other regions (Lee *et al.*, 2007; Araujo *et al.*, 2011). It is important to make this comparison to facilitate assessing the relative contribution of PAs to the protection of regional biodiversity (Araujo *et al.*, 2011). Therefore, SDMs approaches can be used as guideline for managing PAs or other environments (Fois *et al.*, 2016; Kaky and Gilbert, 2016)

Species richness is just one of the criteria to assess PAs in conservation planning (Newbold *et al.*, 2009). Alternative measures are possible: Kershaw *et al.* (1995) combined biotic diversity, species uniqueness, and the degree of endangerment, while (Wilson *et al.*, 2007) focussed on specific threats such as land acquisition and invasive species. There are many other factors that impact on species richness distribution and species losses inside and outside PAs: for instance, growing human land use (DeFries *et al.*, 2007; Joppa *et al.*, 2009) or plant productivity (Carrara and Vázquez, 2010). Botkin *et al.* (2007) suggested that the interaction between climate change and resource use by humans could have undesirable effects on biodiversity, greater than each of them alone. Therefore it is important for the Egyptian government to take quick steps to allow for all the possibilities of habitat loss in the future. Genetic erosion may happen in some species, and we must pre-empt the possibility of future extinctions by collecting and preserving seeds.

Overall it is clear that even a modest quantity of data can produce informative and useful guidance for the likely effects of climate change. The first step is the collation, checking and updating of records into a usable database: nearly all countries can do this. Once done, studies can suggest reasonable and evidence-based precautionary measures that can be taken to mitigate climate change.

Table 4.1. Overview of greenhouse gas emissions between 1990 – 2100, modified from the IPCC special report on emission scenarios (Nakicenovic *et al.*, 2000). Units are given in the table.

Gases	Current	Scenario group					
		A2			B2		
	1990	2020	2050	2100	2020	2050	2100
Carbon dioxide, fossil fuels (GtC/yr)	6	11	16.5	28.9	9	11.2	13.8
Carbon dioxide, land use (GtC/yr)	1.1	1.2	0.9	0.2	0	-0.2	-0.5
Cumulative carbon dioxide, fossil fuels (GtC) 1990-2100		1773			1160		
Cumulative carbon dioxide, land use (GtC) 1990-2100		89			4		
Cumulative carbon dioxide, total (GtC) 1990-2100		1862			1164		
Methane (MtCH ₄ /yr)	310	424	598	889	384	505	597
Nitrous oxide (MtN/yr)	6.7	9.6	12	16.5	6.1	6.3	6.9
NO _x (MtN/yr)	30.9	50	71	109	43	55	61

Table 4.2. Standardized anthropogenic emissions (CO₂, N₂O, CH₄, and NO_x) for the ALM region (Africa and Latin America), the region containing our study area; modified from (Nakicenovic *et al.*, 2000) Units given in the table.

Gases	Current	Scenario group					
		A2			B2		
	1990	2020	2050	2100	2020	2050	2100
Carbon dioxide, fossil fuels (GtC/yr)	1.30	1.22	1.52	2.41	0.81	1.24	1.18
Carbon dioxide, land use (GtC/yr)	0.00	0.00	0.00	0.00	-0.18	-0.04	-0.04
Total CO ₂	1.30	1.22	1.52	2.41	0.63	1.20	1.14
Methane total (MtCH ₄ /yr)	47.10	45.80	78.00	143.20	39.80	52.90	47.00
Nitrous oxide total (MtN/yr)	0.60	0.70	0.80	1.00	0.60	0.60	0.70
NO _x (MtN/yr)	4.70	4.00	5.30	7.60	3.20	5.20	3.70

Table 4.3. Mean number of species gained, lost, and turnover under both dispersal assumptions (unlimited and no dispersal) for both scenarios (A2 and B2) at various future times (2020, 2050, and 2080).

Measurements	Unlimited dispersal						No dispersal					
	A2 Scenario			B2 Scenario			A2 Scenario			B2 Scenario		
	2020	2050	2080	2020	2050	2080	2020	2050	2080	2020	2050	2080
Mean species gained	7.41	6.44	9.21	6.19	5.37	5.58	There are no species gained under this assumption					
Mean species lost	1.84	1.83	2.85	1.8	2.08	2.22	1.47	0.69	1.07	1.8	1.06	0.77
Mean species turnover	9.24	8.27	12.05	7.99	7.45	7.8	1.47	0.69	1.07	1.8	1.06	0.77

Table 4.4. Mean value for all environmental variables related to temperature and precipitation.

Environmental Variables	Current	Scenario groups					
		A2			B2		
		2020	2050	2080	2020	2050	2080
Isothermality (Bio3)	47.93	46.44	46.06	44.63	47.09	46.40	45.70
Temperature seasonality (Bio4)	5843.36	5959.45	6051.81	6378.62	5868.28	6063.21	6207.14
Minimum temperature of the coldest month (Bio6)	57.58	67.63	82.48	98.58	71.21	80.12	87.41
Mean temperature of the wettest quarter (Bio8)	169.95	173.86	189.36	202.97	182.35	184.74	194.62
Mean temperature of the driest quarter (Bio9)	200.94	199.16	218.48	224.28	199.22	213.3	218.4
precipitation of the wettest month (Bio13)	3.83	3.37	3.56	3.21	3.42	3.25	3.20
precipitation seasonality (Bio15)	45.19	36.77	42.44	40.41	40.21	36.18	40.53

5 Chapter Five: Using species distribution modelling to assess regional risk under climate change in data-sparse countries: the case of Egypt's medicinal plants

Abstract

The IUCN Red List of Threatened Species is one of the most important of all conservation indicators, but most developing countries do not have enough information with which to make assessments. Species distribution modelling (SDM) represents one of the best methods of predicting the potential occurrence of species, both currently and in the future under the effects of climate change, and offers a potential solution. Taking advantage of a set of validated observations, in this study we used SDMs in evaluating 114 Egyptian medicinal plants based on IUCN Red-List Criteria and Categories. Using MaxEnt and eleven environmental variables, distributions were projected for 2020, 2050, and 2080 under two emission scenarios (A2a and B2a) assuming unlimited and no dispersal. Assessments used actual and predicted extent of occurrence (EOO) and area of occupancy (AOO). There was a positive correlation between EOO estimates based on actual records and those based on SDMs. Most species could be classified as Least Concern (LC) at the current time, whilst in the future under climate change, a few species face some risk of extinction, depending on assumptions. In conclusion, SDM is a good tool with which to make IUCN Red-List assessments for countries where data are sparse.

5.1 Introduction

The IUCN Red List of Threatened Species is widely perceived as one of the most important frameworks for classifying species threatened with worldwide extinction (Lamoreux *et al.*, 2003; Rodrigues *et al.*, 2006). The IUCN Categories and Criteria (IUCN, 2012b) were created to enhance objectivity and clarity in evaluating extinction risk, improving consistency and understanding among users (IUCN, 2010). Currently the Red List is considered to be a classification of sufficient accuracy for the assessments to be used for conservation planning (Mace *et al.*, 2008). The Red List uses various Criteria of assessment (rate of population decline, population size, range restriction, distribution fragmentation and quantitative analysis of extinction risk) (IUCN, 2016) to classify species into nine Categories: Extinct (EX); Extinct in the wild (EW); Critically Endangered (CR); Endangered (EN); Vulnerable (VU); Near Threatened (NT); Least Concern (LC); and Data Deficient (DD). These classifications are very useful in conservation planning and management to prioritize conservation actions (Ricketts *et al.*, 2005; Cassini, 2011).

The definitions of the Categories and Criteria of the Red List must be fully understood by researchers in order to assess species accurately (IUCN, 2016). Range restriction, the whole area encompassing validated records (not necessarily occupied), is measured using the Extent of Occurrence (EOO), whilst occupancy is measured using the Area of Occupancy (AOO), the actual area of the squares occupied by records. The EOO is the minimum convex polygon which includes all occurrence points within the area being considered, excluding vagrant records. However, care is needed because often the EOO measured from the records plotted on a map can include areas of non-habitat where the species cannot possibly be present (Joppa *et al.* (2016). The AOO is the total area of all grid squares inside the Extent of Occurrence where the species has actually been recorded, again excluding vagrants (IUCN, 2012b). Both EOO and AOO can be estimated from “known, inferred, or predicted locations of observed occurrences”, which clearly include

model predictions ((IUCN, 2016). The IUCN-recommended method of calculating the AOO is to divide the study area into a 2x2-km grid and use the validated observations, or a binarized map from a model under certain conditions. The "number of locations" is another criterion used for species with a restricted range. A "location" is defined as a "geographically or ecologically distinct area in which a single threatening event can rapidly affect all individuals of the taxon present. The size of the location depends on the area covered by the threatening event and may include part of one or many subpopulations. Where a taxon is affected by more than one threatening event, location should be defined by considering the most serious plausible threat." (IUCN, 2012b). There are a number of different strategies used to choose the best grid-cell size, and also to decide on the number of locations see (Schatz *et al.*, 2000; Willis *et al.*, 2003; Callmander *et al.*, 2007).

The IUCN Red-List Categories and Criteria are designed to classify species under risk of extinction on a global scale (Gärdenfors, 2001), but have developed to be applicable at national, local, and regional levels (Ginsburg, 2001; IUCN, 2012a). The first assessment for an entire group on a global scale was done on birds (Butchart *et al.*, 2010), and then other taxonomic groups such as reef corals and fish (Carpenter *et al.*, 2008; Hughes *et al.*, 2014), amphibians (Stuart *et al.*, 2004), mammals (Schipper *et al.*, 2008; Hoffmann *et al.*, 2011). The Red List has also been applied successfully at national and regional scales (Zamin *et al.*, 2010): here we are concerned with National assessments.

Indicators such as the IUCN Red Lists are vital because a concerted international effort is needed to achieve the biodiversity targets of the Convention on Biological Diversity to reduce the decline and loss of species at risk of extinction by 2020, and to improve conservation planning (see (CBD). Interestingly, despite their importance to ecosystem function (Brummitt *et al.*, 2015b), most plants still have not been evaluated using the Red List criteria, although a start has been made using a sampling approach (Brummitt *et al.*, 2015a), especially, plants of African countries infrequently evaluated (McClean *et al.*, 2006). One the main barriers to

this effort is a lack of information: most developing countries have few validated data, and even if the data are available, they have little capacity or political will to carry out IUCN assessments, and in particular those that take into account the risks of climate change.

The Millennium Ecosystem Assessment recognized climate change as the greatest threat to biodiversity (MEA, 2005). Climate change is one of the main factors driving changes in species distributions (Parmesan and Yohe, 2003; Root *et al.*, 2003; Thomas *et al.*, 2004; Hannah, 2011); others are, for example, human activity, invasive species, habitat loss and degradation, and changes in land-use (Chapin *et al.*, 2000; Sala *et al.*, 2000). Climate change affects most countries and conservation planning needs to take it into account in order to mitigate its effects. Therefore, currently there is a huge effort to improve conservation planning to include possible changes in distributions, and hence reduce predicted species declines. The best example is the jump in Protected Area coverage from less than 2% of land cover in 1970 to about 15.4% in 2014 (Deguignet *et al.*, 2014; Di Marco *et al.*, 2014). Currently one of the ways to plan for climate change in conservation is to use various Global Circulation Models and different future emission scenarios together with species distribution modelling to predict the potential effects of future climate change on biodiversity (Thuiller *et al.*, 2005; Araujo *et al.*, 2011).

Species distribution modelling (SDM) is a very useful method of predicting distributions even when few data are available (Elith *et al.*, 2006; Phillips and Dudik, 2008). There is strong evidence that SDMs result in accurate portrayals of distributions (Guisan and Thuiller, 2005; Elith and Leathwick, 2009). They use occurrence (presence/absence or just presence) data and associated environmental variables to create models to predict distributions, which can then give a great deal of information useful for conservation planning, especially about possible future changes. When there are no systematic surveys or not enough information on absences, presence-only data from the literature, atlases and herbaria/museums are considered the best sources (Callmander *et al.*, 2005; Newbold, 2010;

Anderson, 2012). Using these data, SDMs provide estimates of the spatial variation of habitat suitability rather than the realised distribution (Marcer *et al.*, 2013), which given certain assumptions can provide estimates of threats to species from climate change, and be used in the Red-Listing process on a large scale for ranking species according to extinction risk (Cassini, 2011; Maes *et al.*, 2015; Collen *et al.*, 2016).

The potential effects of climate change and its threats on biodiversity promote the combining of different modelling methods to understand the impacts (Conlisk *et al.*, 2013). SDMs only predict habitat suitability based on environmental factors (Franklin, 2010) and do not include population parameters or their determinants (e.g. species interaction, fertility, migration) (Conlisk *et al.*, 2013). However, there is a relationship between presence-absence and abundance (Conlisk *et al.*, 2009) and SDMs can be used to estimate abundance (VanDerWal *et al.*, 2009; Anadon *et al.*, 2010; Hwang and He, 2011). The IUCN Guidelines (2016: 86) allow the assumption that changes in suitability be equated to population decline in the absence of other information. For data-sparse countries where the urgency for action means that we cannot afford to wait for ideal data, therefore, SDM-based estimates of extinction risk can provide a useful overview of what needs to be done.

Plants are essential to all terrestrial ecosystems, and plant extinctions will affect many animal species including humans (Díaz *et al.*, 2006). Currently there is no comprehensive assessment of overall extinction risk for plant species (Brummitt *et al.*, 2015b), with only approximately 3% having been Red Listed by 2010, and only 5% by 2014 (Kew, 2010; Brummitt *et al.*, 2015b). There is no distribution map for most plants, and most countries do not have up-to-date checklists (Kew, 2010). Based on the sample of plants in the latest Red List, about 22253 species have been assessed, with about 52% classified as Threatened, but these are unlikely to be representative of all plants.

In this study, National evaluations are made for 114 Egyptian medicinal plant species according to IUCN Red List Categories and Criteria, using SDMs for

current conditions and then projecting to different future times under different emissions scenarios and dispersal assumptions. Only a handful of Egyptian plants have been assessed, but many of these assessments have not used IUCN methodology. Medicinal plants are especially at risk in Egypt because the main threat comes from the large and rapacious pharmaceutical industry (GEF, 2000). Assessments are needed to help Egyptian conservation planning, and to start the process of adapting conservation efforts to climate change. We classify the species in current conditions depending on the actual records by calculating the EOO and AOO. Then we calculate the loss or gain of range size between two different times by measuring the EOO from the model output, and assessing the predicted declines against the Red-List Criteria to estimate the risk of extinction (IUCN, 2010).

5.2 Methods

Occurrence data for the medicinal plant species (Appendix 2) used in this assessment were extracted from the databases of the Cairo-based BioMap project of 2004–8 (see Gilbert and Zalut, 2008), one of whose aims was the production of databases of records where each record had been validated taxonomically by experts and carefully georeferenced. All plants labelled as 'medicinal' in Egypt were included (taken from a UNDP/GEF project: see Hurst *et al.* 2006). Plant nomenclature follows Boulos (1999-2005). There were 14396 presence-only occurrence records of sufficient accuracy from various sources (i.e. the literature, herbaria, and field surveys). Much of the plant data come from recent systematic surveys with coordinates from hand-held GPS (of Sinai in particular), but the literature data date from between 1900 and 2008, all assumed to be a product of the 'current' environment for modelling purposes. Species with fewer than 10 spatially separate records were not modelled to avoid poor model performance (Pearson *et al.*, 2007; van Proosdij *et al.*, 2015). There are virtually no available validated records of these species from surrounding countries, so we were unable

to model the entire range of non-endemic species: this will often be the case for developing countries.

MaxEnt version 3.3.3k was used to build the models (Phillips *et al.*, 2006), because its performance is good with presence-only data and it can cope with relatively few records (Elith *et al.*, 2006; Pearson *et al.*, 2007); it has become the standard method of choice for studies such as ours. MaxEnt was run using the standard default options (i.e. feature classes QPT [Quadratic, Product, Threshold - different shapes of non-linear responses to environmental variables], regularization parameter = 1 [a smoothing function], background 10000 points, convergence threshold 0.00001, 1000 iterations, k-fold cross-validation [k=10] with 10 replicates [for estimating prediction errors], and logistic output [i.e. habitat suitability values]) after an exhaustive check to find the best (highest Area Under the Curve [AUC] or True Skill Statistic [TSS], the standard measures of goodness-of-fit for SDMs: Allouche *et al.* 2006) combination of options. All mean values are given $\pm$ one SE.

The environmental variables consisted of 23 predictors, 19 of them (the standard set of Bio-layers, different measures of maximal, minimal and seasonality of temperature and precipitation created to represent biologically relevant environmental variables: see chapter two Table 2.1) along with altitude downloaded from the WorldClim v. 1.4 dataset at resolutions of 30 arc-sec and 2.5 arc-min (Hijmans *et al.*, 2005). A layer of the normalized difference vegetation index (NDVI) was downloaded from the Spot website (<http://free.vgt.vito.be>), an average over seven years of satellite imaging (Jan 2004 – Dec 2010); from these data we created two predictors, the maximum NDVI (Max_NDVI) and difference between the minimum and the maximum (NDVI_differences). The final predictor was a habitat layer consisting of 11 classes (sea, littoral coastal land, cultivated land, sand dune, wadi, metamorphic rock, igneous rock, gravels,serir sand sheets, sabkhas and sedimentary rocks) based on remote sensing and extensive ground truthing (a product of the Biomap project: for more details see (Newbold *et al.*,

2009). 11 of these 23 predictors (bio3, bio4, bio6, bio8, bio9, bio13, bio15, altitude, habitat, max_NDVI, NDVI_differences) were eventually used after removal of collinearity by applying Variance Inflation Factor analysis (using the 'car package' - R Development Core Team 2012) (see chapter two Table 2.1). This sorts out the best set of uncorrelated variables (see Bombi *et al.* 2012) .

For each species, distributions were modelled for the 'current' time (assumed to be the year 2000: the data come from 1900-2008, mainly 1990-2005), and then projected to three different future times (2020s, 2050s, and 2080s) under two emission scenarios (A2a and B2a) and assuming two kinds of dispersal abilities (unlimited and no-dispersal). We chose to use the IPCC 4th assessment (IPCC, 2007: obtained from the International Centre for Tropical Agriculture website <http://www.ccafs-climate.org/>) and emission scenarios A2 and B2, rather than the latest 5th assessment and its very different scenarios, for continuity with previous work (e.g. El-Gabbas *et al.*, 2016) and because the differences in SDMs are slight (Wright *et al.*, 2016). The A2a and B2a scenarios (see IPCC 2007) involve different assumptions about the levels of CO₂ emissions, and are regularly used in climate-change assessments for biodiversity, with A2 denoting large changes and B2 relatively small changes (Hannah, 2011). The two extreme dispersal assumptions are the ones usually applied in studies such as ours (for example, (Peterson *et al.*, 2002; Thuiller *et al.*, 2005; Broennimann *et al.*, 2006) because they assume species can perfectly (unlimited) or cannot at all (no-dispersal) track climate changes. We should see greater range change under no-dispersal, with impacts on the IUCN categorization. Both assumptions have been criticized for not involving the impact of biotic interactions on species distributions (Araújo and Peterson, 2012), but there is no practical way of incorporating any putative interactions for the poorly studied Egyptian species. We used data from the Global Circulation Model generated by the UK Hadley Centre (HadCM3) for the two scenarios because, compared with others, the HadCM3 is more highly correlated with the observed data (Turner *et al.*, 2006; Farzaneh *et al.*, 2012).

The IUCN Red List Categories and Criteria (IUCN, 2012b) were used to assess extinction risk under the impacts of climate change. There are many studies that have used these to assess plant species based on their distribution (e.g. (Keith *et al.*, 2000; Callmender *et al.*, 2007; Cardoso *et al.*, 2011), but often they do not apply all the rules completely. For example, grid-size guidelines are ignored (see Table S8): Pena *et al.* (2014) and Syfert *et al.* (2014) used EOO alone with a grid-cell size of 1 km²; Marcer *et al.* (2013) used 1 km² but used both EOO and AOO; Jiménez-Alfaro *et al.* (2012) used various grid resolutions with just the AOO; Fivaz and Gonseth (2014) used EOO and AOO based on IUCN rules, but scaled the AOO using small watersheds. Various authors have used SDMs under climate change in this process: Thuiller *et al.* (2005) and Araujo *et al.* (2011) used different grid-cell sizes contingent on the estimated reduction in range size.

Here, we used the IUCN-recommended grid-cell size of 2x2 km in order to calculate the EOO_{records} and AOO_{records} from which the IUCN assessments for the current conditions were made. Estimates of predicted future changes (%) in range size under climate change used a grid-cell size of 2.5 arc-min (~4.6x4.6 km = ~20 km²), chosen to match the level of positional uncertainty of the non-GPS records, and also because of the uncertainty of interpolations from the very non-random distribution of weather stations producing most of the environmental data. The scaling-down (to 2x2 km) process recommended by IUCN (2016: 49-50) is not necessary for these percentages, which are identical whether one scales down or not. Each map was binarized (i.e. predicted habitat suitabilities turned into predicted presences) using the 10%-training-presence threshold rule to distinguish between suitable and unsuitable habitat ('presence'/'absence') (see (Liu *et al.*, 2005), and then EOO_{model} and AOO_{model} calculated from the resulting set of 'presences'.

To estimate the number of "locations" (IUCN, 2012b), we considered that over-collection by pharmaceutical companies is the biggest threat (GEF, 2000). They often destroy entire patches of plants (cf. Hoyle & James 2005), and the

extent of the destruction is probably driven by their knowledge of the areas where the plants grow. We assume this is area-based rather than based on national-scale mapping (because there are no such maps available for Egypt). We therefore estimated the number of subpopulations on a national scale from the records by applying three different assumptions about the possible size of gaps among the records (>20, >50 and >100 km) and assessing how many subpopulations there were under each assumption. The number of locations was also estimated in the same way for the SDMs of the future maps, but in fact did not add useful information for the assessments, and was not used.

Preliminary IUCN assessments based on the actual records used both $EOO_{records}$ and $AOO_{records}$, and depended mainly on criterion B (small geographic range) or on criterion D (a very small range). For criterion B, there are no previous data apart from the records, and therefore we could not assess two of the three sub-Criteria, 'continuing decline' or 'degree of fragmentation'. Thus we could only use sub-Criterion a (small number of 'locations') - it is for this reason that the assessments are called 'preliminary'. It was enough if either index (EOO or AOO) met one of the relevant criteria to categorize each species, and then the regional adjustment was made if appropriate.

To assess how realistic the EOO measurements were for the projected future maps, we estimated the similarity between real and projected values, and their correlation. We explored whether there were systematic estimation errors by correlating them and their difference with the number of records. We used a Jaccard Similarity Index (Araújo *et al.*, 2005; Syfert *et al.*, 2014) (see Figure 5.1) to measure the similarity in the areas of the current EOO_{model} and the $EOO_{records}$. The relationships between these variables, the number of records and the difference ($EOO_{model} - EOO_{records}$) were then explored using rank correlations.

For assessments using future scenarios, IUCN criterion A was used, relevant when species are predicted to undergo large reductions (IUCN, 2016), especially A3 for projected population reductions. No-one has any idea of the generation times of

most Egyptian medicinal plants: they could be several or many years or many decades. Thus we scaled all estimates of declines to a ten-year period (IUCN, 2016) as well as using the absolute declines between the modelled time periods. The predicted change in suitable habitat was calculated as the difference in EOO/AOO between the current and each future map (both at 2.5 arc-min resolution), expressed as a percentage. The percentages were then used to classify each species according to the IUCN criteria, and then the regional adjustment was applied (Table 5.1): LC = loss < 30%, VU = loss > 30%, EN = loss > 50%, CE = loss > 80%, EX = 100% loss (IUCN, 2012b). The NT category was used in this study with a threshold loss > 15%. The categorization assumes that changes in habitat suitability convert directly into changes in population size: given the almost complete lack of data coupled with the need for countries to act according to the precautionary principle, we think this is a reasonable assumption (see also Introduction). Again it was enough if either index (EOO or AOO) met one of the relevant criteria to categorize each species.

Most of the plant species in this study have not been evaluated yet, either globally or locally. Global assessments for those species that have been assessed were obtained from (IUCN, 2015) and national assessments from (NRL, 2015). We found global assessments for just four species, all classified as LC (*Ephedra alata* (Bell and Bachman, 2011)], *Juncus rigidus* (Lansdown and Juffe Bignoli, 2013)], *Phragmites australis* (Lansdown, 2015)], and *Tamarix nilotica* (Akhani, 2014)]). Most species have not been assessed in any local region either: there were National assessments for just four plant species in Egypt, all of them classified as VU (*Colutea istria*, *Teucrium leucocladum*, *Zilla spinosa biparmata*, *Zygophyllum dumosum*) (Hadidi *et al.*, 1992).

The IUCN recommend estimating the proportion of the global population of each species that occurs in the local region being assessed (IUCN, 2012a). We did this by downloading all the global records from the Global Biodiversity Information Facility (<http://www.gbif.org>) and using the Geospatial Conservation Assessment

Tool (GeoCAT) developed by the Royal Botanical Gardens at Kew to measure EOO and AOO for Red List assessment (see <http://geocat.kew.org/editor>). We calculated the proportion of the total records represented by Egyptian records, and the proportion of the global AOO made up of the AOO for Egypt.

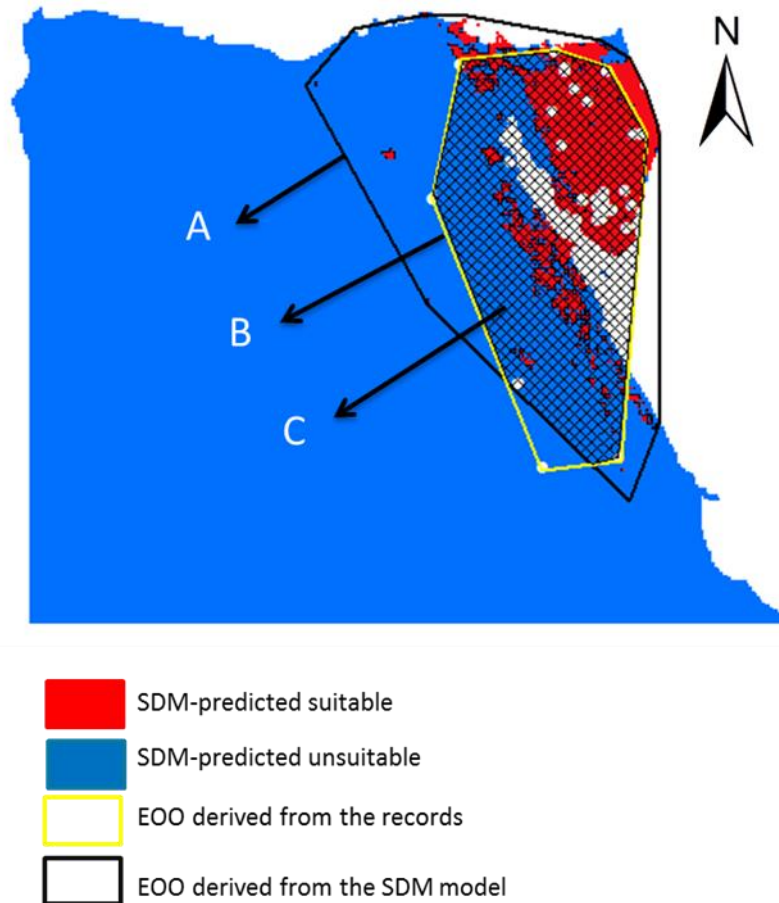


Figure 5.1. Binarized map for *Chiliadenus montanus* showing the calculation of the Jaccard similarity index (in this case equal to 0.61) = $C / (A+B-C)$, where A is the EOO derived from the SDM model, B is the EOO derived from the records, and C is the area of overlap between A and B.

Table 5.1. IUCN Red List Categories and Criteria used to assess the plant species. Because of a lack of information, the highlighted sub-Criteria were not able to be used, resulting in preliminary assessments only for the 'current' assessments (IUCN, 2016).

No.	Categories	Critically Endangered	Endangered	Vulnerable	Near Threatened
1	Criterion A3c: population reduction				
	Decline in Extent of Occurrence (EOO) (%)	> 80	> 50	> 30	> 15
	Decline in Area of Occupancy (AOO) (%)	> 80	> 50	> 30	> 15
2	Criterion B1 and B2: Geographic range size				
	Extent of Occurrence (EOO) (km ²)	< 100	< 5000	< 20000	< 30000
	Area of Occupancy (AOO) (km ²)	< 10	< 500	< 2000	< 3000
	And the following subcriteria:				
	a) number of locations	1	2-5	6-10	11-15
	b) continuing decline				
	c) extreme fluctuations				
3	Criterion D: Very small or restricted population				
	(2) restricted area of occupancy	N/A	N/A	AOO < 20 km ² or locations ≤ 5	N/A

5.3 Results

The performance of the models was good in terms of AUC (0.90 ± 0.004 , 0.80-0.98) and TSS (0.63 ± 0.01). Temperature was always one of the most important environmental predictors (for more details see chapter three Table 3.2). There was significant positive correlation between EOO_{model} and EOO_{records} (Figure 5.2a), and a significant negative correlation between EOO_{model} and AUC values (Figure 5.2b). The number of records was significantly positively related to both EOO_{records} and EOO_{model} (Figure 5.3a,b), and negatively to the differences between EOO_{records} and EOO_{model} (Figure 5.3c). The Jaccard Similarity Index was significantly positively related to the EOO_{records} and the number of records (figure 5.4a,b), but the relationship was not significant for EOO_{model} (figure 5.4b).

For the present-day data, most of the species classified preliminarily using EOO_{records} and AOO_{records} were LC (Tables 5.2 & Appendix 3). When only using EOO_{records} , two species were classified as VU (*Lavandula pubescens*, *Solanum elaeagnifolium*), whilst with AOO_{records} there were up to 10 species classified as EN and 29 as VU, depending on the assumptions made about the minimum distance between 'locations' (Tables 5.2, Appendix 3 & Appendix 4). All species were classified as LC when using modelled current distributions (Tables 5.3 & Appendix 5). The comparison between our Egyptian data and the GBIF global data (see Appendix 6) suggest that Egyptian records represent a reasonable proportion of the global data, and hence that it is worth assessing them regionally; rather than accepting this as accurate, this highlights the inadequacies of the GBIF dataset.

Under both future scenarios, and under both dispersal assumptions, when based on declines over 10 years, nearly all species were classified as LC, with just a few classified as NT (Tables 5.3, 5.4 & Appendix 5).

When declines were based on the absolute time gap, not surprisingly there was more change. Assuming unlimited dispersal, no species were predicted to become extinct at any future time (Tables 5.3 & Appendix 7). There was one species evaluated as CR (*Andrachne aspera*) because in the A2a scenario it was

predicted to lose more than 80% of its suitable habitat by 2080. Two species (*Asclepias sinaica* and *Teucrium leucocladum*) were classified as EN because under the B2a scenario they were predicted to lose more than 50% of their suitable habitat by 2080. Under the A2a scenario, 17 species were classified as VU: three of them by 2020 (*Agathophora alopecuroides*, *Cymbopogon schoenanthus*, and *Deverra tortuosa*), two by 2050 (*Andrachne aspera* and *Salvia aegyptiaca*) and a further 12 by 2080 (Tables 5.3 & Appendix 7). Under the B2a scenario there were 13 species classified as VU, three by 2020 (*Agathophora alopecuroides*, *Avena barbata*, and *Deverra tortuosa*), another three by 2050 (*Andrachne aspera*, *Cymbopogon schoenanthus*, and *Paronychia argentea*), and a further seven by 2080 (Tables 5.3 & Appendix 7). 43 species were assigned to the NT category. For the A2a scenario there were 23 species: two by 2020, ten by 2050, and 11 by 2080. Under the B2a scenario there were 20 species evaluated as NT: seven by 2020, five by 2050, and a further eight by 2080 (Tables 5.3 & Appendix 7). The only available data for regional adjustments were from Israel, where (because of its small size) all species were assessed as Threatened, and therefore unlikely to act as sources of rescue for Egyptian populations.

With the assumption of no dispersal, and assessed over the absolute time gap rather than scaling to 10 years, again no species was predicted to become Extinct under either scenario. Under the A2a scenario, two species were classified as CR (*Agathophora alopecuroides*, *Andrachne aspera*), but only by 2080 when they were predicted to lose more than 80% of their suitable habitat. By 2020, one species was classified as EN (*Acacia pachyceras*), but no other species joined it at any of the future times (Tables 5.4 & Appendix 8). There were 18 species classified as VU: four by 2020 (*Agathophora alopecuroides*, *Ephedra alata*, *Herniaria hirsuta*, and *Moltkiopsis ciliata*), three by 2050 (*Andrachne aspera*, *Cymbopogon schoenanthus*, and *Deverra tortuosa*) and a further 11 by 2080 (Tables 5.4 & Appendix 8). 45 species were classified as NT: 31 by 2020, seven by 2050, and a further seven by 2080. Once again, the majority were consistently classified as LC

(Tables 5.4 & Appendix 8). Under the B2a scenario there were no species classified as CR or EN at any future time (Tables 5.4, Appendix 8). Nine species were classified as VU by 2020, three by 2050 (*Andrachne aspera*, *Cymbopogon schoenanthus*, *Deverra tortuosa*), and four more by 2080 (*Agathophora alopecuroides*, *Anabasis articulata*, *Asclepias sinaica*, *Stipagrostis scoparia*). There were 37 species classified as NT by 2020, seven more by 2050, and a further eight by 2080: again the majority were consistently classified as LC under all circumstances (Tables 5.4 & Appendix 8).

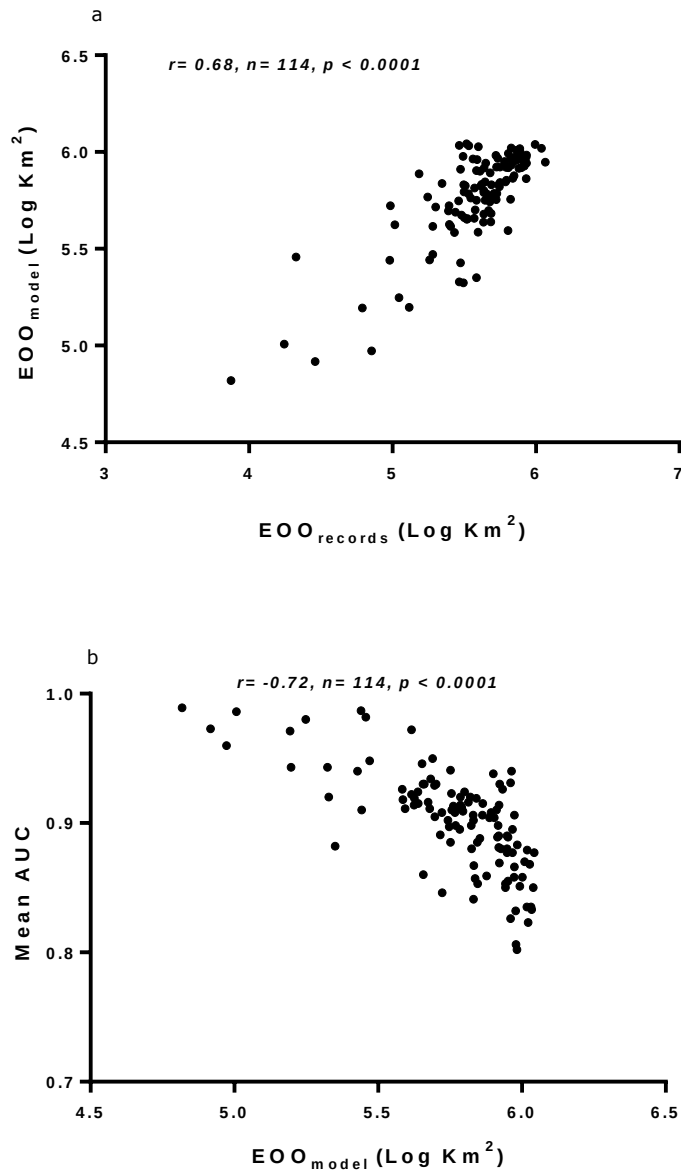


Figure 5.2. Scatterplots showing the relationships between the Extent of Occupancy (EOO) measurements for the records ($EOO_{records}$), the species distribution models (EOO_{model}) and the model quality (area under the curve, AUC) of the SDMs: a) $EOO_{records}$ and EOO_{model} ; and b) EOO_{model} and AUC. These indicate how good the SDMs are in relation to the more traditional IUCN methods of calculating the EOO.

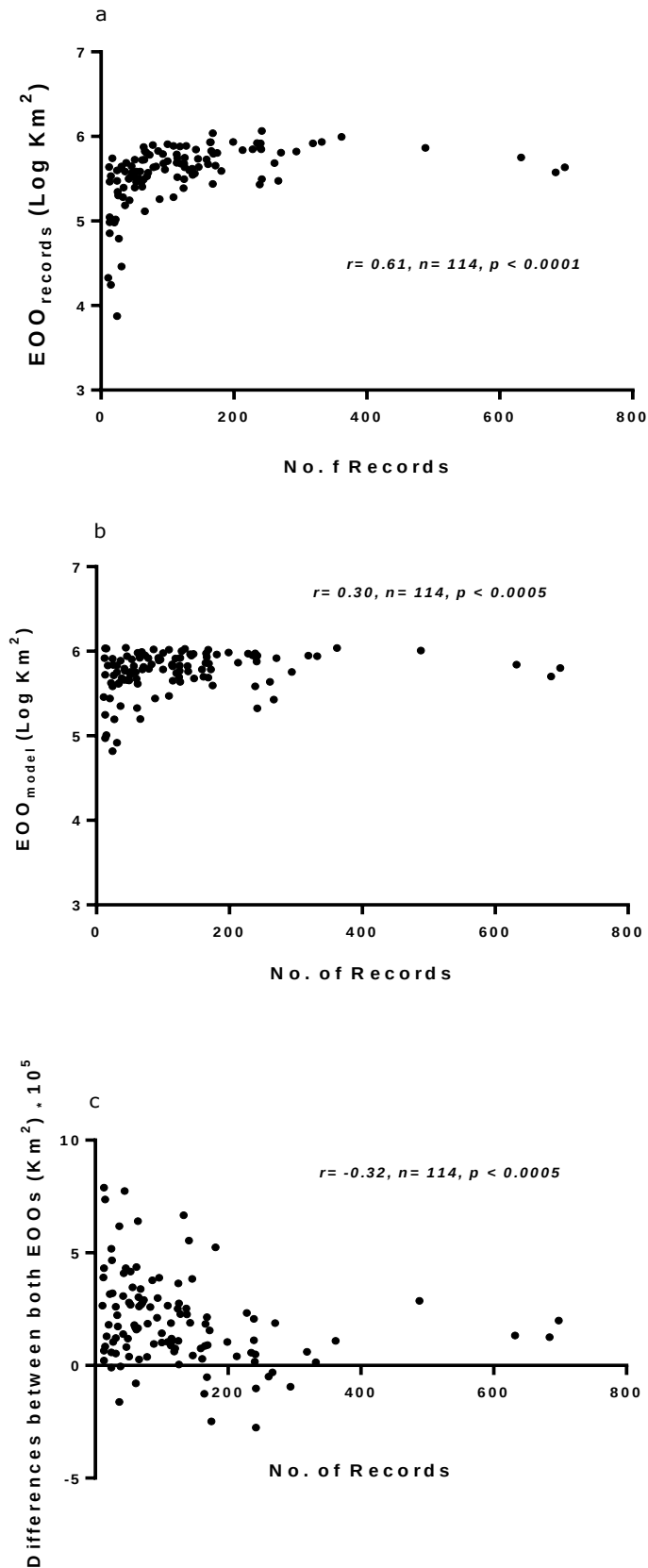


Figure 5.3. Scatterplots exploring variables affecting the validity of measuring the Extent of Occupancy from species distribution models (EOOmodel). The relationships between: a) the number of records and EOOrecords; b) the number of records and EOOmodel; c) the number of records and the differences between EOOrecords and EOOmodel.

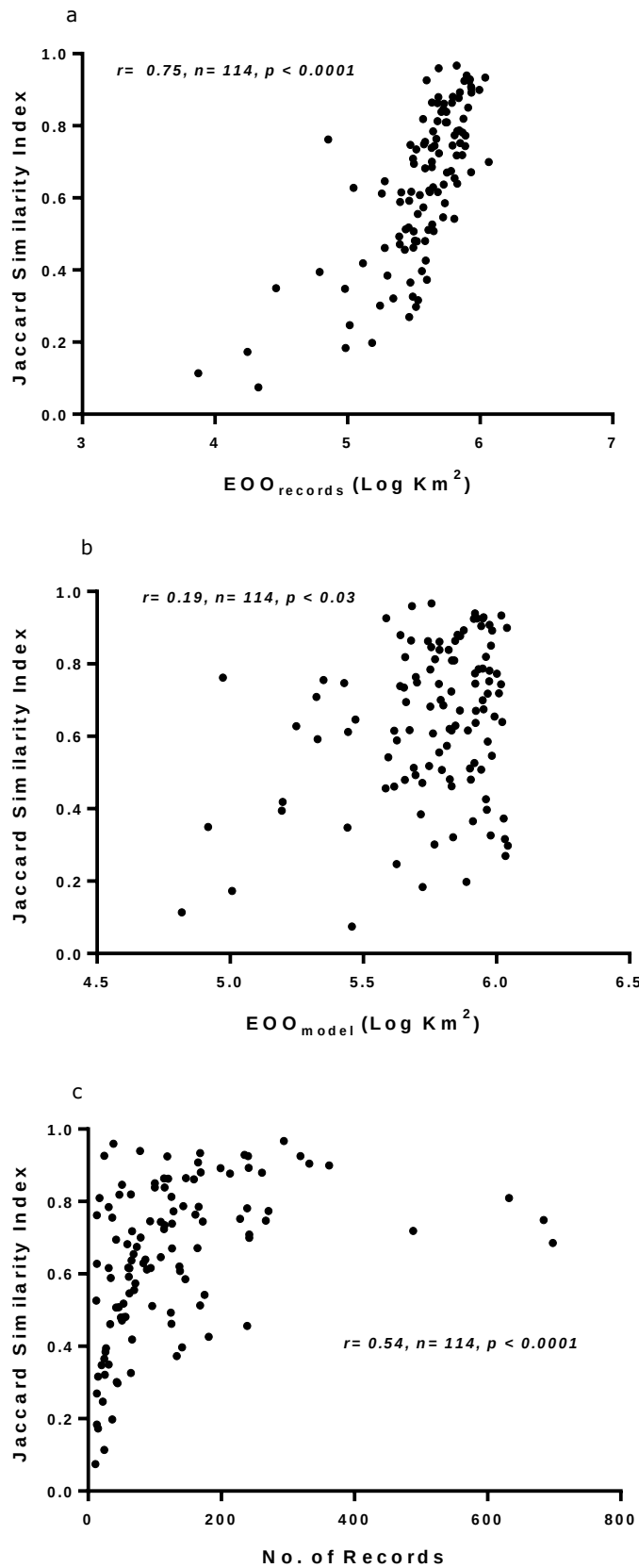


Figure 5.4. Scatterplots with Spearman rank correlations showing: a) the relationship between EOO_{model} and Jaccard Similarity Index; b) the relationship between $EOO_{records}$ and Jaccard Similarity Index; c) the number of the records and Jaccard Similarity Index.

Table 5.2. Number of plant species categorized into each of the preliminary National IUCN categories based on EOOrecords, and on AOOrecords under three different assumptions about the minimum distance between 'locations'. These are 'preliminary' because the lack of data does not allow us to assess the sub-Criteria 'continuing decline' or 'extreme fluctuations'.

Category	EOO	AOO > 20 km²	AOO > 50 km²	AOO > 100 km²
Extinct	0	0	0	0
Critically Endangered	0	0	0	0
Endangered	0	1	4	10
Vulnerable	2	10	13	29
Least Concern	112	103	97	75

Table 5.3. Number of plant species assessed in each IUCN category assuming unlimited dispersal.

Category	Assessments based on the absolute time gap							Assessments based on 10 years						
	Current	A2 2020	A2 2050	A2 2080	B2 2020	B2 2050	B2 2080	Current	A2 2020	A2 2050	A2 2080	B2 2020	B2 2050	B2 2080
Extinct	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Critically Endangered	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Endangered	0	0	0	0	0	0	2	0	0	0	0	0	0	0
Vulnerable	0	3	2	12	3	3	7	0	0	0	0	0	0	0
Near Threat	0	2	10	11	7	5	8	0	0	1	1	1	0	3
Least Concern	114	109	102	90	104	106	97	114	114	113	113	113	114	111

Table 5.4. Number of plant species assessed in each IUCN category assuming no dispersal.

Category	Assessments based on gap between two future times							Assessments based on 10 years						
	Current	A2 2020	A2 2050	A2 2080	B2 2020	B2 2050	B2 2080	Current	A2 2020	A2 2050	A2 2080	B2 2020	B2 2050	B2 2080
Extinct	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Critically Endangered	0	0	0	2	0	0	0	0	0	0	0	0	0	0
Endangered	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Vulnerable	0	4	3	11	9	3	4	0	0	0	0	0	0	0
Near Threat	0	31	7	7	37	7	8	0	1	0	3	2	0	1
Least Concern	114	78	104	94	68	104	102	114	113	114	111	112	114	113

5.4 Discussion

SDM methodology can be a helpful tool in measuring range size (Elith *et al.*, 2006), and hence in assessing species using Red List criteria. SDMs are also important when there is no opportunity for surveying and limited financial support (Fivaz and Gonseth, 2014), and for developing countries we can use even the sparse existing data to guide in the protection of threatened species quickly. There is no time to wait for good quality data. Thus with certain conditions, we agree with (Cassini, 2011) that SDM-based approaches can now be applied for Red-Listing globally and regionally to classify the risk of extinction. This is important for data-sparse developing countries, because our results show that reasonable estimates of the EOO can be made when few data are available (Pena *et al.*, 2014), or for rare species (Marcer *et al.*, 2013). When SDMs can estimate the EOO accurately, then Red-List assessments are facilitated (Syfert *et al.*, 2014). Using Egyptian data controlled for quality by experts, there was a respectable relationship between the $EOO_{records}$ and EOO_{model} , indicating that the SDM predictions were reasonable, as (Syfert *et al.*, 2014) found. The relationship between mean AUC and EOO_{model} is negative, implying that small predicted ranges work better than large ones (Elith *et al.*, 2006; Hernandez *et al.*, 2006). However, there is no strong evidence for a high correlation between the number of the records and model accuracy (Elith *et al.*, 2006), and one of the advantages of MaxEnt is that it obtains accurate models with small sample sizes (Pearson *et al.*, 2007). Accuracy increases in species occupying a limited geographical range and restricted environmental ranges (Hernandez *et al.*, 2006). It is interesting that the relationship between the number of records and the difference $EOO_{records} - EOO_{model}$ was negative, falling almost to zero for the larger sample sizes. This implies that as long as there are enough records, the estimates of EOO from SDMs are likely to be good. Of course one of the main sources of prediction bias in SDMs is sampling bias (Syfert *et al.*, 2013): we are exploring current techniques that claim to allow for sampling bias.

When species were preliminarily Red Listed using the actual records, the AOO was more critical than the EOO, because using the EOO_{records} only two species were assessed as threatened. Using AOO_{records} was provisional because the lack of information about population size, or trends in habitat quality or populations, meant that the number of locations was the only available criterion. Even here, given the generalised threat of over-collection, it was difficult to decide the number of the locations based on occurrence records: we used three assumptions based on the gaps between records on the map (Martín, 2009). Increasing the minimum gap increased the number of plants assessed as threatened because it decreased the deduced number of locations.

Many studies have used different grid-cell sizes to calculate the AOO, and some used the AOO for calculating the locations or subpopulations (see Appendix 9). The Red List claims that a cell size of 4 km² is suitable for all cases, and smaller or coarser sizes are inappropriate. On the other hand, the IUCN state that it is “impossible to provide any strict but general rules for mapping taxa or habitats; the most appropriate scale will depend on the taxon in question, and the origin and comprehensiveness of the distribution data ” (IUCN, 2010). This allows the rescaling of grid-cell size according to the distribution, and perhaps encourages studies not to follow the advice (see Appendix 9 for details). This variability and uncertainty leads researchers into confusion in choosing the best grid-cell size, especially when there are knock-on effects on the number of locations or subpopulations.

SDMs have proved their ability to predict distributions reasonably well (Elith *et al.*, 2006; Elith and Leathwick, 2009), and there is an argument that EOO estimates from SDMs are more representative than those drawn around occurrence points (Syfert *et al.*, 2014). However, the technique carries several uncertainties (Pearson and Dawson, 2003), and therefore care in interpretation is important. Combining them with IUCN Red List assessment under climate changes risks misapplying the Criteria, leading to inaccurate assessments (Akçakaya *et al.*,

2006). Therefore there has been some concern that the Criteria may not be appropriate to assess species under climate-change threats (Hannah, 2012). Conversely, recent studies show that they can identify species that are vulnerable to the effects of climate changes (Keith *et al.*, 2014; Pearson *et al.*, 2014; Stanton *et al.*, 2015). We believe that as long as a carefully validated dataset can be created, because of the ability of SDMs to build good models from relatively few data, even data-sparse developing countries can begin to assess their preparedness to adapt their conservation efforts to climate change. We have identified a key knowledge deficiency, however, in the way the time horizon affects the assessments. The most important issue is the period over which declines are estimated. Since we know nothing about the generation times of our plants, it is uncertain whether 10 years is an appropriate period over which to estimate declines. Ecological knowledge about the species is vital.

Our models show that no plant species is currently at risk of extinction, a much lower estimate than the mean risk reported previously for plants (Brummitt *et al.* 2015b). Plants and birds may be more able to respond to climate change than other taxa (e.g. reptiles and amphibians) because of their ability to disperse, and therefore are less at risk of extinction since they can track climate change (Araujo and Pearson, 2005). The actual evidence suggests that all plant groups are more threatened than birds, but less threatened than amphibians (Butchart *et al.*, 2007; Brummitt *et al.*, 2015b), although this comparison may be biased by the way plants have been selected to be assessed.

At about 15% of the total land, PAs in Egypt potentially represent a good level of conservation (El-Gabbas *et al.*, 2016) compared with the global average of about 12% (Chape *et al.*, 2005), and are poised to play a positive role in preserving species. Egyptian PAs have higher species richness within them than areas outside (Newbold *et al.*, 2009; Leach *et al.*, 2013), even in future projections under climate change (Kaky and Gilbert 2017). Many species are now known to be shifting their

range northwards under climate change (Parmesan and Yohe, 2003; Thuiller, 2007), and therefore dispersal capacity is undeniably important.

Assuming unlimited dispersal, there were more plant species classified as threatened or Near Threatened under the A2a than the B2a scenario, with greater risks by 2080. These findings are consistent with the IPCC report on emission scenarios, where greenhouse gases gradually increase more under the A2 scenario than the B2a (Nakicenovic *et al.*, 2000), and risks of extinction increase with time under both scenarios. As expected, the risks of extinction under the assumption of unlimited dispersal were less harmful than under no dispersal, especially with the B2a scenario, because species can track the effect of climate change by find new suitable habitat (Thomas *et al.*, 2004; Thuiller *et al.*, 2005). In view of this increased risk of extinction, conservation needs to be prioritized quickly and given more resources to avoid this outcome.

From this case study, we conclude that SMDs are helpful tools for estimating range sizes both now and in the future, especially for developing countries if a validated dataset can be engineered. It would be very interesting if there were available data for same species in neighbouring countries so as to make a more general view of the range-size changes. For species assessment in a small region, it is probably important to assess across a larger region than used for conservation planning (IUCN, 2012a): however, the data are completely lacking.

6 Chapter Six: Allowing for human socioeconomic impacts in the conservation of plants under climate change

Abstract

In this study we analyse the impact of climate change on conservation planning when socioeconomic impacts are taken into account, and checking the existing network of Protected Areas is adequate, using Egyptian medicinal plants as a model system. We build species distribution models using MaxEnt for 114 Egyptian plants, and project them to different future times (2020, 2050, and 2080) under two emission scenarios (A2a and B2a) assuming unlimited and no dispersal. We compare the effect of two indices of socioeconomic activity (the Human Influence Index, and human population density per km²) as cost layers in spatial prioritization using Zonation. We compare predicted conservation value inside and outside Egyptian Protected Areas (the PA value excess) under the various scenarios. The results show that there are many locations in Egypt (the main cities, agricultural land, coastal areas) that are highly ranked for conservation when human socioeconomic impacts are not recognized; there are also a few areas ranked as low priority for conservation that become high priority when human impacts are included. The use of the Human Influence Index had a stronger impact than using human population density. The PA value excess varied significantly with the type of cost and dispersal, but not with climate-change scenario or Zonation settings; using the Human Influence Index made this excess on average negative, implying greater biodiversity outside rather than inside PAs. Including human impacts reveals large highly ranked areas that are unprotected. We conclude that human socioeconomic impacts add new scope and insights for future conservation planning; and that conservation planning without consideration of such impacts cannot be complete.

6.1 Introduction

Recent work shows that climate change is one of the main factors affecting the distribution of species and ecosystems (Alkemade *et al.*, 2010); species really are shifting northwards (Parmesan and Yohe, 2003; Root *et al.*, 2003), and projections under future climate change predict much larger shifts (Thuiller *et al.*, 2005; Araújo *et al.*, 2006). These impacts are of concern to conservation biologists (Brooks *et al.*, 2006), in particular because one of the predicted impacts is to change the efficiency of Protected Areas (PAs) in conserving species in the future (Leach *et al.*, 2013). The increasing impact of climate change on plants is predicted to affect northern and Mediterranean countries in particular (Bakkenes *et al.*, 2006). Thus it is important to understand the likely future of the current network of PAs; with such knowledge, we can prepare suitable conservation plans.

Species distribution modelling approaches have been used extensively for conservation and conservation planning (Alagador *et al.*, 2011; Araujo *et al.*, 2011; Dobrovolski *et al.*, 2014). They model the relationships between species records and environmental predictors to create current predicted distributions, which can be projected into the future using models of climate change. The resulting maps are very valuable in highlighting the predicted differences between the current and future distributions of habitat suitability (Thuiller *et al.*, 2005), and can be used to identify locations important for conservation (Zhang *et al.*, 2012) with the many techniques and tools developed to prioritize areas for conservation (e.g. Zonation (Moilanen *et al.*, 2014)], ResNet (Sarkar *et al.*, 2002)], Marxan (Game and Grantham, 2008)], ConsNet (Ciarleglio *et al.*, 2008)], MultCSync (Moffett *et al.*, 2005)] and WorldMap (Williams, 2001). We chose the Zonation framework, because it creates a priority ranking (Moilanen *et al.*, 2011) useful in assessing and analysing the efficiency of the PA network (Leach *et al.*, 2013). Spatial conservation planning is an important approach for identifying priority areas for conservation when data are sparse (Moilanen *et al.*, 2009b). Spatial conservation prioritization can be applied at different scales, national to global (Butchart *et al.*, 2015; Di Minin *et al.*, 2016; Di

Minin *et al.*, 2017), and supports the complementarity principle, i.e. areas are chosen taking into account the protection afforded elsewhere (Cabeza and Moilanen, 2001; Klorvuttimontara *et al.*, 2011).

Socioeconomic information is very important in conservation planning and management. The huge expansion of the human population and its economic activity over the 20th century has altered habitats increased invasive species, and created climate change and pollution (Polasky, 2008), creating a biodiversity crisis (Pimm *et al.*, 1995). Conservation planning strategies are essential if we are to minimize biodiversity loss, because the threats to biodiversity are unevenly distributed (Brooks *et al.*, 2006). Many studies have used spatial prioritization for conservation planning based only on biological data (Moffett and Sarkar, 2006; Naidoo *et al.*, 2006; Leach *et al.*, 2013; El-Gabbas *et al.*, 2016), which without taking into consideration socioeconomic impacts can undermine the conservation process (Knight *et al.*, 2008; Faleiro *et al.*, 2013). Recently, several studies have used socioeconomic data in conservation planning (Sarkar and Garson, 2004; Rangel *et al.*, 2007; Liu *et al.*, 2008; Ban *et al.*, 2009; Faleiro *et al.*, 2013; Di Minin *et al.*, 2017) to see how such information changes spatial prioritization for conservation. It is clear that successful conservation prioritization occurs when land-use considerations have been involved at the design stage (Moilanen *et al.*, 2011).

Protected areas are considered to be vital and fundamental units for conservation. In the face of climate changes, species may become maladapted to the set of ecological conditions in a given area (Bellard *et al.*, 2012), and therefore must move to find suitable habitat. Changing in distributions can lead to shifts of biodiversity distribution (Menéndez *et al.*, 2007), and as a consequence PAs could lose species richness, and hence lose their efficiency in conservation. Therefore, recently international conservation planning has been encouraged to reduce such kinds of decline in conjunction with the attempt to expand the global network reserve to cover 17% of all terrestrial land by 2020 (CBD).

In this study the distributions of 114 plant species were used to assess the efficiency of a PA network for conservation under climate change. Species were weighted based on their conservation status and relative rarity, and then we applied systematic conservation planning (Margules and Pressey, 2000) using *Zonation* (Moilanen *et al.*, 2014) to find the areas suitable for conservation. We assumed we might be able to save 20% of Egypt's land, given that 15% is already within PAs. The difference in the conservation value of land inside and outside each PA was averaged across PAs as the test of the efficiency of the PA network. We made this assessment with different assumptions about the pattern of human influence and plant dispersal abilities.

6.2 Methods

The data consist of occurrence records of 121 medicinal plant species across Egypt, collated by the BioMAP project in Cairo in 2004–2008, funded by Italian Debt Swap. The data are presence-only records collected from different sources (i.e. literature, herbarium, and field work). We deleted species with fewer than ten records to avoid overfitting (Baldwin, 2009), and species with more than ten records but spatially very close together and with a mean AUC less than 0.5 to avoid inaccurate predictions. We ended up with 114 species of Egyptian medicinal plants, with 14396 point records.

The environmental variables consisted of 23 predictors, 19 of them (Bio-layers) downloaded from the WorldClim v1.4 dataset at resolution of 2.5 arc-minutes (<http://www.worldclim.org/bioclim>) (Hijmans *et al.*, 2005) (see chapter two Table 2.1). Normalized Difference Vegetation Index (NDVI) data for seven years (2004 to 2010) were downloaded from the Spot Vegetation website (<http://free.vgt.vito.be/>), and then we created two layers from them: maximum NDVI (Max_NDVI), and the difference between the Minimum and Maximum NDVI values (NDVI_differences). A further environmental predictor was a categorical habitat layer, derived from the Biomap project (for more detail, see (Newbold *et*

et al., 2009). Altitude data were downloaded from <http://www.cgiar-csi.org/data/elevation> and the resolution rescaled from 90 m to be 2.5 arc-minutes (see (El-Gabbas *et al.*, 2016). Eleven of the 23 environmental variables remained for use after 12 were removed based on collinearity analysis using the Variance Inflation Factor (see chapter two Table 2.1), implemented in R v2.15 (the *car* package: R Development Core Team 2012).

We used Maximum Entropy (MaxEnt) version 3.3.3k (Phillips *et al.*, 2006) (downloaded from: <http://www.cs.princeton.edu/~schapire/maxent/>) to run the models, choosing a set of options (i.e. feature classes QPT, 10000 background points, 1000 iterations, cross-validation with 10 replications, 10% training presence threshold, and logistic output format) to create both 'probability' (i.e. raw values of habitat suitability) and 'binary' (via thresholding) maps. The chosen options maximised measures of model fit (AUC and TSS) see chapter three for more details. MaxEnt performance is good with presence-only data and small numbers of records (Elith *et al.*, 2006; Franklin, 2009), and its performance is good in comparison with other algorithms (Elith *et al.*, 2006).

Current distribution models for each species were projected into the future at three different time slices (2020, 2050, and 2080). The data of the predicted future climates came from the Intergovernmental Panel on Climate Change's (IPCC) 4th assessment data (IPCC 2007) taken from the International Centre for Tropical Agriculture website (see <http://www.ccafs-climate.org/>). We used data from the Global Circulation Model (GCM) generated by the UK Hadley Centre for Climate Prediction and Research (HadCM3) for two scenarios (A2a and B2a), rather than the latest 5th assessment and its very different scenarios, for continuity with previous work (e.g. El-Gabbas *et al.*, 2016) and because the differences in SDMs are slight (Wright *et al.*, 2016). Such GCMs are widely used in species distribution models to explore the effect of climate change on biodiversity (Thuiller *et al.*, 2005; Araújo *et al.*, 2006; Fitzpatrick and Hargrove, 2009; Hickler *et al.*, 2012; Hamann and Aitken, 2013).

The A2a and B2a scenarios (see IPCC special reports; (Hannah, 2011) have different assumptions about the amount of CO₂ emissions. The A2a scenario expects that the level of CO₂ emissions increases without any barriers, because in this future scenario the world is represented by high growth rate in human population, not much technological development, expanded land-use changes, and people are less environmentally aware. The B2a scenario expects that the level of CO₂ emission will not change much, because human population growth will be slower, with fewer changes in land-use, people are more environmentally conscious, and there is increasing invention in technology (Nakicenovic *et al.*, 2000; Zhang and Nearing, 2005; Saupe *et al.*, 2011). We assume no phenological or evolutionary reactions to climate change: species will attempt to find their climatically suitable habitat dependent on their dispersal capability. We assumed that some environmental variables (such as habitat and NDVI) in future models will not change because there is no information on how these predictors might change; other variables such as altitude will clearly not change in the future. These unchanging predictors were included in the predictor set because we sought the best model in each case.

We made two assumptions about dispersal: unlimited, and no dispersal. For unlimited dispersal, MaxEnt probability output was used directly. For no dispersal, we produced a consensus binary (presence/ absence) map from the 10 replicate runs manually for each species, allotting a 'presence' to a pixel in the consensus map that had presence values in more than 50% of the model runs (i.e. >5 replicates). For times in the future, the consensus binary map was compared to the 'current' one, allocating a pixel to be a 'presence' in the event that it was a 'presence' in both maps.

Once the maps of the predicted distributions were available, Zonation v.4 software (Moilanen *et al.*, 2014) was used to evaluate the performance of Egypt's existing PA network under climate change, and to suggest new PAs for the future. Using the distribution of species and their relative weights (see below) to create a sum for each pixel, Zonation then ranks every pixel in the landscape (Moilanen *et al.*, 2005; Moilanen *et al.*, 2014) by removing them one by one (or N by N, with N set by

the 'warp factor') according to chosen removal and aggregation rules, and recalculating across the remaining pixels. We used two removal rules: (a) core-area zonation, which removes the grid cell with the smallest value for the most valuable occurrence of all species occurring in the cell (emphasizing rarity); and (b) the additive benefit function, which removes the grid cell that results in the smallest decline in the sum of the loss in representation of species (emphasizing species richness) (Arponen *et al.*, 2005; Moilanen *et al.*, 2005; Moilanen *et al.*, 2011). The 'warp factor' was set at 100; this is the number of cells removed at a time - it greatly reduced the run times. For our aggregation rule, which promotes aggregated over unduly fragmented areas, we chose distribution smoothing (Moilanen *et al.*, 2014), which estimates how species use the landscape based on their dispersal ability (α values) (Moilanen *et al.*, 2005; Moilanen and Wintle, 2006). We assumed that plants with wind-dispersed seeds can disperse about 20 km, while those with seeds that simply drop can disperse 1 km, basing our judgments on the descriptions in (Boulos, 1999-2005) (see (Cain *et al.*, 2000). From these figures we calculated the α values (Moilanen *et al.*, 2014) using grid-cell units (2.5 arc-minutes, 0.0416°, about 4.6388 km):

$$\alpha = \frac{2}{\text{Dispersal distance (in km)} * \left[\frac{0.0416}{4.6388}\right]}$$

When 'no dispersal' was the assumption, all α values were set to zero (see (Moilanen *et al.*, 2014).

Species were weighted by multiplying together scores representing national assessments of conservation status (IUCN assessments: Kaky & Gilbert 2017), the relative importance of Egypt's populations (world distribution), and the distribution of the species within Egypt (see Table 6.2).

Human impacts were assessed using a 'cost layer'. Two types were used, the human influence index (HII) (1995-2004) and population density/km² (2015) Figure 6.1 a and b, both downloaded from the Socioeconomic Data and Applications

Centre (SEDAC) (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016). The former was created from nine other layers covering human population density, land use and infrastructure (built-up areas, night-time lights, land use/land cover), and human access (coastlines, roads, railroads, navigable rivers) (WCS, 2005). In HII layer we reweight the buffer around the roads to be zero, and we based on main roads which they suggest 5km, because after discussion with experts which they have a good experience in Egypt 15km buffer on each side road not logic in Egypt case Figure 6.1 a. These cost layers were used unaltered for the future scenarios because we have no predictions available for the way in which either will change in the next 60-odd years. Both were used as a cost layer with the additive benefit function removal rule, to give low priority to areas with high human influence. As recommended (Moilanen *et al.*, 2014), both were used as a mask layer with core-area zonation, with a threshold below which pixels are available for use by Zonation.

Each Zonation output file ranks each pixel between 0 (low) and 1 (high) conservation value. Cells >0.7 were regarded as important locations for conservation planning. The distribution of the PA network (see Figure 6.1c) was compared with these important locations visually and quantitatively to their effectiveness in conserving plants under the effect of future climate change. Designed by local biodiversity experts, PAs cover about 15% of Egypt's land surface (El-Gabbas *et al.*, 2016), all established since 1983 (Newbold *et al.*, 2009). Zonation allows an assessment of the proportion of species protected for given proportion of the land conserved. We set the target as protection of 20% of the land, and compare each scenario/assumptions on the base of the proportion of species protected.

Pixels were placed inside each PA and within a 50-km buffer around each PA, allowing a comparison of the mean conservation value inside and outside each PA. The mean Zonation scores for the chosen areas inside and outside each PA were obtained for each combination of scenario (A2, B2), year (current, 2020, 2050, 2080), dispersal (unlimited, no-dispersal), cost (no-cost, Human II, population density) and zonation

setting (abf, core-area zonation). The paired difference inside-outside each PA was calculated, and the difference became the response variable of a GLM with normal errors. In all there were 2100 differences created.

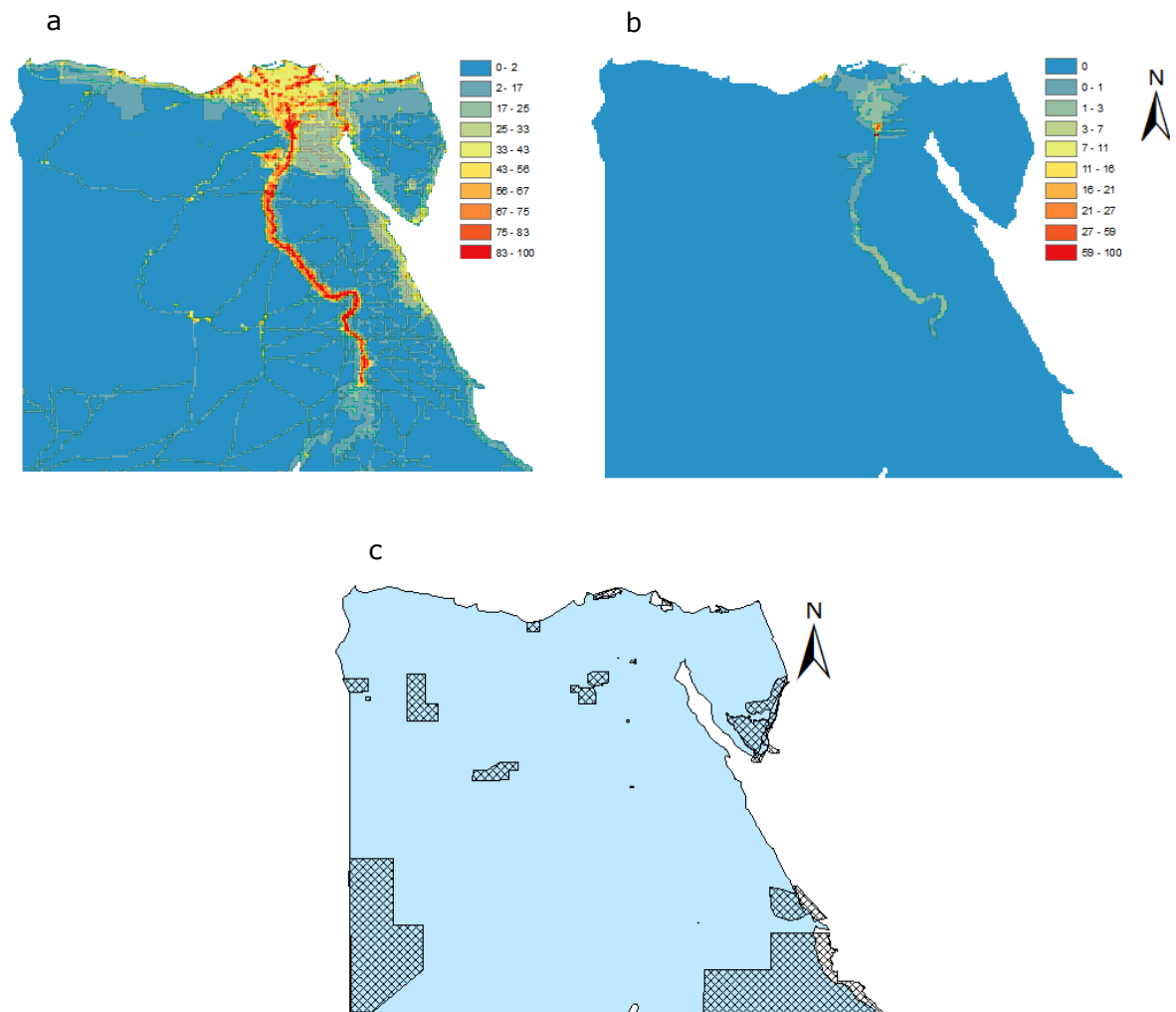


Figure 6.1. Cost layer used in Zonation and Egyptian Protected Areas. a) is Human Influence Index (HII), b) Population density grids both used with unlimited and no dispersal assumptions. Both layers rescaled to be in the same scale. c) Egyptian Protected Areas overlying on Egypt's political boundaries.

6.3 Results

Under the assumption of unlimited dispersal, and using the “additive benefit function”, the best areas for conservation were the whole of Sinai, across the Mediterranean coast, the Suez Canal area, and the Red Sea coast (Figure 6.2). The map implies that by protecting 20% of the Egyptian landscape, we can protect about 63% of the medicinal plant species (Appendix 10). With future climate change under both scenarios A2a and B2a there were slight differences but the same areas were identified as the best locations for conservation. The maps again imply that by protecting 20% of the land, we can protect from 53-60% (A2a) or 56-62% (B2a) of the plant species (Appendix 10). Using “core-area zonation” but still with unlimited dispersal, the best locations were the whole of Sinai, the Mediterranean coast, the Nile Delta, greater Cairo, the Red Sea coastal area (Figure 6.3). 61% of species are predicted to be conserved by protecting 20% of the land (Appendix 11). There were few predicted differences in the future under climate change for either scenario (Figure 6.3). 20% of the land was predicted to protect 51-57% (A2a) or 54-59% (B2a) of medicinal plant species (Appendix 11).

Under the no-dispersal assumption and using “additive benefit function”, similar areas were prioritized but the conservation values increased, and 20% of the land protected 82% of the species (Figure 6.4 and Appendix 12). There were only trivial differences predicted in the future scenarios (Figure 6.4 and Appendix 12). Using “core-area zonation” was similar, with about 79% of species protected in 20% of the land (Figure 6.5 and Appendix 13), and slightly higher conservation value under both scenarios for the Nile Delta and slightly lower for the Red Sea coast. 20% of the land protected 81-83% across all scenarios (Figure 6.5 and Appendix 13).

Using the HII cost layer changed the results dramatically. Assuming unlimited dispersal and the “additive benefit function”, all the coastal areas along the Mediterranean and the Red Sea, the main cities of Cairo, Fayoum, Alexandria, and from Suez to Ismailia, and entirety of the Nile Delta were removed because

they were poor for conservation (Figure 6.6). There were no major differences between current and future times: protecting 20% of the land was predicted to conserve only about 34-36% of species (Appendix 14). Using "core-area zonation" the prioritization values increased across Sinai, Farafra oasis (Figure 6.7). The top 20% of the land was predicted to protect about 44-47% of the species under all scenarios (Appendix 15). Using the population density cost layer increased the Zonation rank scores significantly, again with only slight differences among scenarios and future times (Figures 6.8, 6.9), and the top 20% of the land could protect 51-62% of the species (Appendices 16, 17).

With no dispersal and the "additive benefit function", the best areas for conservation were whole Saini, Qattara Depression, Siwa oasis, and areas from south of Ras Zaafarana to Halayeb excluding the Red Sea coastal areas under (HII). There were only very small differences between the current prediction and future scenarios in north Sinai and the Red Sea coast, and the top 20% of the land could protect 50-55% of the species (Figure 6.10 and Appendix 18). Using "core-area zonation" was similar, with the main differences among scenarios located around the Qattara Depression and Siwa oasis, and protecting 20% of the land could protect 54-55% of the species (Figure 6.11 and Appendix 19). Using the population density cost layer, no dispersal and the "additive benefit function", the best areas for conservation in all scenarios were the whole of Sinai, the Nile Delta, all the Mediterranean and most of the Red Sea coasts, the Qattara Depression, and areas around Halayeb, and the top 20% of the land could protect 82-84% of the species (Figure 6.12 and Appendix 20). Using "core-area zonation" was similar, but excluded the Nile Delta, while including areas between Aswan to Lake Nasser, and south of Kharga and Farafra oases, again the top 20% of the land could protect 71-75% of the species (Figure 6.13 and Appendix 21).

Differences in conservation value between inside and outside PAs based on the final model showed significant effects of the type of cost and of dispersal and their interaction (Table 6.1 and Figure 6.14 a). The average difference for most PAs

was higher inside than outside (Figure 6.14 b), While, just for the HII cost there were many positive (inside > outside) differences out weighted by the large negative differences of some PAs. (Figure 6.14 c). There were no significant effects of climate-change scenario or the removal rule of Zonation (Abf/Caz).

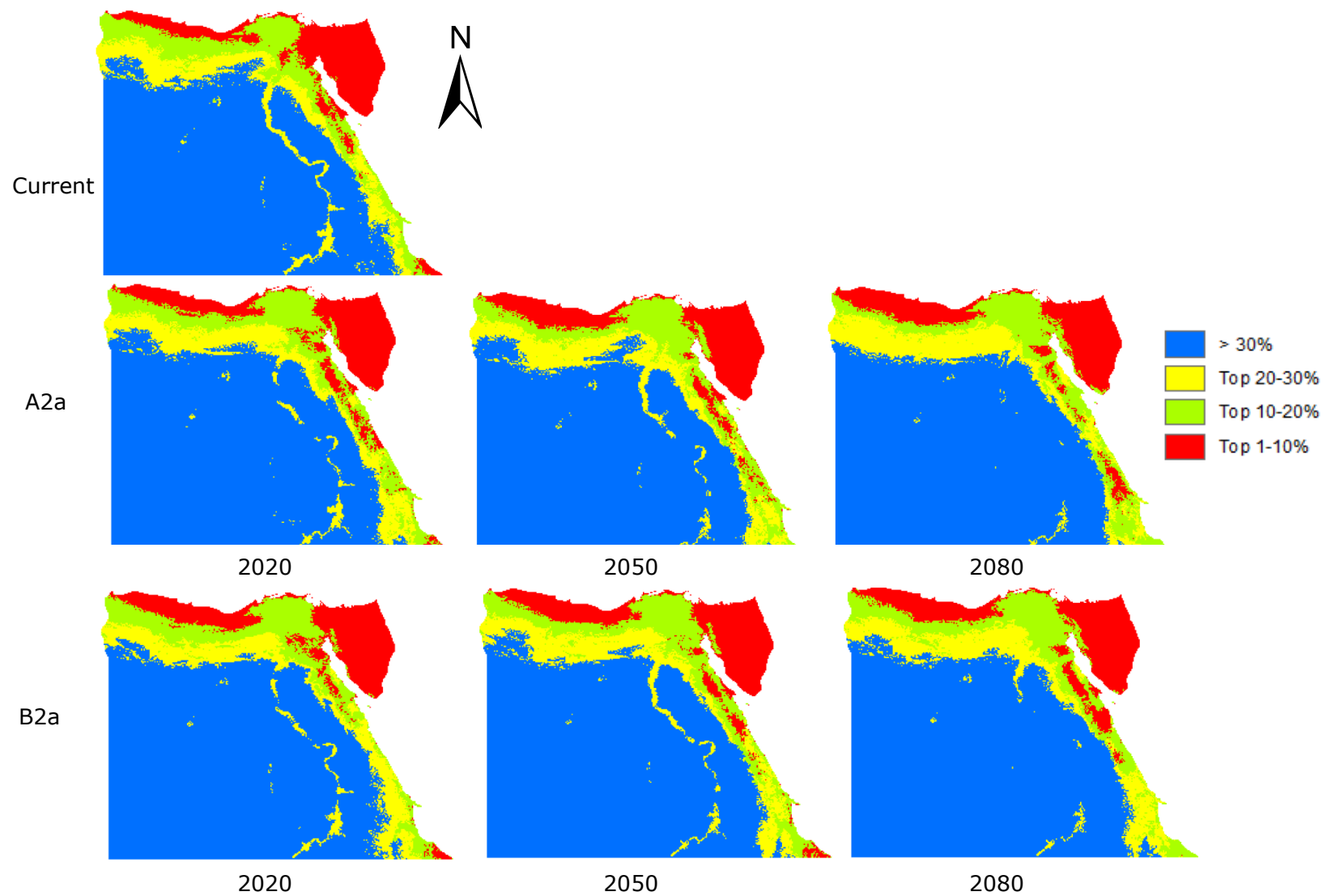


Figure 6.2. Conservation prioritization ranked values using Additive Benefit Function removal cell for current and future assuming unlimited dispersal without using costs. The colours ramp from red colour high conservation values, for blue colour low conservation value.

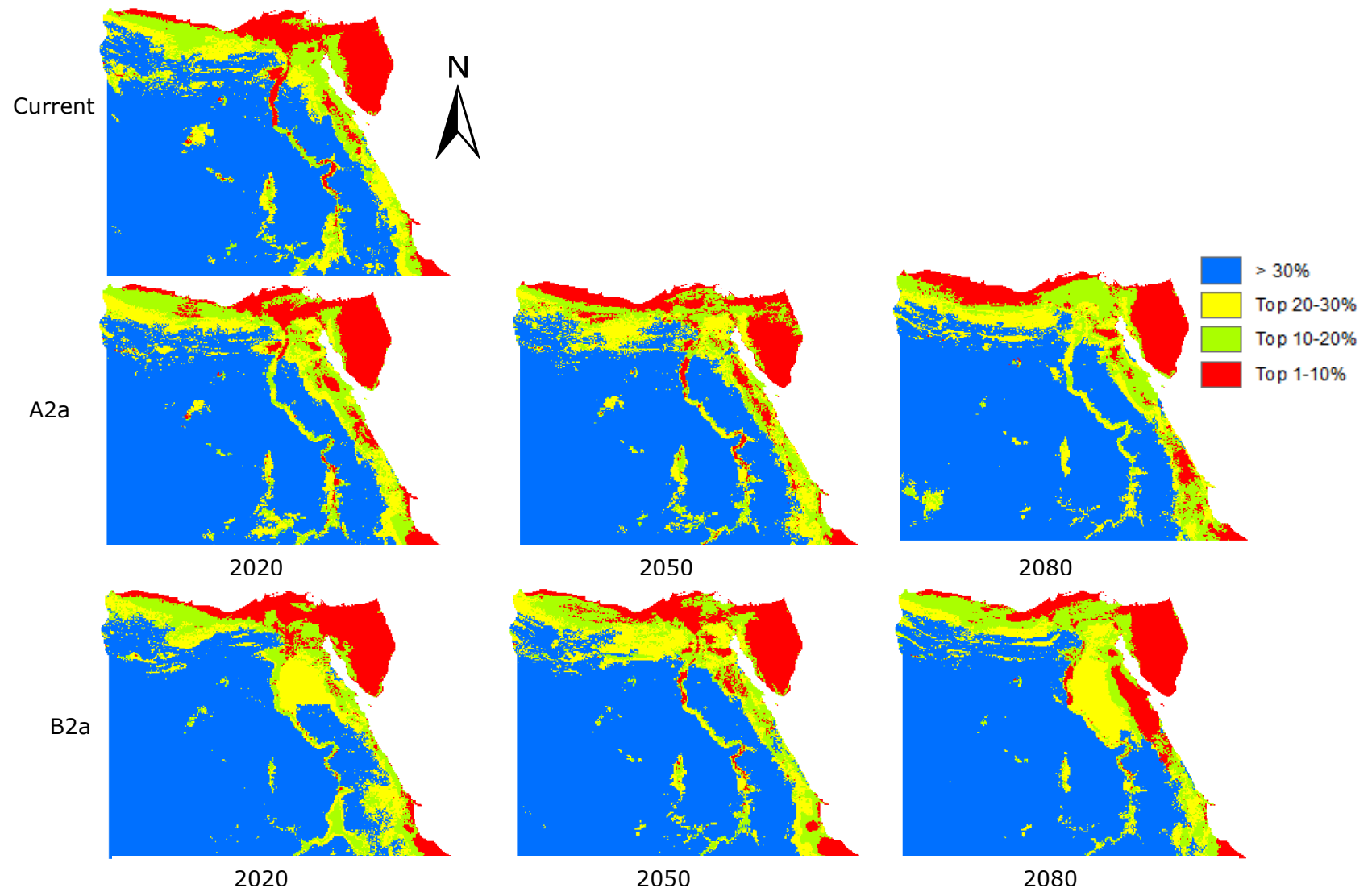


Figure 6.3. Conservation prioritization ranked values using Core – Area Zonation removal cell for current and future assuming unlimited dispersal without using costs. The colours ramp from red colour high conservation value, for blue colour low conservation value.

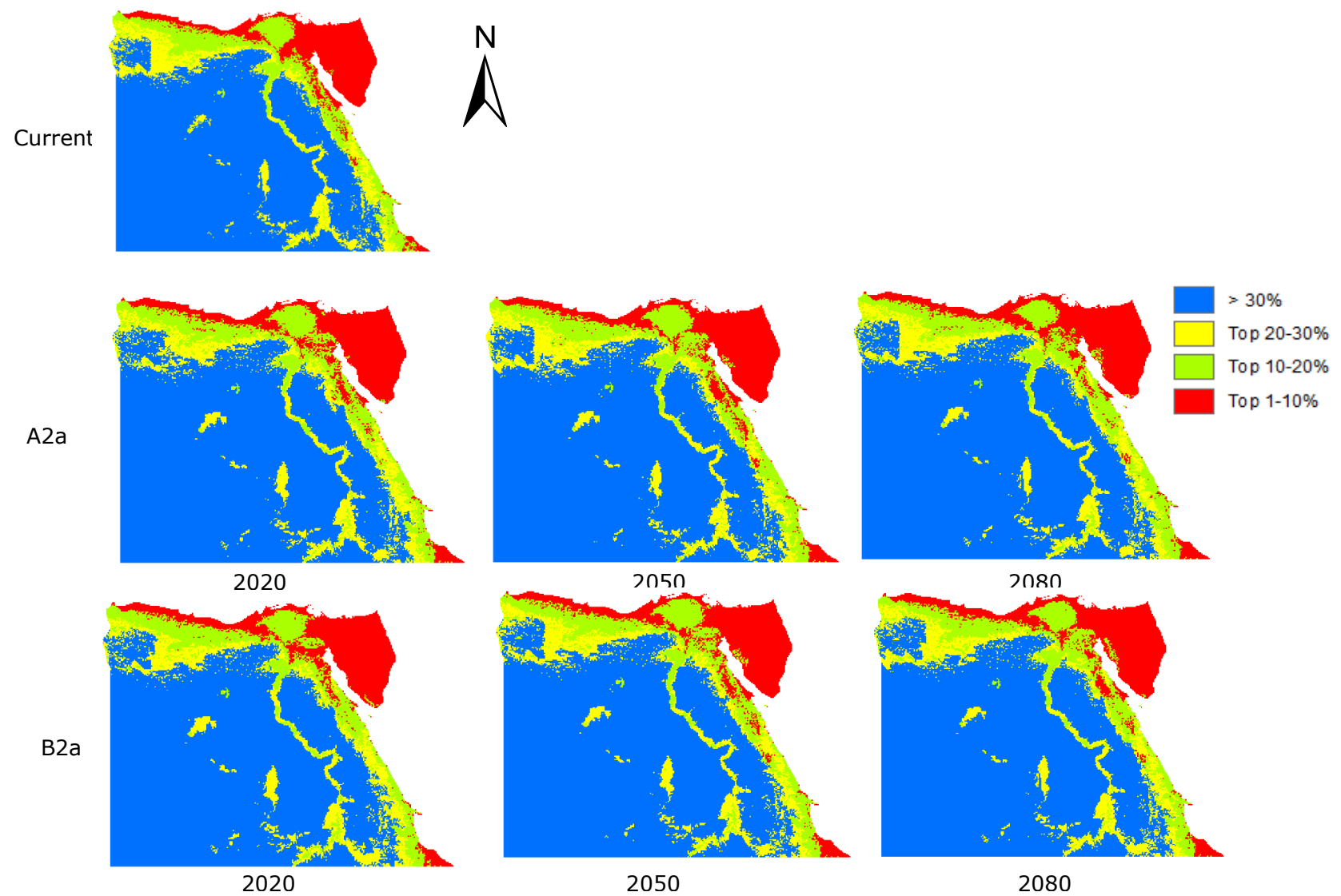


Figure 6.4. Conservation prioritization ranked values using Additive Benefit Function removal for current and future assuming no dispersal without using a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.

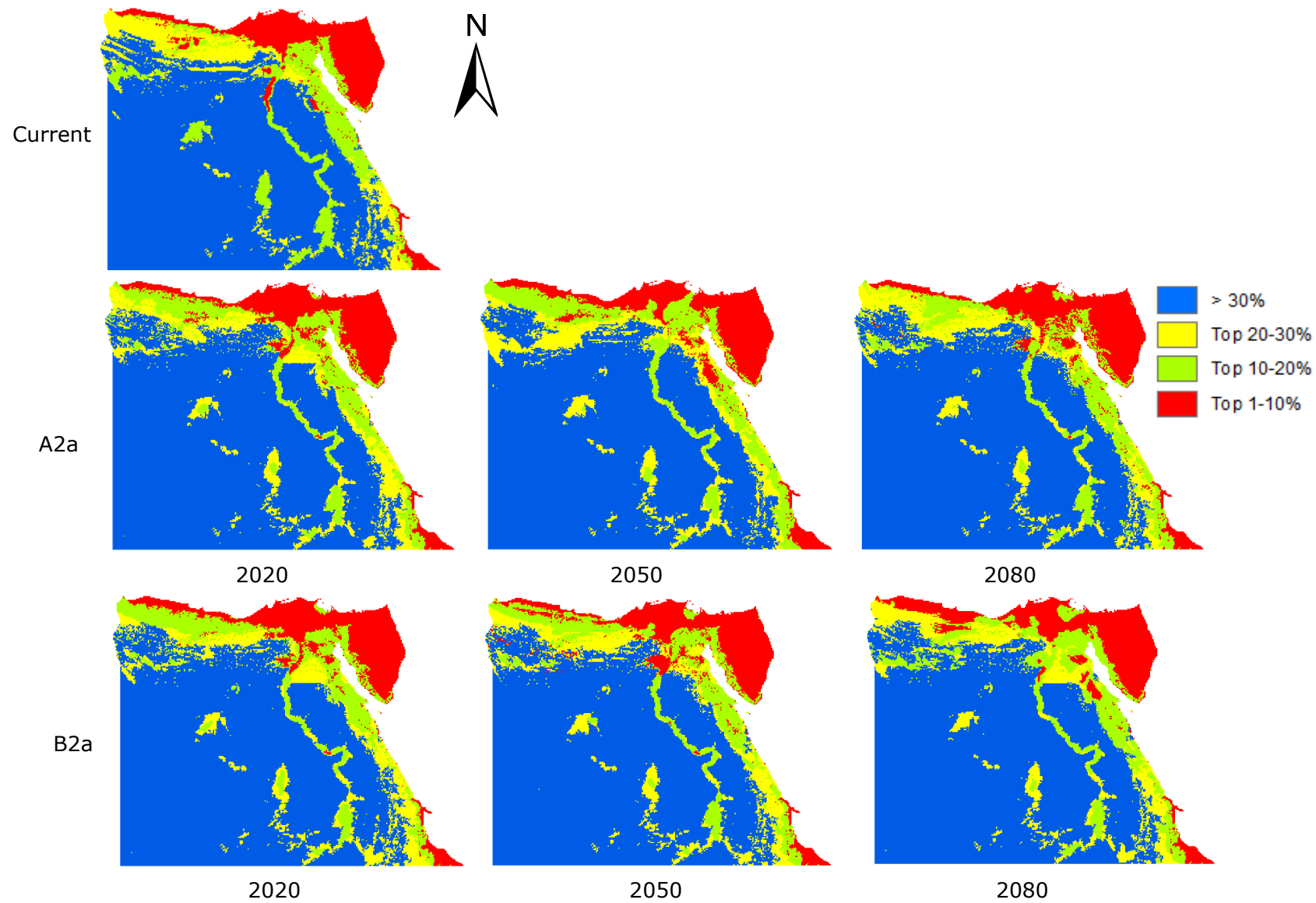


Figure 6.5. Conservation prioritization ranked values using Core – Area Zonation removal for current and future assuming no dispersal without using a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.

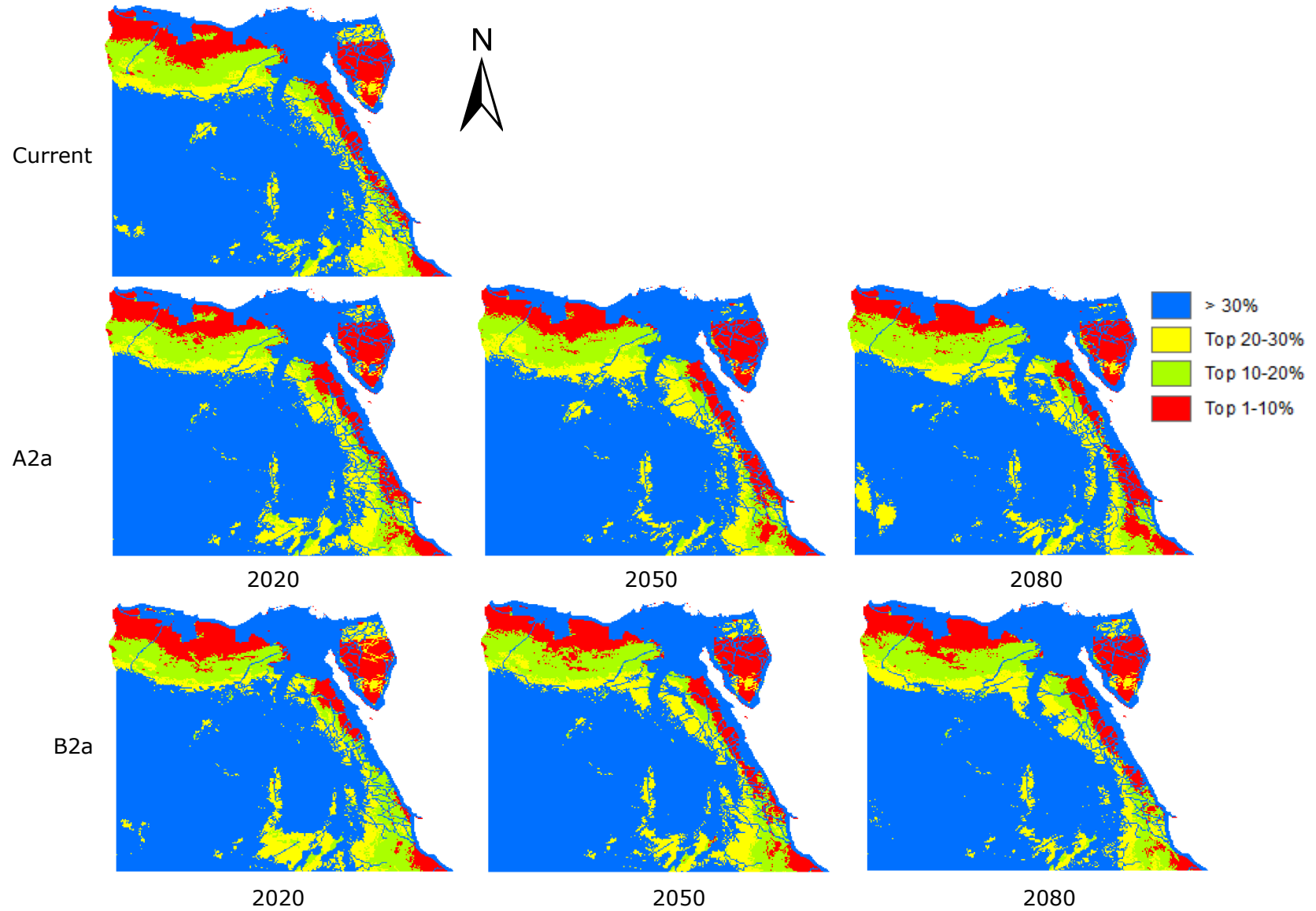


Figure 6.6. Conservation prioritization ranked values using Additive Benefit Function removal cell for current and future assuming unlimited dispersal using HII cost layer. The colours ramp from red colour high conservation values, for blue colour low conservation value.

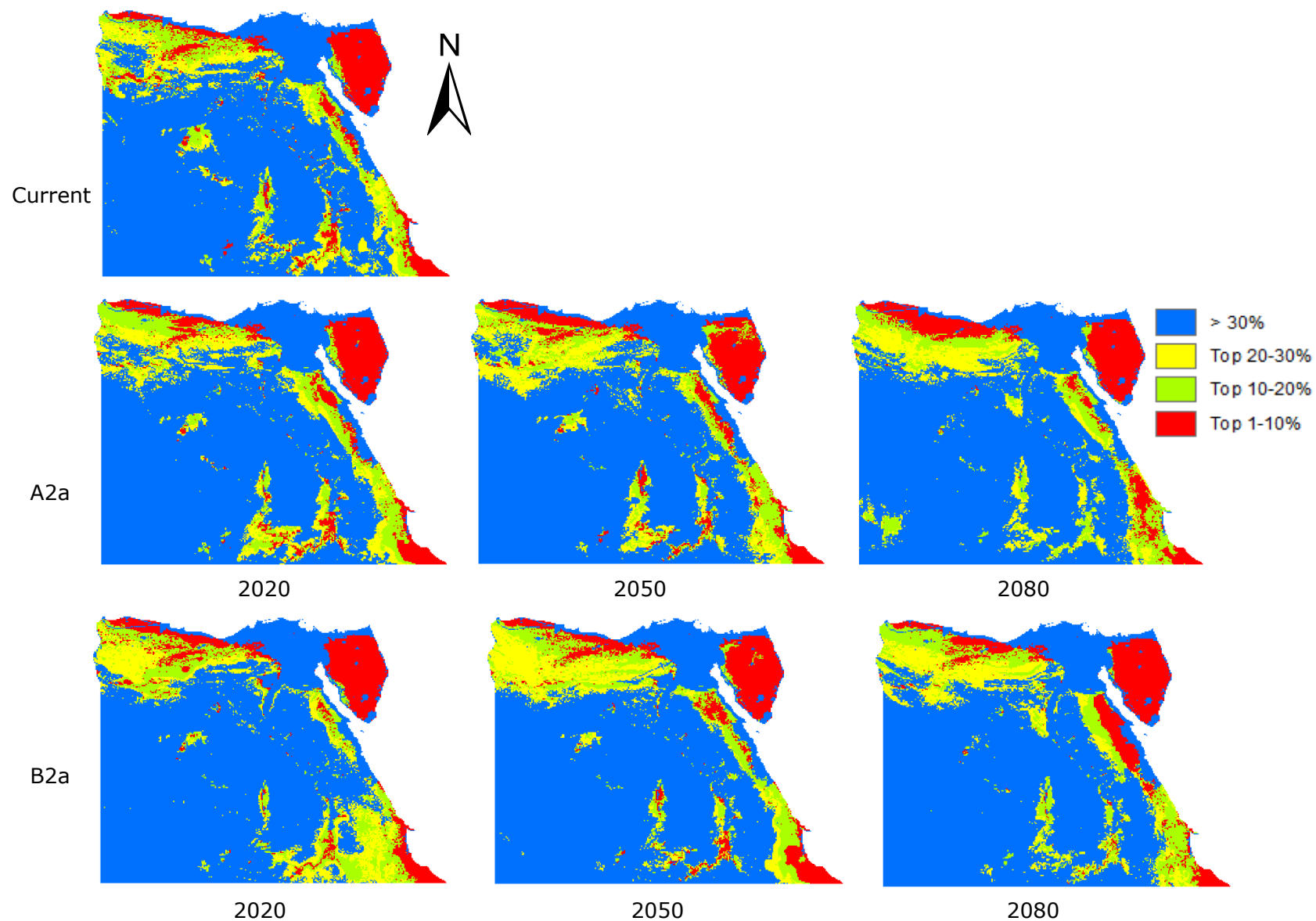


Figure 6.7. Conservation prioritization ranked values using Core – Area Zonation removal cell for current and future assuming unlimited dispersal using HII cost layer. The colours ramp from red colour high conservation value, for blue colour low conservation value.

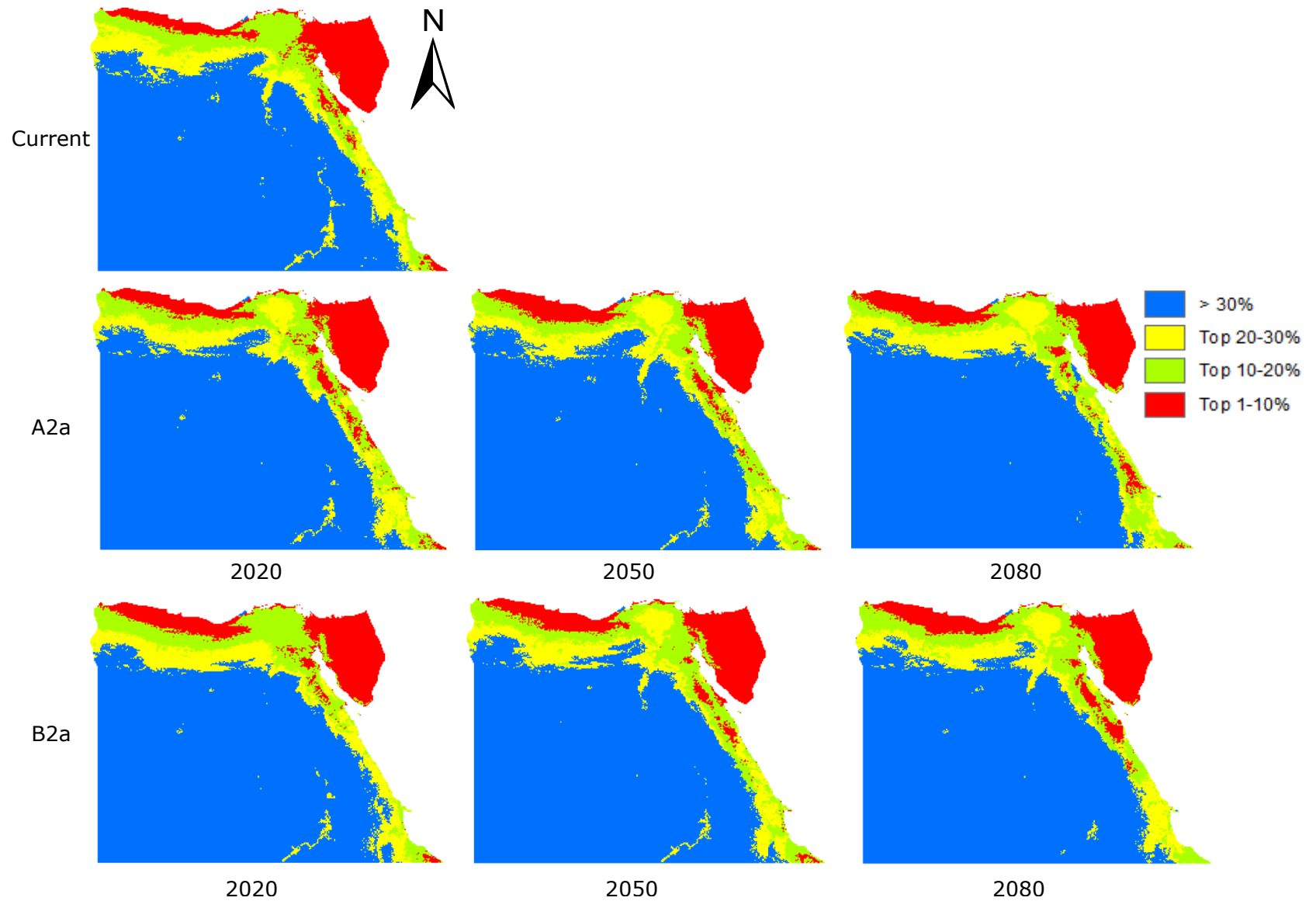


Figure 6.8. Conservation prioritization ranked values using Additive Benefit Function removal for current and future assuming unlimited dispersal using population density as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.

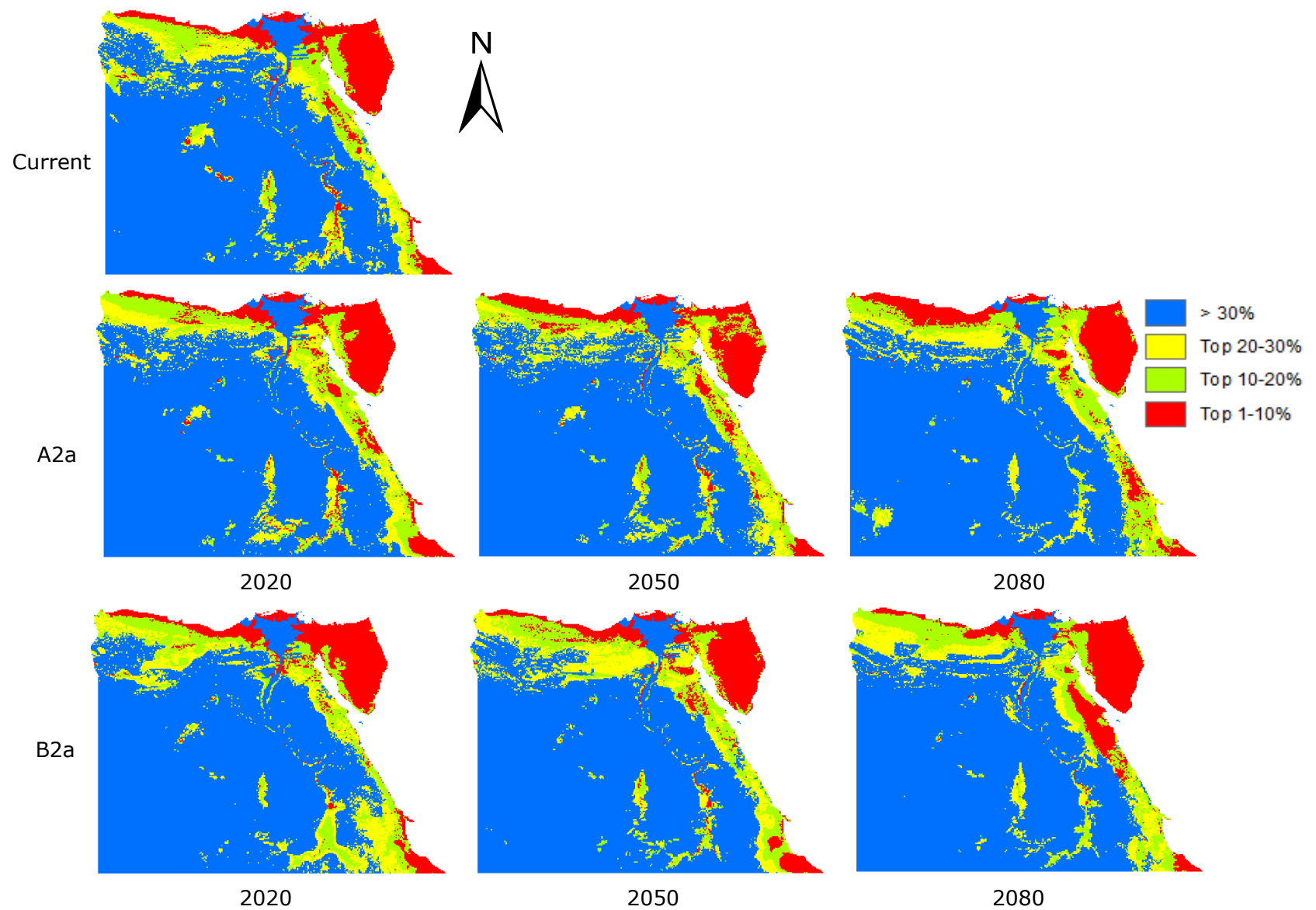


Figure 6.9. Conservation prioritization ranked values using Core – Area Zonation removal for current and future assuming unlimited dispersal using population density as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.

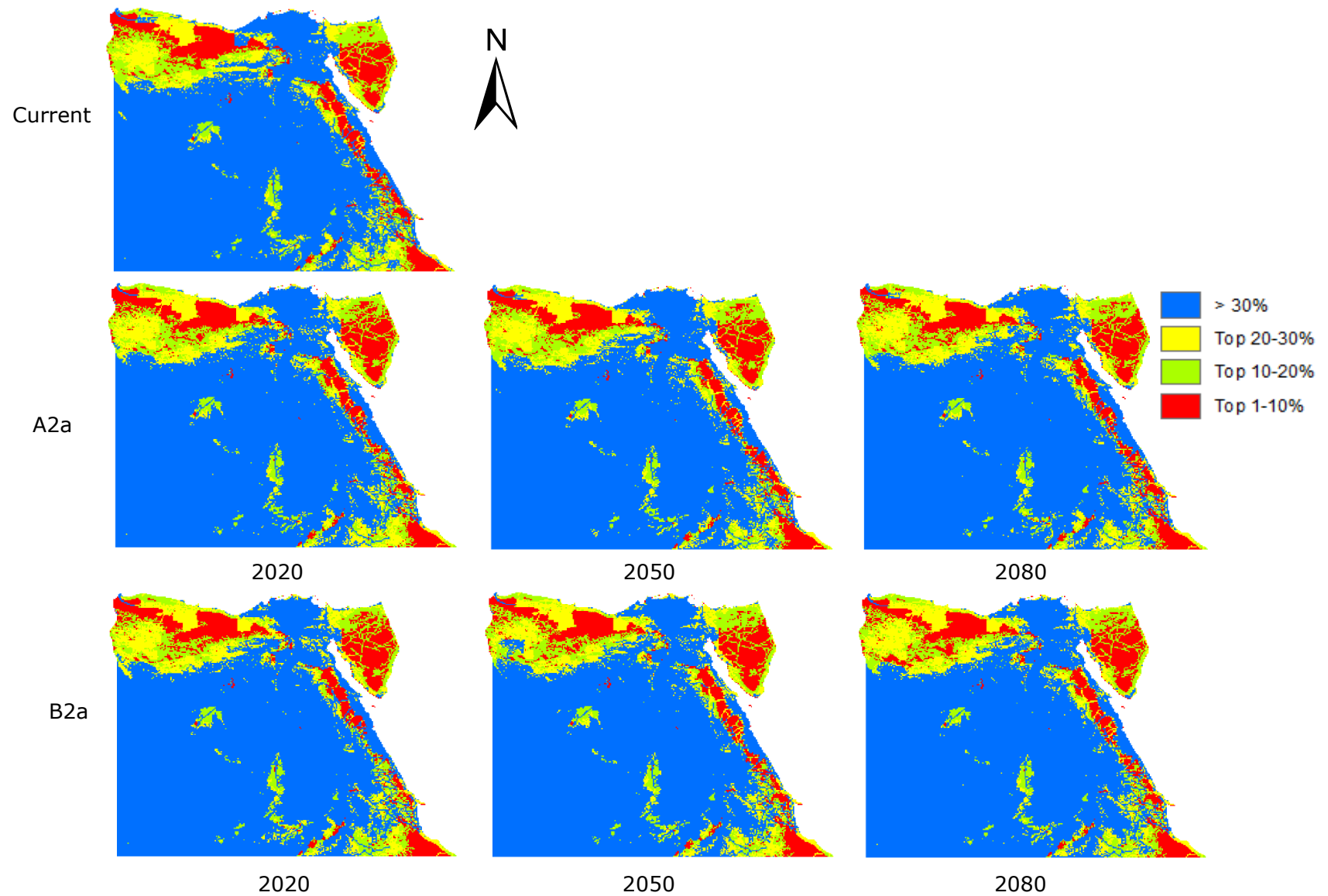


Figure 6.10. Conservation prioritization ranked values using Additive Benefit Function removal for current and future assuming no dispersal using HII as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.

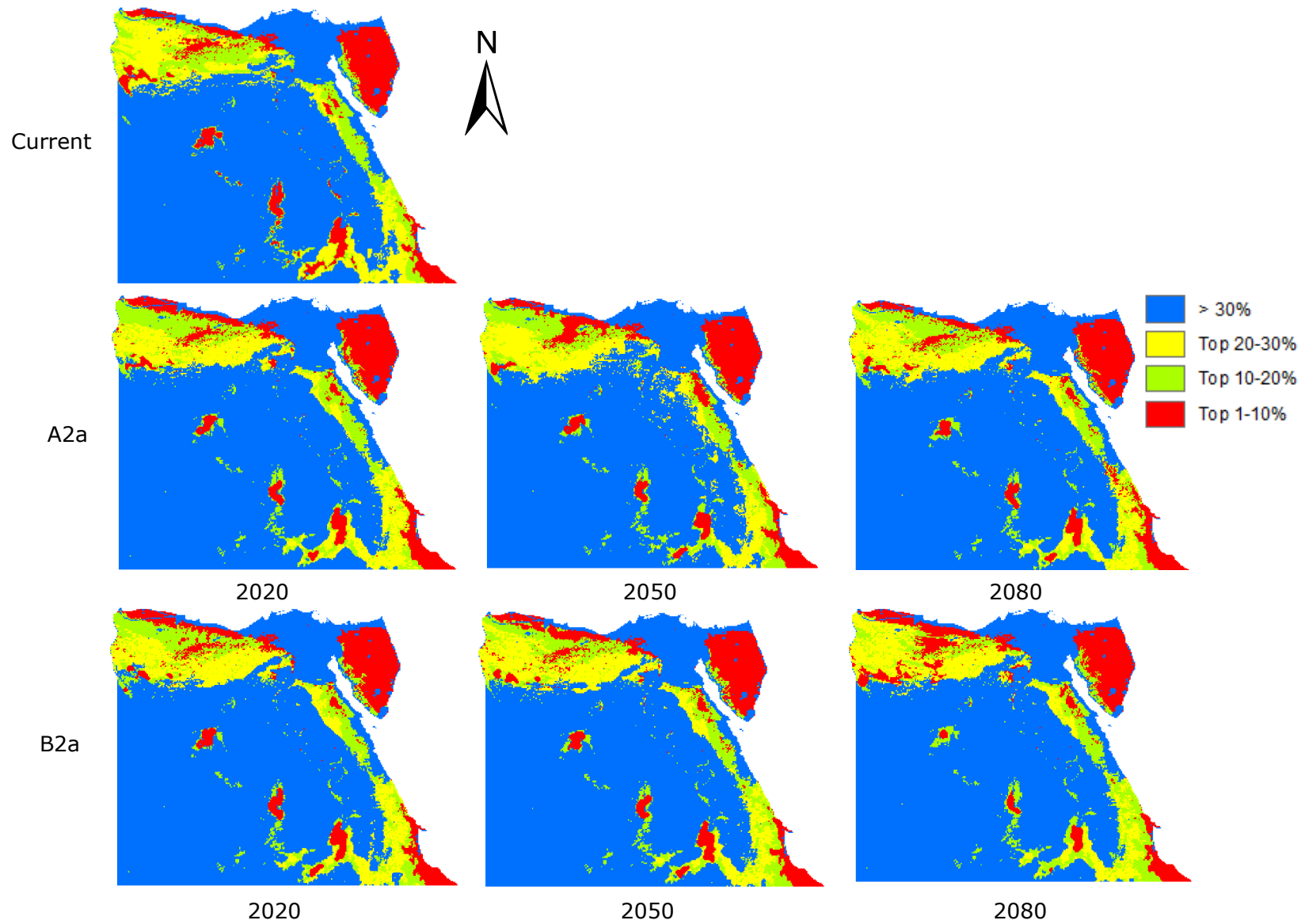


Figure 6.11. Conservation prioritization ranked values using Core – Area Zonation removal for current and future assuming no dispersal using HII as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.

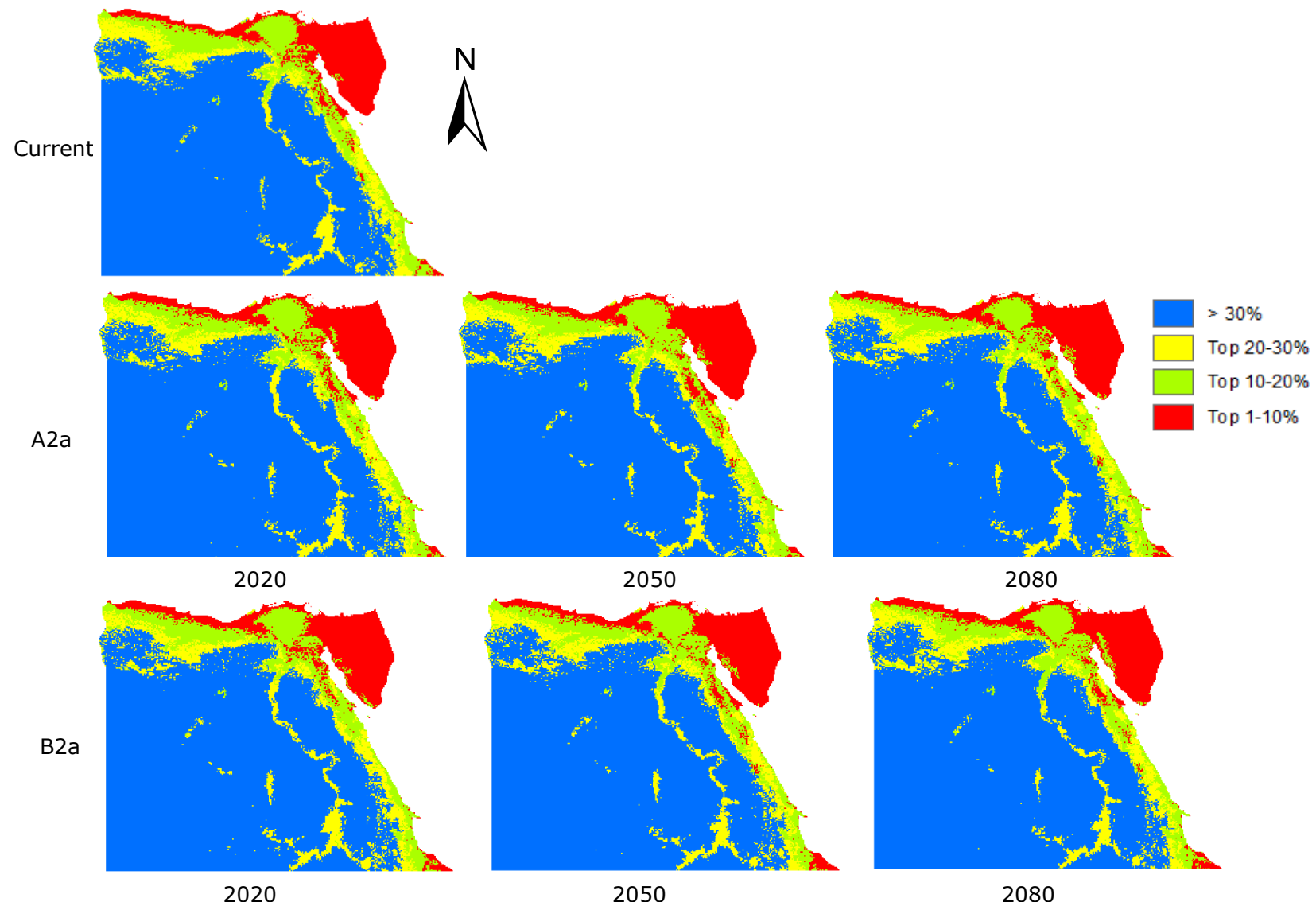


Figure 6.12. Conservation prioritization ranked values using Additive Benefit Function removal for current and future assuming no dispersal using population density as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.

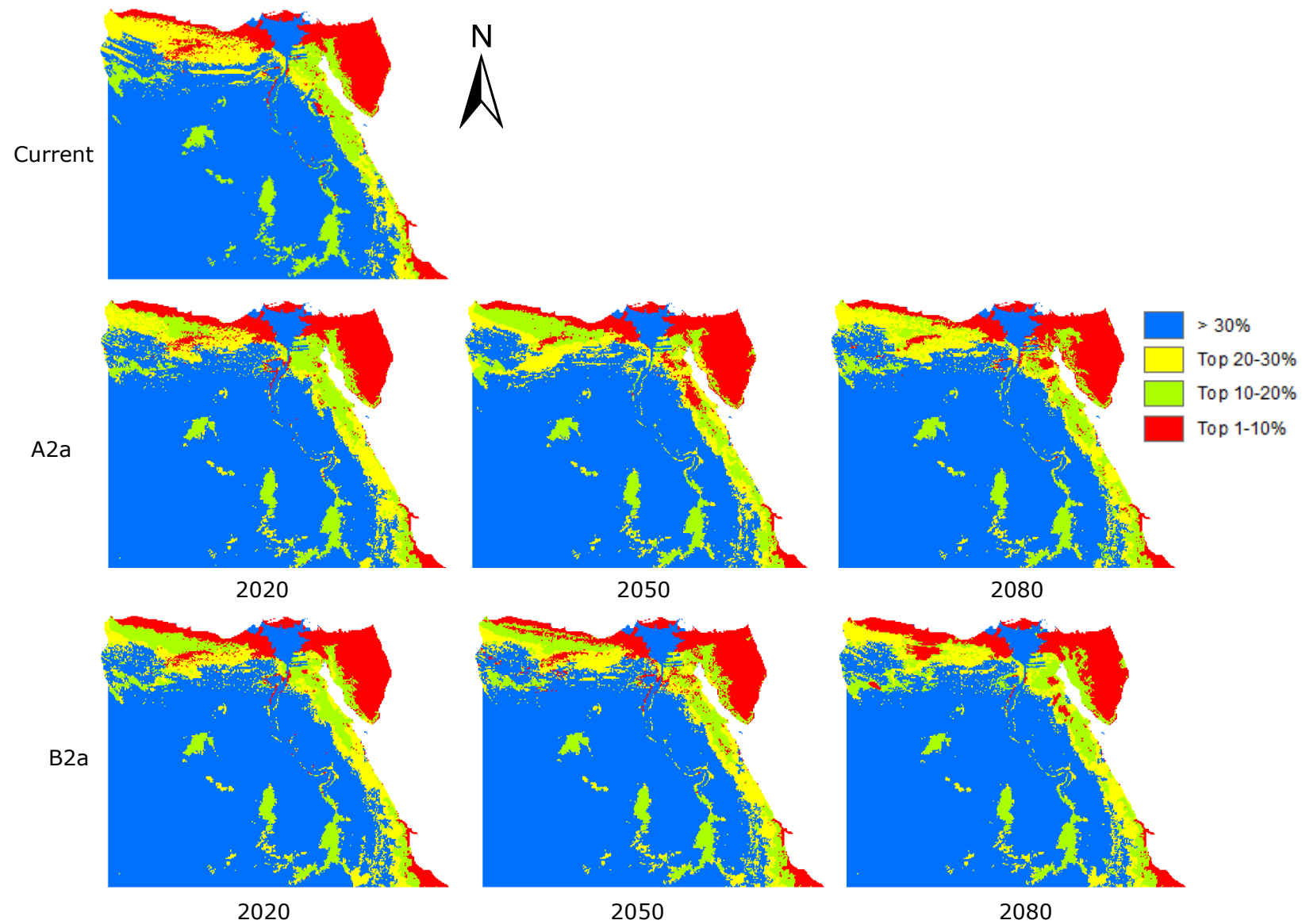
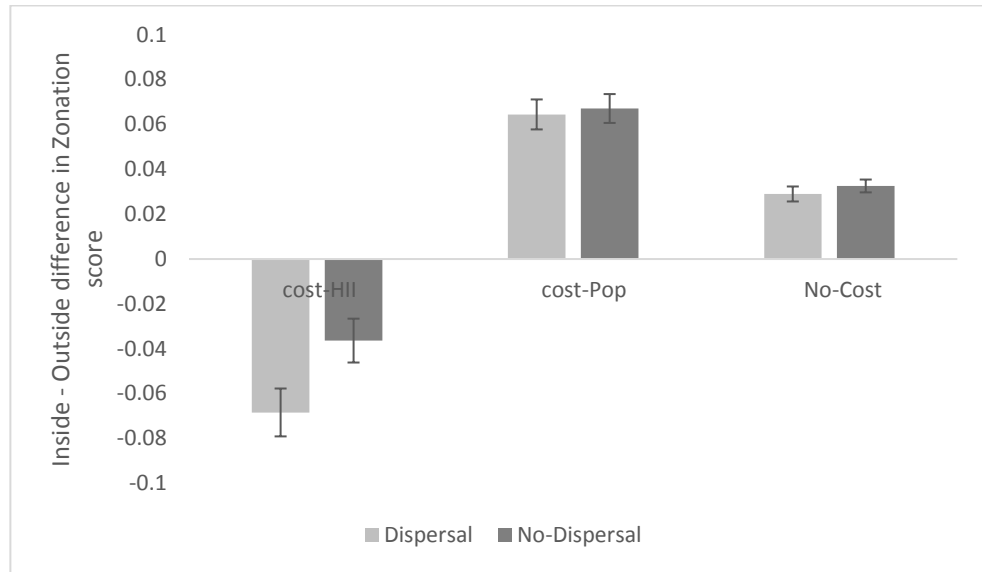
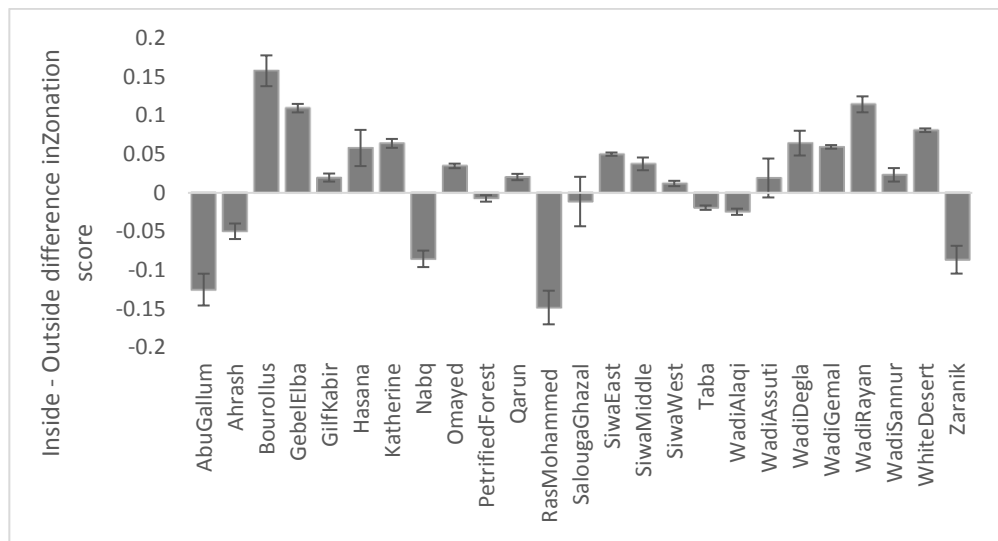


Figure 6.13. Conservation prioritization ranked values using Core – Area Zonation removal for current and future assuming no dispersal using population density as a cost layer. The colour ramp goes from red (high) to blue (low) conservation value.

a



b



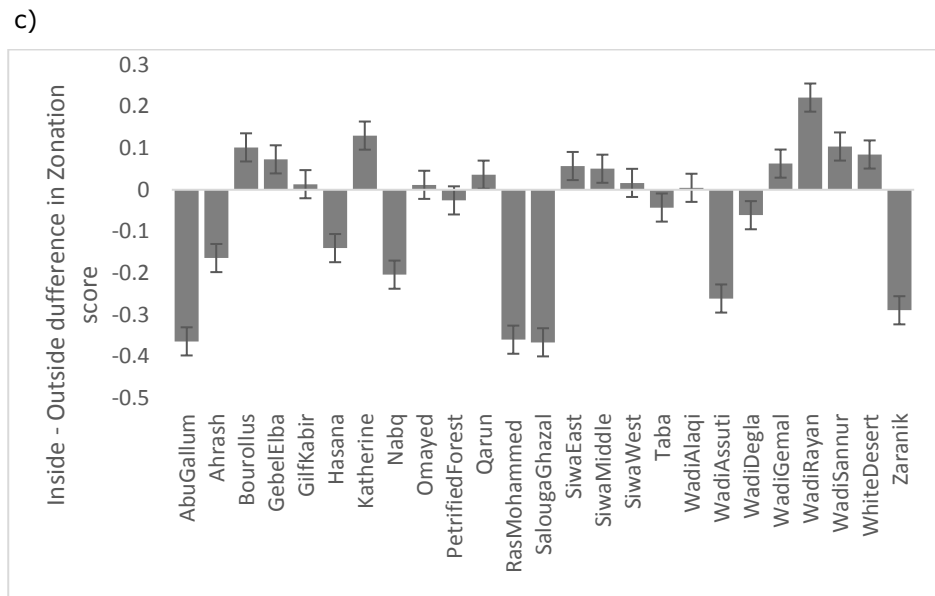


Figure 6.14. a) mean Zonation PA value excess for different cost layers (human influence index HII, population density Pop, and No-cost) for both dispersal assumptions; b) mean Zonation PA value excess for each PA, across all assumptions; c) mean Zonation PA value excess for each PA just for the HII cost, across all other assumptions.

Table 6.1. Results of Anova based on GLM for difference inside - outside PAs in Zonation Score.

Anova table					
	Deviance	df	df error	F	p
final model					
dispersal	0.09	1	2072	6.38	<0.02
cost	5.16	2	2072	192.87	<<0.001
pa	10.86	24	2072	33.83	<<0.001
dispersal: cost	0.10	2	2070	3.66	<0.03

* The results show non-significant results among (current, A2, and B2), year (2020, 2050, and 2080), and Zonation removal cells (abf and caz) based on the final model in GLM.

Table 6.2. Species weighting based on different kind of scoring.

Species world distribution	Score	Species distribution within Egypt	Score
Widespread	1	Widespread	1
Narrow	2	Narrow	2
Restricted	3	Localized	3
Endemic/ Near Endemic	4	Endemic/ Near Endemic	4

National IUCN status (based on model)	Score
Least Concern	1
Near Threatened	2
Vulnerable	3
Endangered	4
Critically Endangered	5

6.4 Discussion

These results highlight for the first time conservation planning for Egyptian plants under climate change while incorporating human socioeconomic impacts, a first at the national scale for North Africa: most conservation planning studies in the literature focus on Europe, North America, Oceania, and South Africa (Kukkala and Moilanen, 2013). Our findings support the idea that socioeconomic data have a vital role in conservation planning, because they make a huge impact on planning advice. Land-use, opportunity costs and socio-economic data have all been used before in conservation prioritization process (Miller *et al.*, 2009; Moilanen *et al.*, 2011; Di Minin *et al.*, 2017). We wanted to choose the best areas for conservation taking into account land suitability and the effect of human activities to reduce the conflict between these.

Conservation planning using other Egyptian taxa (reptiles, mammals and butterflies) has been implemented without allowing for human activities (Leach *et al.*, 2013; El-Gabbas *et al.*, 2016), and their results concur with our findings before using any cost layer. Looking in detail at these results, many of the locations chosen by Zonation to be a part of a network of reserves are already occupied by the main cities, building areas, coastal areas, and agricultural lands. The use of the cost layer gave such areas low priority for conservation, thus avoiding conflict between conservation planning and human activities (Knight *et al.*, 2009; Moilanen *et al.*, 2011; Faleiro *et al.*, 2013; Di Minin *et al.*, 2016): such areas also offer more threats and fewer conservation opportunities than other locations (Faleiro *et al.*, 2013; Di Minin *et al.*, 2017). This tool gives the applied conservation community the opportunity to choose areas that are likely to be economically cheaper, and furthermore balance conservation planning and human activity. We could not include land value in our analysis because of a lack of information, but this would be useful to do to select among the large areas indicated by our analysis (Naidoo *et al.*, 2006; Zhu *et al.*, 2015).

Coping with climate change is a key issue in conservation planning. Most such planning has been applied without any consideration of climate change (Araujo *et al.*, 2011), but this is changing (Dawson *et al.*, 2011) because the aim of establishing PAs is not just to maintain current geographical ranges but also to protect species that change their distributions in the future. Linking this with allowing for human activities helps the scope of planning (Jones *et al.*, 2016). For Egypt there were only slight differences in conservation prioritization between the current state and future scenarios: areas of high conservation value were very similar under most assumptions. However, when human activity was included, the priority areas for conservation changed substantially. Of course, this makes final conclusions about future areas for conservation unstable, because any change in the pattern of human activities in the future will affect the prioritization pattern. Such scenarios are valuable for conservation planning whether the results are optimistic or pessimistic (Hamann and Aitken, 2013).

Dispersal ability is a key attribute for species to track climate change. When species can move easily over any distance, then almost any new locations in whatever pattern will do, regardless of distance (Williams *et al.*, 2005). Here we found that conservation prioritization values increase under the no-dispersal assumption relative to unlimited dispersal, and the proportion of species conserved by protecting 20% of the land increased under no dispersal; this happened for all assumptions and scenarios. This may be an artefact because the no-dispersal assumption requires binarized maps, where occupied cells all have equal value (1) and hence there are no "core-areas" vital for the species (Moilanen *et al.*, 2014). For individual species the ranking procedure within Zonation creates artefacts, perhaps because the smoothing function distributes value into surrounding cells, which can be a problem if there are high peaks of probability (as in binarized data). As a result Zonation may prioritize areas with overall lower species richness, just because they are well connected to other occurrences. There is no evidence in the literature comparing unlimited and no-dispersal maps as input for conservation

planning using Zonation, and hence we cannot compare our results with those of others. However, all the evidence indicates that under the no-dispersal assumption, species will lose more suitable area under climate change (Araújo *et al.*, 2006), and hence this will affect conservation planning. Therefore, although the results for 'no dispersal' appear more optimistic, those for unlimited dispersal (i.e. using probability distributions) are probably more realistic. These aspects require more work for clarification.

The Egyptian PA network covers about 15% of Egypt's land surface (El-Gabbas *et al.*, 2016), a good ratio compared to other countries. If no allowance is made for human activity, then the current PAs are well located to protect biodiversity since the PA value excess is positive. This finding is consistent with other recent studies on different Egyptian taxa (Newbold *et al.*, 2009; Leach *et al.*, 2013; El-Gabbas *et al.*, 2016). However, when socioeconomic costs are included, and more particularly the HII, the PA value excess became on average negative since areas around the PAs were ranked higher than inside, although there were substantial differences among PAs. Thus allowing for human activities changes substantially the strategy in conservation planning.

In conclusion, our findings about PAs in Egypt support the idea of including socioeconomic information in conservation planning, to indicate the best spatial conservation priorities and hence to decrease the conflict between conservation and human land-use. The results highlight many currently unprotected locations that should be part of the Egyptian network of reserves. The limitations of our study were the lack of information about changing patterns of human activity in the future, and the availability of data for the same species outside Egypt in neighbouring countries to make the species distribution modelling more robust. More work is needed on the use of binarized distribution maps as input to Zonation analysis.

7 Chapter Seven: General discussion

Ecological information about geographical distribution is vital in ecosystem, conservation planning, and ecological change biology (Rushton *et al.*, 2004; Araújo and Peterson, 2012). Species distribution modelling (SDM) approaches have become very popular to predict geographical distributions based on occurrence records (Elith *et al.*, 2006; Franklin, 2009; Peterson *et al.*, 2011). SDMs include numerous very different techniques whose performance varies from one technique to another (see (Elith *et al.*, 2006). One of the challenges of this field is how to select one modelling method over another (Syfert *et al.*, 2013). Throughout this project we chose to use Maxent, a machine-learning approach that depends on the maximum entropy principle. We chose it because Maxent has consistently been shown to produce accurate models even when there is only a small number of available records, often the case in developing countries such as Egypt (Elith *et al.*, 2006; Baldwin, 2009). Other researchers advocate the use of 'ensemble' techniques, averages across a number of different methods, in order to try to reduce uncertainty and to obtain more robust forecasts (Araujo and New, 2007; Thuiller *et al.*, 2009). However, in the literature there is no clear evidence to indicate whether any one SDM method is appropriate for a particular dataset, and using ensemble methods may then lead to combining together poor with good models in variable and unpredictable combinations, especially because unlike MaxEnt many methods fail with low numbers of records. I tried in this thesis to keep the modelling simple and comparable by using only Maxent.

Evaluating the accuracy of the modelling is a key step in species distribution modelling. The accuracy of the model depends on the purpose of the study. For example, if the aim of the study is to predict effect of climate change, conservation planning, invasive species, or any other ecological question, then the criteria used for evaluation can be specific (Newbold, 2009). In this study, Maxent was used with a variety of settings to produce different models (see chapter 2) and AUC was used as a criterion to compare performance. The results across all the models showed

good performance much better than random based on mean AUC values. About 86% of the models achieved mean AUC values of 0.9 and above, usually taken to indicate good model performance (Pearson, 2007). More complex models with different feature classes had slightly higher AUC values, but the differences were small across all the models. Some researchers do not support using AUC as criteria for model performance, because it is easy to obtain high AUC values with small numbers of occurrence records (Jiménez-Valverde *et al.*, 2008; Lobo *et al.*, 2008). They advocate use of the True Skill Statistic (TSS) (Allouche *et al.*, 2006). Our results show that TSS values across all species were about 0.63 ± 0.01 , again indicating good model performances (Beauregard and de Blois, 2014). However, many authors still use AUC as their indicator to assess model performance in SDMs, including the creators of MaxEnt (Phillips and Elith, 2010; Warren and Seifert, 2011; Beauregard and de Blois, 2014).

Data partitioning is an important step in the evaluation of SDMs, again because there are different methods and techniques to divide the occurrence records. One of the methods is to use part of the records to build the model and the remaining part to evaluate it (Fielding and Bell, 1997). K-fold cross-validation partitioning is another method, which divides the sample randomly into a number of groups (Peterson *et al.*, 2011), and one can also divide geographically into different areas and use the records from one area to build the model and use other areas to evaluate it (Peterson and Shaw, 2003; Heikkinen *et al.*, 2007). In this study, both single and K-fold partitioning have been tested, and there were no great differences between them. Maxent allows both techniques to be used. I used K-fold throughout this study because with this technique every single record enters the evaluation of the models, and it provides a more reliable prediction of the niche and distribution (Peterson *et al.*, 2011).

Choosing environmental variables is also one of the challenges in SDM. To produce a robust model, it is important to choose appropriate environmental predictors and a modelling technique (Elith and Leathwick, 2009), because

predictors need to have significant impacts on the distribution (Austin, 2007). Climate and habitat are considered the most important elements of species distribution based on niche theory (Pulliam, 2000). Selecting unsuitable predictors impacts on the utility of the relationship between the environmental variable and the species distribution (Araújo and Peterson, 2012). It is also important to avoid collinearity, i.e. to avoid having highly correlated environmental predictors, since this will affect the prediction performance of the models (Merow *et al.*, 2013). The results show that the temperature and altitude are more powerful than other predictors in representing plant distributions across Egypt, just as Newbold *et al.* (2009) and El-Gabbas *et al.* (2016) found for Egyptian butterflies and reptiles respectively. Some claim that altitude cannot be used as a predictor variable in SDMs focusing on climate change (Stanton *et al.*, 2012) because it does not change with time; in this study I included altitude to help to produce better models, and there are perfectly valid reasons why one might think it important to include altitude in one's model, for example as a dispersal barrier (Engler *et al.*, 2009).

There are other factors that impact species distributions, for example, forest disturbance, kinds of soil, landscape heterogeneity, competition, and biotic factors (Anderson *et al.*, 2006; Kuussaari *et al.*, 2007; Uehara-Prado *et al.*, 2007; Ekroos *et al.*, 2013; Leach *et al.*, 2016). Including biotic factors in SDMs is an important next step since spatial distribution is shaped by both abiotic and biotic factors (Wisz *et al.*, 2013; Urban *et al.*, 2016), and recent studies show that including biotic factors improves model prediction (de Araújo *et al.*, 2014; Leach *et al.*, 2016). However, to include them requires a high level of ecological knowledge since there are countless interactions with the potential to influence distribution; such knowledge is available for only one or two Egyptian plants. In addition, the aim of this project was to identify the hotspot locations of Egyptian plants for conservation.

Medicinal plants are very important features of biodiversity (Klein *et al.*, 2008), because of their role in ecosystem services like healthcare, culture value and heritage, and human wellbeing (Klein *et al.*, 2008; Okigbo *et al.*, 2008).

Protecting and conserving these kinds of plants are important, and there is rising awareness among all stakeholders to protect this heritage. The aim of this study was to identify the pattern of species richness for these plants in current time and in the future, and then to assess the efficiency of the Egyptian network of reserves, and the extent to which it can protect these species now and in the future. The results show that predicted species richness is mostly located in the northern parts of Egypt, especially in Sinai and areas near the Mediterranean coast. This distribution is congruent with that for other taxa (Gilbert and Zalut, 2008; Newbold *et al.*, 2009; Leach *et al.*, 2013; El-Gabbas *et al.*, 2016; Kaky and Gilbert, 2016), probably because in such a hyper arid environment everything is driven by temperature and rainfall. Most areas in Egypt receive between 0 and 50 mm precipitation annually, while the northern coastal areas can receive up to 80 – 200 mm (El-Nahrawy, 2011).

Egypt's PAs cover about 15% of the land (El-Gabbas *et al.*, 2016), compared with 12% of global terrestrial land, but many PAs fail to protect biodiversity (Seiferling *et al.*, 2012). Our results show that predicted species richness at the current time within PAs is higher than outside, just as in other studies in Egypt and elsewhere (Lee *et al.*, 2007; Newbold *et al.*, 2009; Leach *et al.*, 2013; Sciberras *et al.*, 2013; El-Gabbas *et al.*, 2016; Kaky and Gilbert, 2016). Some researchers have found the opposite (Pawar *et al.*, 2007; Traba *et al.*, 2007), whilst others found no difference (Joppa *et al.*, 2008). In our data PAs are predicted to maintain their excess of species under climate change under all the assumptions tested, as in other taxa (Leach *et al.*, 2013; El-Gabbas *et al.*, 2016), and hence despite this not being considered when they were established (Araujo *et al.*, 2011), Egypt's PAs do seem well positioned to protect plants in the future. One of the reasons that cause PAs to fail in protecting biodiversity is human activities (DeFries *et al.*, 2005). It is important to sustain heterogeneity both inside reserves and in the surrounding areas to enable good management (Oliver *et al.*, 2010), and to prevent land use from isolating PAs (Joppa *et al.*, 2009).

The IUCN Red List of threatened species is one of the most important of all conservation indicators (Lamoreux *et al.*, 2003; Rodrigues *et al.*, 2006). The IUCN Red List categories and criteria are established to categorise species under risk of extinction on a global scale (Ginsburg, 2001), but have then developed to be appropriate at regional, national and local scales (Ginsburg, 2001; IUCN, 2016). I used SDMs to assess the Egyptian medicinal plants both now and into the future under climate change using Red List criteria. SDMs demonstrate their utility when there is not enough funding for systematic surveys and monitoring of biodiversity (Fivaz and Gonseth, 2014), and can be helpful in estimating range size (Elith *et al.*, 2006), one of the main criteria for Red Listing (Cassini, 2011). Waiting for good quality data will not be adequate, and developing countries like Egypt can use even the existing sparse data to guide conservation efforts. Our results show that reasonable estimates of the range size (EOO) can be made even when few data are available (cf. Pena *et al.*, 2014), or for rare species (cf. Marcer *et al.*, 2013) . When SDMs can estimate the EOO accurately, then Red-List assessments are facilitated (Syfert *et al.*, 2014). Using Egyptian data controlled for quality by experts, there was a respectable relationship between the traditional estimation of EOO based on the records, and estimating EOO from SDM models, indicating that the SDM predictions were reasonable, as Syfert *et al.* (2014) found.

With distribution predictions under climate change, SDMs can be used for Red List assessments based on the A3 criterion, despite projection uncertainties (Pearson and Dawson, 2003; Akçakaya *et al.*, 2006) . There has been some concern that IUCN criteria are perhaps not suitable for assessing species under climate change (Hannah, 2012). Conversely, recent studies claim that this is perfectly possible (Keith *et al.*, 2014; Pearson *et al.*, 2014; Stanton *et al.*, 2015). Over and above the use of the assessments themselves in conservation action, we can use the classification to weight species in spatial conservation prioritization, giving greater weights to species that are more endangered.

Thus the final element of this thesis is spatial conservation prioritization, one of the methods used to find suitable networks of locations for conservation; they are effective even when data are sparse (Moilanen *et al.*, 2009a). Many factors are driving biodiversity loss, including habitat loss, invasive species, intensive agriculture adding excessive nitrogen and land-use change (Hoffmann *et al.*, 2010), but the majority of studies claim that climate change is the main threat (Thomas *et al.*, 2004; Brook *et al.*, 2008; Araujo *et al.*, 2011; Urban, 2015). One of the advantages of using these methods is that we can incorporate the impacts of human activities and climate change into the spatial prioritization framework (Jones *et al.*, 2016). Without these, conservation planning will be incomplete (Faleiro *et al.*, 2013).

Recent conservation planning for Egypt have used different taxa, but without any consideration of human activities or land use (Leach *et al.*, 2013; El-Gabbas *et al.*, 2016). We therefore tried to highlight this issue and its impact on Egyptian plant conservation by using species distribution modelling and Zonation prioritization software (Moilanen *et al.*, 2014). Without take human activities into account, our results are very similar to those of both Leach *et al.* (2013) on butterflies and mammals, and El-Gabbas *et al.* (2016) on reptiles, but when we look at the resulting spatial patterns of conservation value, many or even most of the locations ranked as high priority are in the main cities, agricultural land or coastal areas used for recreation. It was therefore important to reduce this land-use conflict by using socioeconomic data to give these areas low priority (Moilanen *et al.*, 2011; Faleiro *et al.*, 2013; Di Minin *et al.*, 2016), helping conservation planners to look for other areas, and to build realistic future plans for conservation of biodiversity and Protected Areas.

It was then important to test again the efficiency of Egypt's PAs under climate change but incorporating the impact of human activities on the spatial prioritization, since PAs will remain the cornerstone of protecting biodiversity (Araujo *et al.*, 2011; Watson *et al.*, 2014). Interestingly, the results depended on

what indicator was used for the cost. Using population density as a proxy for human influence led to very similar results as not using any indicator at all (i.e. that PAs have higher conservation value than surrounding areas under all scenarios). This all changed when the Human Influence Index was used as a cost layer to take into account human activities. Then priority areas for conservation outside PAs were higher than inside under all scenarios and assumptions. This demonstrates that the form of socioeconomic cost matters for conservation planning.

7.1 Conclusions

In conclusion, global climate changes are happening very quickly, driving alterations in the species distributions and leading to biodiversity losses if there is no meaningful action taken. SDMs are suitable tools for estimating these effects and hence for conservation planning, to produce guideline for managing PAs or other environments even when there are very few data. SDMs are associated with various kinds of uncertainties, especially when projected into the future, but recent studies suggest that despite these uncertainties SDMs are able to predict geographical distributions reasonably well, even under climate change, and can be used as a tool to assess extinction risks (Keith *et al.*, 2014; Pearson *et al.*, 2014; Stanton *et al.*, 2015). Our finding support this interpretation. Our results show that some Egyptian medicinal plants could be under the threat of extinction in the near future if there is no conservation action taken. But our findings also support the fact that the use of socioeconomic information to downgrade areas affected by human activity is vital in conservation planning. We found there are large areas with high priority for conservation that are not protected, and Egyptian plants cannot be protected within the existing PA locations, especially with the certainty of changes in land use in the near future.

The limitations of this study include a lack of data for the same species outside Egypt in neighbouring countries, which is probably important to make the species distribution modelling more robust. Therefore, surveys of biodiversity for

these regions are important to make the assessments for conservation planning more robust, but this will need more funding and more time. Our SDMs lack biotic influences and more sophisticated biological information, and are basically regressions. Truly predictive biological models will incorporate the important biological mechanisms (e.g. evolution, environment, physiology, demography, dispersal, and species interactions: Urban et al., 2016) in a biologically realistic way, but such realism is a long way off.

8 Bibliography

- Akçakaya, H. R., Butchart, S. H. M., Mace, G. M., Stuart, S. N. & Hilton-Taylor, C. 2006. Use and misuse of the IUCN Red List Criteria in projecting climate change impacts on biodiversity. *Global Change Biology*, 12, 2037-2043.
- Akhani, H. 2014. *Tamarix nilotica*. The IUCN Red List of Threatened Species 2014: e.T19179434A46081355. <http://dx.doi.org/10.2305/IUCN.UK.2014-1.RLTS.T19179434A46081355.en>. Downloaded on 12 December 2016.
- Alagador, D., Martins, M. J., Cerdeira, J. O., Cabeza, M. & Araújo, M. B. 2011. A probability-based approach to match species with reserves when data are at different resolutions. *Biological Conservation*, 144, 811-820.
- Algar, A. C., Kharouba, H. M., Young, E. R. & Kerr, J. T. 2009. Predicting the future of species diversity: macroecological theory, climate change, and direct tests of alternative forecasting methods. *Ecography*, 32, 22-33.
- Algar, A. C., Mahler, D. L., Glor, R. E. & Losos, J. B. 2013. Niche incumbency, dispersal limitation and climate shape geographical distributions in a species-rich island adaptive radiation. *Global Ecology and Biogeography*, 22, 391-402.
- Alkemade, R., Bakkenes, M. & Eickhout, B. 2010. Towards a general relationship between climate change and biodiversity: an example for plant species in Europe. *Regional Environmental Change*, 11, 143-150.
- Alkemade, R., Bakkenes, M. & Eickhout, B. 2011. Towards a general relationship between climate change and biodiversity: an example for plant species in Europe. *Regional Environmental Change*, 11, 143-150.
- Allouche, O., Tsoar, A. & Kadmon, R. 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology*, 43, 1223-1232.
- Anadon, J. D., Gimenez, A. & Ballestar, R. 2010. Linking local ecological knowledge and habitat modelling to predict absolute species abundances on large scales. *Biodiversity & Conservation* 19, 1443-54.
- Anderson, R. P., Peterson, A. T. & Egbert, S. L. 2006. Vegetation-Index Models Predict Areas Vulnerable To Purple Loosestrife (*Lythrum Salicaria*) Invasion In Kansas. *The Southwestern Naturalist*, 51, 471-480.
- Anderson, R. P. & Gonzalez, I. 2011. Species-specific tuning increases robustness to sampling bias in models of species distributions: An implementation with Maxent. *Ecological Modelling*, 222, 2796-2811.
- Anderson, R. P. 2012. Harnessing the world's biodiversity data: promise and peril in ecological niche modeling of species distributions. *Annals of the New York Academy of Sciences*, 1260, 66-80.
- Araújo, M. B., Cabeza, M., Thuiller, W., Hannah, L. & Williams, P. H. 2004. Would climate change drive species out of reserves? An assessment of existing reserve-selection methods. *Global Change Biology*, 10, 1618-1626.
- Araújo, M. B. & Pearson, R. G. 2005. Equilibrium of species' distributions with climate. *Ecography*, 28, 693-695.
- Araújo, M. B. & New, M. 2007. Ensemble forecasting of species distributions. *Trends in Ecology and Evolution*, 22, 42-7.
- Araújo, M. B., Alagador, D., Cabeza, M., Nogues-Bravo, D. & Thuiller, W. 2011. Climate change threatens European conservation areas. *Ecology Letters*, 14, 484-492.
- Araújo, M. B., Pearson, R. G., Thuiller, W. & Erhard, M. 2005. Validation of species-climate impact models under climate change. *Global Change Biology*, 11, 1504-1513.
- Araújo, M. B. & Guisan, A. 2006. Five (or so) challenges for species distribution modelling. *Journal of Biogeography*, 33, 1677-1688.
- Araújo, M. B., Thuiller, W. & Pearson, R. G. 2006. Climate warming and the decline of amphibians and reptiles in Europe. *Journal of Biogeography*, 33, 1712-1728.

- Araújo, M. B. & Peterson, A. T. 2012. Uses and misuses of bioclimatic envelope modeling. *Ecology*, 93, 1527–1539.
- Arnell, N. W., Livermore, M. J. L., Kovats, S., Levy, P. E., Nicholls, R., Parry, M. L. & Gaffin, S. R. 2004. Climate and socio-economic scenarios for global-scale climate change impacts assessments: characterising the SRES storylines. *Global Environmental Change*, 14, 3–20.
- Arponen, A., Heikkinen, R. K., Thomas, C. D. & Moilanen, A. 2005. The Value of Biodiversity in Reserve Selection: Representation, Species Weighting, and Benefit Functions. *Conservation Biology*, 19, 2009–2014.
- Aublet, J. F., Festa-Bianchet, M., Bergero, D. & Bassano, B. 2009. Temperature constraints on foraging behaviour of male Alpine ibex (*Capra ibex*) in summer. *Oecologia*, 159, 237–47.
- Austin, M. 2007. Species distribution models and ecological theory: A critical assessment and some possible new approaches. *Ecological Modelling*, 200, 1–19.
- Bakkenes, M., Eickhout, B. & Alkemade, R. 2006. Impacts of different climate stabilisation scenarios on plant species in Europe. *Global Environmental Change*, 16, 19–28.
- Baldwin, R. A. 2009. Use of Maximum Entropy Modeling in Wildlife Research. *Entropy*, 11, 854–866.
- Balunas, M. J. & Kinghorn, A. D. 2005. Drug discovery from medicinal plants. *Life Sci*, 78, 431–41.
- Ban, N. C., Hansen, G. J. A., Jones, M. & Vincent, A. C. J. 2009. Systematic marine conservation planning in data-poor regions: Socioeconomic data is essential. *Marine Policy*, 33, 794–800.
- Barry, S. & Elith, J. 2006. Error and uncertainty in habitat models. *Journal of Applied Ecology*, 43, 413–423.
- Basuony, M. I., Gilbert, F. & Zalat, S. 2010. Mammals of Egypt : Atlas, Red Data Listing & Conservation. BioMAP & CultNat, EEAA & Bibliotheca Alexandrina, Cairo. 273pp. available <http://ecology.nottingham.ac.uk/~plzfg/>. .
- Beaumont, L. J., Hughes, L. & Pitman, A. J. 2008. Why is the choice of future climate scenarios for species distribution modelling important? *Ecology Letters*, 11, 1135–1146.
- Beauregard, F. & de Blois, S. 2014. Beyond a climate-centric view of plant distribution: edaphic variables add value to distribution models. *PLoS One*, 9, e92642.
- Bell, A. & Bachman, S. 2011. *Ephedra alata*. The IUCN Red List of Threatened Species 2011: e.T201688A9165505. <http://dx.doi.org/10.2305/IUCN.UK.2011-2.RLTS.T201688A9165505.en>. Downloaded on 12 December 2016.
- Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W. & Courchamp, F. 2012. Impacts of climate change on the future of biodiversity. *Ecology Letters*, 15, 365–377.
- Berg, M. P., Kiers, E. T., Driessen, G., van der Heijden, M., Kooi, B. W., Kuenen, F., Liefing, M., Verhoef, H. A. & Eilers, J. 2010. Adapt or disperse: understanding species persistence in a changing world. *Global Change Biology*, 16, 587–598.
- Berry, J. & Bjorkman, O. 1980. Photosynthetic Response And Adaptation To Temperature In Higher Plants. *Annual Review of Plant Physiology* 31, 491–543.
- Bojórquez-Tapia, L. A., Azuara, I., Ezcurra, E. & Flores-Villela, O. 1995. Identifying Conservation Priorities in Mexico Through Geographic Information Systems and Modeling. *Ecological Applications*, 5, 215–231.
- Bombi, P., Salvi, D., Bologna, M. A. & Pettorelli, N. 2012. Cross-scale predictions allow the identification of local conservation priorities from atlas data. *Animal Conservation*, 15, 378–387.
- Bonte, D., Bossuyt, B. & Lens, L. 2007. Aerial dispersal plasticity under different wind velocities in a salt marsh wolf spider. *Behavioral Ecology*, 18, 438–443.

- Bonte, D., Van Dyck, H., Bullock, J. M., Coulon, A., Delgado, M., Gibbs, M., Lehouck, V., Matthysen, E., Mustin, K., Saastamoinen, M., Schtickzelle, N., Stevens, V. M., Vandewoestijne, S., Baguette, M., Barton, K., Benton, T. G., Chaput-Bardy, A., Clobert, J., Dytham, C., Hovestadt, T., Meier, C. M., Palmer, S. C., Turlure, C. & Travis, J. M. 2012. Costs of dispersal. *Biological Reviews* 87, 290-312.
- Botkin, D. B., Saxe, H., Araújo, M. B., Betts, R., Bradshaw, R. H. W., Cedhagen, T., Chesson, P., Dawson, T. P., Etterson, J. R., Faith, D. P., Ferrier, S., Guisan, A., Hansen, A. S., Hilbert, D. W., Loehle, C., Margules, C., New, M., Sobel, M. J. & Stockwell, D. R. B. 2007. Forecasting the Effects of Global Warming on Biodiversity. *BioScience*, 57, 227-236.
- Boulos, L. 1999-2005. *Flora of Egypt*, 4 vols. Al Hadara Publishing, Cairo, Egypt.
- Broennimann, O., Thuiller, W., Hughes, G., Midgley, G. F., Alkemade, J. M. R. & Guisan, A. 2006. Do geographic distribution, niche property and life form explain plants' vulnerability to global change? *Global Change Biology*, 12, 1079-1093.
- Broennimann, O. & Guisan, A. 2008. Predicting current and future biological invasions: both native and invaded ranges matter. *Biology Letters*, 4, 585-9.
- Brook, B. W., Sodhi, N. S. & Bradshaw, C. J. 2008. Synergies among extinction drivers under global change. *Trends in Ecology and Evolution*, 23, 453-60.
- Brooks, T. M., Mittermeier, R. A., da Fonseca, G. A., Gerlach, J., Hoffmann, M., Lamoreux, J. F., Mittermeier, C. G., Pilgrim, J. D. & Rodrigues, A. S. 2006. Global biodiversity conservation priorities. *Science*, 313, 58-61.
- Brummitt, N., Bachman, S. P., Aletrari, E., Chadburn, H., Griffiths-Lee, J., Lutz, M., Moat, J., Rivers, M. C., Syfert, M. M. & Nic Lughadha, E. M. 2015a. The sampled Red List Index for plants, phase II: ground-truthing specimen-based conservation assessments. *Philosophical Transactions of the Royal Society B*, 370, 20140015.
- Brummitt, N. A., Bachman, S. P., Griffiths-Lee, J., Lutz, M., Moat, J. F., Farjon, A., Donaldson, J. S., Hilton-Taylor, C., Meagher, T. R., Albuquerque, S., Aletrari, E., Andrews, A. K., Atchison, G., Baloch, E., Barlozzini, B., Brunazzi, A., Carretero, J., Celesti, M., Chadburn, H., Cianfoni, E., Cockel, C., Coldwell, V., Concetti, B., Contu, S., Crook, V., Dyson, P., Gardiner, L., Ghanim, N., Greene, H., Groom, A., Harker, R., Hopkins, D., Khela, S., Lakeman-Fraser, P., Lindon, H., Lockwood, H., Loftus, C., Lombrici, D., Lopez-Poveda, L., Lyon, J., Malcolm-Tompkins, P., McGregor, K., Moreno, L., Murray, L., Nazar, K., Power, E., Quito Tuijtelars, M., Salter, R., Segrott, R., Thacker, H., Thomas, L. J., Tingvoll, S., Watkinson, G., Wojtaszekova, K. & Nic Lughadha, E. M. 2015b. Green Plants in the Red: A Baseline Global Assessment for the IUCN Sampled Red List Index for Plants. *PLoS One*, 10, e0135152.
- Butchart, S. H., Resit Akcakaya, H., Chanson, J., Baillie, J. E., Collen, B., Quader, S., Turner, W. R., Amin, R., Stuart, S. N. & Hilton-Taylor, C. 2007. Improvements to the Red List Index. *PLoS One*, 2, e140.
- Butchart, S. H., Walpole, M., Collen, B., Strien, A. v., Scharlemann, J. P. W., Almond, R. E. A., Baillie, J. E. M., Bomhard, B., Brown, C., Bruno, J., Carpenter, K. E., Carr, G. M., Chanson, J., Chenery, A. M., Csirke, J., Davidson, N. C., Dentener, F., Foster, M., Galli, A., Galloway, J. N., Genovesi, P., Gregory, R. D., Hockings, M., Kapos, V., Lamarque, J.-F., Leverington, F., Loh, J., McGeoch, M. A., McRae, L., Minasyan, A., Morcillo, M. H., Oldfield, T. E. E., Pauly, D., Quader, S., Revenga, C., Sauer, J. R., Skolnik, B., Spear, D., Stanwell-Smith, D., Stuart, S. N., Symes, A., Tierney, M., Tyrrell, T. D., Vié, J.-C. & Watson, R. 2010. Global Biodiversity: Indicators of Recent Declines. *Science*, 328.
- Butchart, S. H. M., Clarke, M., Smith, R. J., Sykes, R. E., Scharlemann, J. P. W., Harfoot, M., Buchanan, G. M., Angulo, A., Balmford, A., Bertzky, B., Brooks, T. M., Carpenter, K. E., Comeros-Raynal, M. T., Cornell, J., Ficetola, G. F., Fishpool, L. D. C., Fuller, R. A., Geldmann, J., Harwell, H., Hilton-Taylor, C., Hoffmann, M., Joolia, A., Joppa, L., Kingston, N., May, I., Milam, A.,

- Polidoro, B., Ralph, G., Richman, N., Rondinini, C., Segan, D. B., Skolnik, B., Spalding, M. D., Stuart, S. N., Symes, A., Taylor, J., Visconti, P., Watson, J. E. M., Wood, L. & Burgess, N. D. 2015. Shortfalls and Solutions for Meeting National and Global Conservation Area Targets. *Conservation Letters*, 8, 329-337.
- Cabeza, M. & Moilanen, A. 2001. Design of reserve networks and the persistence of biodiversity. *Trends in Ecology & Evolution*, 16, 242-248.
- Cain, M. I., Milligan, B. G. & Strand, A. E. 2000. Long-distance seed dispersal in plant populations. *American Journal of Botany*, 87, 1217-1227.
- Callmander, M. W., Schatz, G. E. & Lowry, P. P. 2005. IUCN Red List assessment and the Global Strategy for Plant Conservation: taxonomists must act now. *Taxon*, 54, 1047-1050.
- Callmander, M. W., Schatz, G. E., Lowry II, P. P., Laivao, M. O., Raharimampionona, J., Andriambololona, S., Raminosoa, T. & Consiglio, T. K. 2007. Identification of priority areas for plant conservation in Madagascar using Red List criteria: rare and threatened Pandanaceae indicate sites in need of protection. *Oryx*, 41, 168.
- Cardoso, P., Borges, P. A. V., Triantis, K. A., Ferrández, M. A. & Martín, J. L. 2011. Adapting the IUCN Red List criteria for invertebrates. *Biological Conservation*, 144, 2432-2440.
- Carpenter, K. E., Abrar, M., Aeby, G., Aronson, R. B., Banks, S., Bruckner, A., Chiriboga, A., Cortes, J., Delbeek, J. C., Devantier, L., Edgar, G. J., Edwards, A. J., Fenner, D., Guzman, H. M., Hoeksema, B. W., Hodgson, G., Johan, O., Licuanan, W. Y., Livingstone, S. R., Lovell, E. R., Moore, J. A., Obura, D. O., Ochavillo, D., Polidoro, B. A., Precht, W. F., Quibilan, M. C., Reboton, C., Richards, Z. T., Rogers, A. D., Sanciangco, J., Sheppard, A., Sheppard, C., Smith, J., Stuart, S., Turak, E., Veron, J. E., Wallace, C., Weil, E. & Wood, E. 2008. One-third of reef-building corals face elevated extinction risk from climate change and local impacts. *Science*, 321, 560-3.
- Carrara, R. & Vázquez, D. P. 2010. The species-energy theory: a role for energy variability. *Ecography*, 33, 942-948.
- Cassini, M. H. 2011. Ranking threats using species distribution models in the IUCN Red List assessment process. *Biodiversity and Conservation*, 20, 3689-3692.
- CBD. *Decision Adopted by the Conference of the Parties to the Convention of Biological Diversity at its Tenth meeting. Convention on Biological Diversity. 2010* [Online]. available: <http://www.cbd.int/sp/> [Accessed].
- Center for International Earth Science Information Network - CIESIN - Columbia University 2016. Gridded Population of the World, Version 4 (GPWv4): Population Density. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC).
- Chape, S., Harrison, J., Spalding, M. & Lysenko, I. 2005. Measuring the extent and effectiveness of protected areas as an indicator for meeting global biodiversity targets. *Philosophical Transactions of The Royal Society B*, 360, 443-455.
- Chapin, F. S., Zavaleta, E. S., Eviner, V. T., Naylor, R. L., Vitousek, P. M., Reynolds, H. L., Hooper, D. U., Lavorel, S., Sala, O. E., Hobbie, S. E., Mack, M. C. & Díaz, S. 2000. Consequences of changing biodiversity. *Nature*, 405, 234-242.
- Chase, J. M. & Leibold, M. A. 2003. *Ecological Niches: Linking Classical and Contemporary Approaches*, University of Chicago Press, Chicago.
- Chefaoui, R. M. 2011. Applying species distribution modeling for the conservation of Iberian protected invertebrates. 3.3.
- Chen, C., Hill, J. K., Ohlemüller, R., Roy, D. B. & Thomas, C. D. 2011. Rapid Range Shifts of Species Associated with High Levels of Climate Warming. *Science*, 333, 1024-1026.
- Chen, S. L., Yu, H., Luo, H. M., Wu, Q., Li, C. F. & Steinmetz, A. 2016. Conservation and sustainable use of medicinal plants: problems, progress, and prospects. *Chin Med*, 11, 37.

- Ciarleglio, M., Barnes, J. W. & Sarkar, S. 2008. ConsNet—A tabu search approach to the spatially coherent conservation area network design problem. *Journal of Heuristics*, 16, 537-557.
- Collen, B., Dulvy, N. K., Gaston, K. J., Gardenfors, U., Keith, D. A., Punt, A. E., Regan, H. M., Bohm, M., Hedges, S., Seddon, M., Butchart, S. H., Hilton-Taylor, C., Hoffmann, M., Bachman, S. P. & Akcakaya, H. R. 2016. Clarifying misconceptions of extinction risk assessment with the IUCN Red List. *Biology Letters*, 12.
- Conlisk, E., Conlisk, J., Enquist, B., Thompson, J. & Harte, J. 2009. Improved abundance prediction from presence-absence data. *Global Ecology and Biogeography*, 18, 1-10.
- Conlisk, E., Syphard, A. D., Franklin, J., Flint, L., Flint, A. & Regan, H. 2013. Uncertainty in assessing the impacts of global change with coupled dynamic species distribution and population models. *Global Change Biology*, 19, 858-69.
- Davis, M. B. & Shaw, R. G. 2001. Range Shifts and Adaptive Responses to Quaternary Climate Change. *Science*, 291, 673-679.
- Dawson, T. P., Jackson, S. T., House, J. I., Prentice, I. C. & Mace, G. M. 2011. Beyond Predictions: Biodiversity Conservation in a Changing Climate. *Science*, 332, 53-58.
- de Araújo, C. B., Marcondes-Machado, L. O., Costa, G. C. & Silman, M. 2014. The importance of biotic interactions in species distribution models: a test of the Eltonian noise hypothesis using parrots. *Journal of Biogeography*, 41, 513-523.
- de Pous, P., Beukema, W., Weterings, M., Dümmer, I. & Geniez, P. 2011. Area prioritization and performance evaluation of the conservation area network for the Moroccan herpetofauna: a preliminary assessment. *Biodiversity and Conservation*, 20, 89-118.
- DeFries, R., Hansen, A., Newton, A. C. & Hansen, M. C. 2005. Increasing Isolation of Protected Areas in Tropical Forests over the past Twenty Years. *Ecological Applications*, 15, 19-26.
- DeFries, R., Hansen, A., Turner, B. L., Reid, R. & Liu, J. 2007. Land Use Change Around Protected Areas: Management To Balance Human Needs And Ecological Function. *Ecological Applications*, 17, 1031-1038.
- Deguignet, M., Juffe-Bignoli, D., Harrison, J., MacSharry, B., Burgess, N. & Kingston, N. 2014. United Nations List of Protected Areas. UNEP-WCMC: Cambridge, UK, 44.
- Di Marco, M., Boitani, L., Mallon, D., Hoffmann, M., Iacucci, A., Meijaard, E., Visconti, P., Schipper, J. & Rondinini, C. 2014. A Retrospective Evaluation of the Global Decline of Carnivores and Ungulates. *Conservation Biology*, 28, 1109-1118.
- Di Minin, E., Slotow, R., Hunter, L. T., Montesino Pouzols, F., Toivonen, T., Verburg, P. H., Leader-Williams, N., Petracca, L. & Moilanen, A. 2016. Global priorities for national carnivore conservation under land use change. *Scientific Reports*, 6, 23814.
- Di Minin, E., Soutullo, A., Bartesaghi, L., Rios, M., Szephegyi, M. N. & Moilanen, A. 2017. Integrating biodiversity, ecosystem services and socio-economic data to identify priority areas and landowners for conservation actions at the national scale. *Biological Conservation*, 206, 56-64.
- Díaz, S., Fargione, J., III, F. S. C. & Tilman, D. 2006. Biodiversity Loss Threatens Human Well-Being. *PLoS Biology*, 4, 1300-1305.
- Distler, T., Schuetz, J. G., Velásquez-Tibatá, J., Langham, G. M. & Ladle, R. 2015. Stacked species distribution models and macroecological models provide congruent projections of avian species richness under climate change. *Journal of Biogeography*, 42, 976-988.
- Dobrovolski, R., Loyola, R., Da Fonseca, G. A. B., Diniz-Filho, J. A. F. & Araujo, M. B. 2014. Globalizing Conservation Efforts to Save Species and Enhance Food Production. *BioScience*, 64, 539-545.

- Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J. R. G., Gruber, B., Lafourcade, B., Leitão, P. J., Münkemüller, T., McClean, C., Osborne, P. E., Reineking, B., Schröder, B., Skidmore, A. K., Zurell, D. & Lautenbach, S. 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, 36, 27-46.
- Dubuis, A., Pottier, J., Rion, V., Pellissier, L., Theurillat, J.-P. & Guisan, A. 2011. Predicting spatial patterns of plant species richness: a comparison of direct macroecological and species stacking modelling approaches. *Diversity and Distributions*, 17, 1122-1131.
- Dudík, M., Phillips, S. J. & Schapire, R. E. 2004. Performance guarantees for regularized maximum entropy density estimation. In: *Proceedings of the 17th Annual Conference on Computational Learning Theory*. (eds. Shawe-Taylor J & Singer Y). Springer Berlin.
- Ekroos, J., Kuussaari, M., Tiainen, J., Heliölä, J., Seimola, T. & Helenius, J. 2013. Correlations in species richness between taxa depend on habitat, scale and landscape context. *Ecological Indicators*, 34, 528-535.
- El-Alqamy, H., Ismael, A., Abdelhameed, A., Nagy, A., Hamada, A., Rashad, S. & Kamel, M. 2010. Predicting The Status And Distribution Of The Nubian Ibex (*Capra Nubiana*) In The High-Altitude Mountains Of South Sinai (Egypt). *Galemys*, 22, 517-530.
- El-Gabbas, A., Baha El Din, S., Zalut, S. & Gilbert, F. 2016. Conserving Egypt's reptiles under climate change. *Journal of Arid Environments*, 127, 211-221.
- El-Nahrawy, M. A. 2011. Country pasture/forage resource profiles: Egypt. In: <http://www.fao.org/ag/AGP/AGPC/doc/Counprof/PDF%20files/Egypt> (ed.) FAO, Rome, Italy. Accessed 10-04-2016. p 15-22.
- Elith, J., Graham, C. H., Anderson, R. P., Dudík, M., Ferrier, S., Guisan, A., Hijmans, R. J., Huettmann, F., Leathwick, J. R., Lehmann, A., Li, J., Lohmann, L. G., Loiselle, B. A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J. M., Peterson, A. T., Phillips, S. J., Richardson, K., Scachetti-Pereira, R., Schapire, R. E., Sobero'n, J., Williams, S., Wisz, M. S. & Zimmermann, N. E. 2006. Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, 29, 129-151.
- Elith, J. & Leathwick, J. R. 2009. Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. *Annual Review of Ecology, Evolution, and Systematics*, 40, 677-697.
- Elith, J., Kearney, M. & Phillips, S. 2010. The art of modelling range-shifting species. *Methods in Ecology and Evolution*, 1, 330-342.
- Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E. & Yates, C. J. 2011. A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions*, 17, 43-57.
- Elton, C. S. 1927. *Animal Ecology*, University of Chicago Press, Chicago.
- Engler, R. & Guisan, A. 2009. MigClim: Predicting plant distribution and dispersal in a changing climate. *Diversity and Distributions*, 15, 590-601.
- Engler, R., Randin, C. F., Vittoz, P., Czaka, T., Beniston, M., Zimmermann, N. E. & Guisan, A. 2009. Predicting future distributions of mountain plants under climate change: does dispersal capacity matter? *Ecography*, 32, 34-45.
- Faleiro, F. V., Loyola, R. D. & Knight, A. 2013. Socioeconomic and political trade-offs in biodiversity conservation: a case study of the Cerrado Biodiversity Hotspot, Brazil. *Diversity and Distributions*, 19, 977-987.
- Farzaneh, M. R., Eslamian, S., Samadi, S. Z. & Akbarpour, A. 2012. An appropriate general circulation model (GCM) to investigate climate change impact. *International Journal Hydrology Science and Technology*, 2, 34-47.
- Ficetola, G. F., Thuiller, W. & Padoa-Schioppa, E. 2009. From introduction to the establishment of alien species: bioclimatic differences between presence and reproduction localities in the slider turtle. *Diversity and Distributions*, 15, 108-116.
- Fielding, A. H. & Bell, J. F. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation*, 24, 38-49.

- Finlay, B. J. 2002. Global Dispersal of Free-Living Microbial Eukaryote Species. *Science* 296, 1061-1063.
- Fitzpatrick, M. C., Gove, A. D., Sanders, N. J. & Dunn, R. R. 2008. Climate change, plant migration, and range collapse in a global biodiversity hotspot: the Banksia (Proteaceae) of Western Australia. *Global Change Biology*, 14, 1337-1352.
- Fitzpatrick, M. C. & Hargrove, W. W. 2009. The projection of species distribution models and the problem of non-analog climate. *Biodiversity and Conservation*, 18, 2255-2261.
- Fivaz, F. P. & Gonseth, Y. 2014. Using species distribution models for IUCN Red Lists of threatened species. *Journal of Insect Conservation*, 18, 427-436.
- Fois, M., Fenu, G., Cuenca Lombraña, A., Cogoni, D. & Bacchetta, G. 2015. A practical method to speed up the discovery of unknown populations using Species Distribution Models. *Journal for Nature Conservation*, 24, 42-48.
- Fois, M., Cuenca-Lombrana, A., Fenu, G., Cogoni, D. & Bacchetta, G. 2016. The reliability of conservation status assessments at regional level: Past, present and future perspectives on *Gentiana lutea* L. ssp. *lutea* in Sardinia. *Journal for Nature Conservation*, 33, 1-9.
- Franklin, J. 2009. *Mapping species distributions: spatial inference and prediction*, Cambridge University Press, Cambridge, UK.
- Franklin, J. 2010. Moving beyond static species distribution models in support of conservation biogeography. *Diversity and Distributions*, 16, 321-330.
- Franklin, J., Keppel, G., Webb, E. L., Seamon, J. O., Rey, S. J., Steadman, D. W., Wiser, S. K., Drake, D. R. & Gillman, L. N. 2013. Dispersal limitation, speciation, environmental filtering and niche differentiation influence forest tree communities in West Polynesia. *Journal of Biogeography*, 40, 988-999.
- Franklin, J., Regan, H. M. & Syphard, A. D. 2014. Linking spatially explicit species distribution and population models to plan for the persistence of plant species under global change. *Environmental Conservation*, 41, 97-109.
- Freeman, E. A. & Moisen, G. G. 2008. A comparison of the performance of threshold criteria for binary classification in terms of predicted prevalence and kappa. *Ecological Modelling*, 217, 48-58.
- Fuentes-Ramírez, A., Pauchard, A., Cavieres, L. A. & García, R. A. 2011. Survival and growth of *Acacia dealbata* vs. native trees across an invasion front in south-central Chile. *Forest Ecology and Management*, 261, 1003-1009.
- Game, E. T. & Grantham, H. S. 2008. Marxan User Manual: For Marxan version 1.8.10. University of Queensland, St. Lucia, Queensland, Australia, and Pacific Marine Analysis and Research Association, Vancouver, British Columbia, Canada.
- Gärdenfors, U. 2001. Classifying threatened species at national versus global levels. *Trends in Ecology & Evolution*, 16, 511-516.
- Gause, G. F. 1934. *The Struggle for Existence*, Williams & Wilkins, Baltimore.
- GEF 2000 (*Global Environment Fund*). *Conservation and sustainable use of medicinal plants in arid and semi-arid ecosystems*. GEF, Washington DC, USA.
- Gilbert, F. & Zalut, S. 2008. The Butterflies of Egypt: Atlas, Red Data Listing & Conservation. BioMAP, EEAA, Cairo. 183pp.
- Ginsburg, J. 2001. The Application of IUCN Red List Criteria at Regional Levels. *Conservation Biology*, 15, 1206-1212.
- Golicher, D. J., Cayuela, L. & Newton, A. C. 2012. Effects of Climate Change on the Potential Species Richness of Mesoamerican Forests. *Biotropica*, 44, 284-293.
- Grinnell, J. 1917. The niche-relationships of the California Thrasher. *Auk*, 34, 427-433.
- Grinnell, J. 1924. Geography and evolution. *Ecology and Society*, 5, 225-229.
- Guillera-Arroita, G., Lahoz-Monfort, J. J., Elith, J. & O'Hara, R. B. 2014. Maxent is not a presence-absence method: a comment on Thibaudet al. *Methods in Ecology and Evolution*, 5, 1192-1197.

- Guisan, A. & Zimmermann, N. E. 2000. Predictive habitat distribution models in ecology. *Ecological Modelling*, 135, 147–186.
- Guisan, A. & Thuiller, W. 2005. Predicting species distribution: offering more than simple habitat models. *Ecology Letters*, 8, 993–1009.
- Guisan, A., Broennimann, O., Engler, R., Vust, M., Yoccoz, N. G., Lehmann, A. & Zimmermann, N. E. 2006a. Using Niche-Based Models to Improve the Sampling of Rare Species. *Conservation Biology*, 20, 501–511.
- Guisan, A., Lehmann, A., Ferrier, S., Austin, M., Overton, J. M. C., Aspinall, R. & Hastie, T. 2006b. Making better biogeographical predictions of species' distributions. *Journal of Applied Ecology*, 43, 386–392.
- Guisan, A., Tingley, R., Baumgartner, J. B., Naujokaitis-Lewis, I., Sutcliffe, P. R., Tulloch, A. I., Regan, T. J., Brotons, L., McDonald-Madden, E., Mantyka-Pringle, C., Martin, T. G., Rhodes, J. R., Maggini, R., Setterfield, S. A., Elith, J., Schwartz, M. W., Wintle, B. A., Broennimann, O., Austin, M., Ferrier, S., Kearney, M. R., Possingham, H. P. & Buckley, Y. M. 2013. Predicting species distributions for conservation decisions. *Ecol Lett*, 16, 1424–35.
- Hadidi, M. N., Abd El Ghani, M. M. & Fahmy, A. G. 1992. *The Plant Red Data Book of Egypt. 1. Woody Perennials*, Palm Press and Cairo University Herbarium. ISBN - 977-5089-04-2.
- Hamann, A. & Aitken, S. N. 2013. Conservation planning under climate change: accounting for adaptive potential and migration capacity in species distribution models. *Diversity and Distributions*, 19, 268–280.
- Hamer, A. J. & McDonnell, M. J. 2008. Amphibian ecology and conservation in the urbanising world: A review. *Biological Conservation*, 141, 2432–2449.
- Hamilton, A. C. 2004. Medicinal plants, conservation and livelihoods. *Biodiversity and Conservation*, 13, 1477–1517.
- Hanna, L., Midgley, G. F. & Millar, D. 2002. Climate change-integrated conservation strategies. *Global Ecology & Biogeography*, 11, 485–495.
- Hannah, L., Midgley, G. F. & Millar, D. 2002. Climate change-integrated conservation strategies. *Global Ecology and Biogeography*, 11, 485–495.
- Hannah, L., Midgley, G., Aneliman, S., Araújo, M., Hughes, G., Martinez-Meyer, E., Pearson, R. & Williams, P. 2007. Protected area needs in a changing climate. *Frontiers in Ecology and the Environment*, 5, 131–138.
- Hannah, L. 2012. *Are a million species at risk?. Saving amillion species: extinction risk from climate change*, Island Press, Washington DC.
- Hannah, L. 2011. *Climate Change Biology*, Elsevier Ltd.
- Hanski, I. A. & Gilpin, M. E. 1997. *Metapopulation Biology: Ecology, Genetics And Evolution*, Academic press, San Diego.
- Hata, K., Kato, H. & Kachi, N. 2010. Litter of an alien tree, *Casuarina equisetifolia*, inhibits seed germination and initial growth of a native tree on the Ogasawara Islands (subtropical oceanic islands). *Journal of Forest Research*, 15, 384–390.
- Hawkins, B. A., Field, R., Cornell, H. V., Currie, D. J., Guegan, J. F., Kaufman, D. M., Kerr, J. T., Mittelbach, G. G., Oberdorff, T., O'Brien, E. M., Porter, E. E. & Turner, J. R. G. 2003. Energy, water, and broad-scale geographic patterns of species richness. *Ecology*, 84, 3105–3117.
- Heikkinen, R. K., Luoto, M., Virkkala, R., Pearson, R. G. & Körber, J.-H. 2007. Biotic interactions improve prediction of boreal bird distributions at macro-scales. *Global Ecology and Biogeography*, 16, 754–763.
- Heller, N. E. & Zavaleta, E. S. 2009. Biodiversity management in the face of climate change: a review of 22 years of recommendations. *Biological Conservation*, 142, 14–32.
- Herborg, L.-M., Jerde, C. L., Lodge, D. M., Ruiz, G. M. & Macisaac, A. H. J. 2007. Predicting Invasion Risk Using Measures Of Introduction Effort And Environmental Niche Models. *Ecological Applications*, 17, 663–674.
- Hernandez, P. A., Graham, C. H., Master, L. L. & Albert, D. L. 2006. The effect of sample size and species characteristics on performance of different species distribution modeling methods. *Ecography*, 29, 773–785.

- Hickler, T., Vohland, K., Feehan, J., Miller, P. A., Smith, B., Costa, L., Giesecke, T., Fronzek, S., Carter, T. R., Cramer, W., Kühn, I. & Sykes, M. T. 2012. Projecting the future distribution of European potential natural vegetation zones with a generalized, tree species-based dynamic vegetation model. *Global Ecology and Biogeography*, 21, 50-63.
- Higgins, S. I., Richardson, D. M., Cowling, R. M. & Trinder-Smith, T. H. 1999. Predicting the Landscape-Scale Distribution of Alien Plants and Their Threat to Plant Diversity. *Conservation Biology*, 13, 303-313.
- Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. & Jarvis, A. 2005. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, 25, 1965-1978.
- Hijmans, R. J. & Graham, C. H. 2006. The ability of climate envelope models to predict the effect of climate change on species distributions. *Global Change Biology*, 12, 2272-2281.
- Hirzel, A. H. & Le Lay, G. 2008. Habitat suitability modelling and niche theory. *Journal of Applied Ecology*, 45, 1372-1381.
- Hoffmann, M., Hilton-Taylor, C., Angulo, A., Böhm, M., et al. 2010. The Impact of Conservation on the Status of the World's Vertebrates. *Science*, 330, 1503-1509.
- Hoffmann, M., Belant, J. L., Chanson, J. S., Cox, N. A., Lamoreux, J., Rodrigues, A. S., Schipper, J. & Stuart, S. N. 2011. The changing fates of the world's mammals. *Philosophical Transactions of the Royal Society B*, 366, 2598-610.
- Holt, R. D. 2009. Bringing the Hutchinsonian niche into the 21st century: ecological and evolutionary perspectives. *Proceedings of the National Academy of Sciences U S A*, 106, 19659-19665.
- Houghton, J. T., Ding, Y., Griggs, D. J., Noguer, M., Linden, P. J. v. d., Dai, X., Maskell, K. & Johnson, C. A. 2001. *Climate change 2001: The Scientific Basis*, Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change, IPCC.
- Hoyle, M. & James, M. 2005. Global warming, human population pressure, and viability of the world's smallest butterfly. *Conservation Biology*, 19, 1113-24.
- Huang, H. 2011. Plant diversity and conservation in China: planning a strategic bioresource for a sustainable future. *Botanical Journal of the Linnean Society*, 166, 282-300.
- Hughes, T. P., Bellwood, D. R., Connolly, S. R., Cornell, H. V. & Karlson, R. H. 2014. Double jeopardy and global extinction risk in corals and reef fishes. *Current Biology*, 24, 2946-51.
- Huntley, B., Berry, P. M., Cramer, W. & McDonald, A. P. 1995. Modelling Present and Potential Future Ranges of Some European Higher Plants Using Climate Response Surfaces. *Journal of Biogeography*, 22, 967-1001.
- Hurst, F., Barakat, H. & Maxted, N. 2006. Conservation and sustainable use of medicinal plants in arid and semi-arid ecosystems. Atlas Project GEF12347, UNDP 12348 PIMS#972, Mid-term review, final report.
- Hutchinson, G. E. 1957. Concluding Remarks. Cold Spring Harbor Symposium On Quantitative Biology.
- Hwang, W. H. & He, F. L. 2011. Estimating abundance from presence/absence maps. *Methods in Ecology & Evolution*, 2, 550-9.
- Ihlow, F., Dambach, J., Engler, J. O., Flecks, M., Hartmann, T., Nekum, S., Rajaei, H. & Rödder, D. 2012. On the brink of extinction? How climate change may affect global chelonian species richness and distribution. *Global Change Biology*, 18, 1520-1530.
- IPCC Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. 2007. IPCC, Geneva, Switzerland.
- IUCN 2010. Guidelines for Using the IUCN Red List Categories and Criteria. Version 8.1. Prepared by the Standards and Petitions Subcommittee in March 2010.
- IUCN 2012a. Guidelines for Application of IUCN Red List Criteria at Regional and National Levels: Version 4.0. Gland, Switzerland and Cambridge, UK.

- IUCN. 2012b. IUCN Red List Categories and Criteria: Version 3.1. Second edition. Gland, Switzerland and Cambridge, UK: IUCN.
- IUCN 2015. The IUCN Red List of Threatened Species. Version 2015-4. <http://www.iucnredlist.org/>. Downloaded on 28 December 2015.
- IUCN 2016. Guidelines for Using the IUCN Red List Categories and Criteria: Version 12. Prepared by the Standards and Petitions Subcommittee.
- Jarnevich, C. S. & Reynolds, L. V. 2011. Challenges of predicting the potential distribution of a slow-spreading invader: a habitat suitability map for an invasive riparian tree. *Biological Invasions*, 13, 153-163.
- Jenkins, D. G., Brescacin, C. R., Duxbury, C. V., Elliott, J. A., Evans, J. A., Grablow, K. R., Hillegass, M., Lyon, B. N., Metzger, G. A., Olandese, M. L., Pepe, D., Silvers, G. A., Suresch, H. N., Thompson, T. N., Trexler, C. M., Williams, G. E., Williams, N. C. & Williams, S. E. 2007. Does size matter for dispersal distance? *Global Ecology and Biogeography*, 16, 415-425.
- Jiménez-Valverde, A., Lobo, J. M. & Hortal, J. 2008. Not as good as they seem: the importance of concepts in species distribution modelling. *Diversity and Distributions*, 14, 885-890.
- Johnson, C. J., Nielsen, S. E., Merrill, E. H., McDonald, T. L. & Boyce, M. S. 2006. Resource Selection Functions Based on Use-Availability Data: Theoretical Motivation and Evaluation Methods. *Journal Of Wildlife Management*, 70, 347-357.
- Jones, K. R., Watson, J. E. M., Possingham, H. P. & Klein, C. J. 2016. Incorporating climate change into spatial conservation prioritisation: A review. *Biological Conservation*, 194, 121-130.
- Joppa, L. N., Loarie, S. R. & Pimm, S. L. 2008. On the protection of "protected areas". *PNAS*, 105, 6673-6678.
- Joppa, L. N., Loarie, S. R. & Pimm, S. L. 2009. On Population Growth Near Protected Areas. *PLoS One*, 4, e4279.
- Joppa, L. N., Butchart, S. H., Hoffmann, M., Bachman, S. P., Akcakaya, H. R., Moat, J. F., Bohm, M., Holland, R. A., Newton, A., Polidoro, B. & Hughes, A. 2016. Impact of alternative metrics on estimates of extent of occurrence for extinction risk assessment. *Conservation Biology*, 30, 362-70.
- Kadmon, R., Farber, O. & Danin, A. 2003. A systematic analysis of factors affecting the performance of climatic envelope models. *Ecological Applications*, 13, 853-867.
- Kaky, E. & Gilbert, F. 2016. Using species distribution models to assess the importance of Egypt's protected areas for the conservation of medicinal plants. *Journal of Arid Environments*, 135, 140-146.
- Kaky, E. & Gilbert, F. 2017. Predicting the distributions of Egypt's medicinal plants and their potential shifts under future climate change. *PLoS One*, 12, e0187714.
- Kearney, M., Simpson, S. J., Raubenheimer, D. & Helmuth, B. 2010. Modelling the ecological niche from functional traits. *Philosophical Transaction of the Royal Society B*, 365, 3469-83.
- Keith, D. A., Auld, T. D., Ooi, M. K. J. & Mackenzie, B. D. E. 2000. Sensitivity analyses of decision rules in World Conservation Union (IUCN) Red List criteria using Australian plants. *Biological Conservation*, 94, 311-319.
- Keith, D. A., Mahony, M., Hines, H., Elith, J., Regan, T. J., Baumgartner, J. B., Hunter, D., Heard, G. W., Mitchell, N. J., Parris, K. M., Penman, T., Scheele, B., Simpson, C. C., Tingley, R., Tracy, C. R., West, M. & Akcakaya, H. R. 2014. Detecting extinction risk from climate change by IUCN Red List criteria. *Conservation Biology*, 28, 810-9.
- Kershaw, M., Mace, G. M. & Williams, P. H. 1995. Threatened Status, Rarity, and Diversity as Alternative Selection Measures for Protected Areas: A Test Using Afrotropical Antelopes. *Conservation Biology*, 9, 324-334.
- Kew 2010. Plants under pressure – a global assessment. The first report of the IUCN Sampled Red List Index for Plants. Royal Botanic Gardens, Kew, UK.

- Khafaga, O., Hatab, E. E. & Omar, K. 2011. Predicting the potential geographical distribution of *Nepeta septemcrenata* in Saint Katherine Protectorate, South Sinai, Egypt using Maxent. *Academia Arena*, 3, 45-50.
- Khafaga, O., Hatab, E. E. & K.Omar 2012. Ecological Niche Modeling As a Tool for Conservation Planning: Suitable Habitat for *Hypericum sinaicum* in South Sinai, Egypt. *Universal Journal of Environmental Research & Technology*, 2, 515-524.
- Klein, J. A., Harte, J. & Zhao, X.-Q. 2008. Decline in Medicinal and Forage Species with Warming is Mediated by Plant Traits on the Tibetan Plateau. *Ecosystems*, 11, 775-789.
- Klorvuttimontara, S., McClean, C. J. & Hill, J. K. 2011. Evaluating the effectiveness of Protected Areas for conserving tropical forest butterflies of Thailand. *Biological Conservation*, 144, 2534-2540.
- Knight, A. T., Cowling, R. M., Rouget, M., Balmford, A., Lombard, A. T. & Campbell, B. M. 2008. Knowing but not doing: selecting priority conservation areas and the research-implementation gap. *Conserv Biol*, 22, 610-7.
- Knight, A. T., Cowling, R. M., Possingham, H. P. & Wilson, K. A. 2009. From theory to practice: designing and situating spatial prioritisation tools for implementing conservation action Spatial Conservation Prioritization: Quantitative Methods and Computational Tools. Oxford University Press, USA.
- Kramer-Schadt, S., Niedballa, J., Pilgrim, J. D., Schröder, B., Lindenborn, J., Reinfelder, V., Stillfried, M., Heckmann, I., Scharf, A. K., Augeri, D. M., Cheyne, S. M., Hearn, A. J., Ross, J., Macdonald, D. W., Mathai, J., Eaton, J., Marshall, A. J., Semiadi, G., Rustam, R., Bernard, H., Alfred, R., Samejima, H., Duckworth, J. W., Breitenmoser-Wuersten, C., Belant, J. L., Hofer, H., Wilting, A. & Robertson, M. 2013. The importance of correcting for sampling bias in MaxEnt species distribution models. *Diversity and Distributions*, 19, 1366-1379.
- Kukkala, A. S. & Moilanen, A. 2013. Core concepts of spatial prioritisation in systematic conservation planning. *Biological Review Cambridge Philosophical Society*, 88, 443-464.
- Kuussaari, M., Heliölä, J., Luoto, M. & Pöyry, J. 2007. Determinants of local species richness of diurnal Lepidoptera in boreal agricultural landscapes. *Agriculture, Ecosystems & Environment*, 122, 366-376.
- Lamoreux, J., Akc, akaya, H. R., Bennun, L., Collar, N. J., Boitani, L., Brackett, D., Bra "utigam, A., Brooks, T. M., Fonseca, G. A. B. d., Mittermeier, R. A., Rylands, A. B., Gardenfors, U., Hilton-Taylor, C., Mace, G., Stein, B. A. & Stuart, S. 2003. Value of the IUCN Red List. *Trends in Ecology and Evolution*, 18.
- Lansdown, R. V. & Juffe Bignoli, D. 2013. *Juncus rigidus*. The IUCN Red List of Threatened Species 2013: e.T185693A13559337. <http://dx.doi.org/10.2305/IUCN.UK.2013-1.RLTS.T185693A13559337.en>. Downloaded on 12 December 2016.
- Lansdown, R. V. 2015. *Phragmites australis*. The IUCN Red List of Threatened Species 2015: e.T164494A79857020. <http://dx.doi.org/10.2305/IUCN.UK.2015.RLTS.T164494A79857020.en>. Downloaded on 12 December 2016.
- Leach, K., Zalat, S. & Gilbert, F. 2013. Egypt's Protected Area network under future climate change. *Biological Conservation*, 159, 490-500.
- Leach, K., Montgomery, W. I. & Reid, N. 2016. Modelling the influence of biotic factors on species distribution patterns. *Ecological Modelling*, 337, 96-106.
- Lee, T. M., Sodhi, N. S. & Prawiradilaga, D. M. 2007. The Importance Of Protected Areas For The Forest And Endemic Avifauna Of Sulawesi (Indonesia). *Ecological Applications*, 17, 1727-1741.
- Leibold, M. A. 1995. The Niche Concept Revisited: Mechanistic Models and Community Context. *Ecological Society of America*, 67, 1371-1382.
- Linares-Palomino, R. & Kessler, M. 2009. The role of dispersal ability, climate and spatial separation in shaping biogeographical patterns of phylogenetically

- distant plant groups in seasonally dry Andean forests of Bolivia. *Journal of Biogeography*, 36, 280-290.
- Linkie, M., Chapron, G., Martyr, D. J., Holden, J. & Leader-Williams, N. 2006. Assessing the viability of tiger subpopulations in a fragmented landscape. *Journal of Applied Ecology*, 43, 576-586.
- Liu, C., Berry, P. M., Dawson, T. P. & Pearson, R. G. 2005. Selecting thresholds of occurrence in the prediction of species distributions. *Ecography*, 28, 385-393.
- Liu, J., Li, S., Ouyang, Z., Tam, C. & Chen, X. 2008. Ecological and socioeconomic effects of China's policies for ecosystem services. *PNAS*, 105, 9477-82.
- Lobo, J. M., Jiménez-Valverde, A. & Real, R. 2008. AUC: a misleading measure of the performance of predictive distribution models. *Global Ecology and Biogeography*, 17, 145-151.
- Lomolino, M. V., Riddle, B. R. & Brown, J. H. 2006. *Biogeography*, Sinauer Associates, Inc, Sunderland, Massachusetts, USA.
- Loydi, A., Donath, T. W., Eckstein, R. L. & Otte, A. 2014. Non-native species litter reduces germination and growth of resident forbs and grasses: allelopathic, osmotic or mechanical effects? *Biological Invasions*, 17, 581-595.
- MacArthur, R. H. 1972. *Geographical Ecology_Patterns in the Distribution of Species*, Harper & Row, New York.
- Mace, G. M., Collar, N. J., Gaston, K. J., Hilton-Taylor, C., Akcakaya, H. R., Leader-Williams, N., Milner-Gulland, E. J. & Stuart, S. N. 2008. Quantification of extinction risk: IUCN's system for classifying threatened species. *Conservation Biology*, 22, 1424-42.
- Maes, D., Isaac, N. J. B., Harrower, C. A., Collen, B., Strien4, A. J. V. & Roy, D. B. 2015. The use of opportunistic data for IUCN Red List assessments. *Biological Journal of the Linnean Society*, 115, 690-706.
- Marcen, A., Sáez, L., Molowny-Horas, R., Pons, X. & Pino, J. 2013. Using species distribution modelling to disentangle realised versus potential distributions for rare species conservation. *Biological Conservation*, 166, 221-230.
- Margules, C. R. & Pressey, R. L. 2000. Systematic conservation planning. *Nature*, 405, 243-253.
- Martín, J. L. 2009. Are the IUCN standard home-range thresholds for species a good indicator to prioritise conservation urgency in small islands? A case study in the Canary Islands (Spain). *Journal for Nature Conservation*, 17, 87-98.
- Martínez-Meyer, E. 2005. Climate change and biodiversity: Some considerations in forecasting shifts in species' potential distributions. *Biodiversity Informatics*, 2, 42-55.
- Matthysen, E. 2012. Multicausality of dispersal: a review. In: Clobert, J., Baguette, M., Benton, T. G. & Bullock, J. M. (eds.) *dispersal ecology and evolution*. Oxford University Press: UK.
- McClean, C. J., Lovett, J. C., Kuper, W., Hannah, L., Sommer, H., Barthlott, W., Termansen, M., Smith, G. F., Tokumine, S. & Taplin, J. R. D. 2005. African Plant Diversity and Climate Change. *Annals of the Missouri Botanical Garden*, 92, 139-152.
- McClean, C. J., Doswald, N., Küper, W., Sommer, J. H., Barnard, P. & Lovett, J. C. 2006. Potential impacts of climate change on Sub-Saharan African plant priority area selection. *Diversity and Distributions*, 12 645-655.
- McInerny, G. J. & Etienne, R. S. 2012. Ditch the niche - is the niche a useful concept in ecology or species distribution modelling? *Journal of Biogeography*, 39, 2096-2102.
- MEA 2005. *Ecosystems and Human Well-Being: Biodiversity Synthesis*. World Resources Institute, Washington, DC.
- Menéndez, R., González-Megías, A., Collingham, Y., Fox, R., Roy, D. B., Ohlemüller, R. & Thomas, C. D. 2007. Direct and Indirect Effects of Climate and Habitat Factors on Butterfly Diversity. *Ecology*, 88, 605-611.

- Merow, C., Smith, M. J. & Silander, J. A. 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography*, 36, 1058-1069.
- Mestre, A., Aguilar-Alberola, J. A., Baldry, D., Balkis, H., Ellis, A., Gil-Delgado, J. A., Grabow, K., Klobucar, G., Kouba, A., Maguire, I., Martens, A., Mulayim, A., Rueda, J., Scharf, B., Soes, M., J. S. M. & Mesquita-Joanes, F. 2013. Invasion biology in non-free-living species: interactions between abiotic (climatic) and biotic (host availability) factors in geographical space in crayfish commensals (Ostracoda, Entocytheridae). *Ecology Evolution*, 3, 5237-53.
- Miller, J. R., Snyder, S. A., Skibbe, A. M. & Haight, R. G. 2009. Prioritizing conservation targets in a rapidly urbanizing landscape. *Landscape and Urban Planning*, 93, 123-131.
- Moffett, A., Garson, J. & Sarkar, S. 2005. MultCSync: a software package for incorporating multiple criteria in conservation planning. *Environ. Model. Softw.*, 20, 1315-1322.
- Moffett, A. & Sarkar, S. 2006. Incorporating multiple criteria into the design of conservation area networks: a minireview with recommendations. *Diversity Distributions*, 12, 125-137.
- Moilanen, A., Franco, A. M., Early, R. I., Fox, R., Wintle, B. & Thomas, C. D. 2005. Prioritizing multiple-use landscapes for conservation: methods for large multi-species planning problems. *Proc Biol Sci*, 272, 1885-91.
- Moilanen, A. & Wintle, B. A. 2006. Uncertainty analysis favours selection of spatially aggregated reserve networks. *Biological Conservation*, 129, 427-434.
- Moilanen, A., Arponen, A., Stokland, J. N. & Cabeza, M. 2009a. Assessing replacement cost of conservation areas: How does habitat loss influence priorities? *Biological Conservation*, 142, 575-585.
- Moilanen, A., Wilson, K. A. & Possingham, H. P. 2009b. Spatial Conservation Prioritization. Oxford University Press, Oxford.
- Moilanen, A., Anderson, B. J., Eigenbrod, F., Heinemeyer, A., Roy, D. B., Gillings, S., Armsworth, P. R., Gaston, K. J. & Thomas, C. D. 2011. Balancing alternative land uses in conservation prioritization. *Ecological Applications*, 21, 1419-1426.
- Moilanen, A., Pouzols, F. M., Meller, L., Veach, V., Arponen, A., Leppänen, J. & Kujala, H. 2014. Zonation - Spatial conservation planning methods and software. Version 4. User Manual. C-BIG Conservation Biology Informatics Group Department of Biosciences University of Helsinki, Finland.
- Morueeta-Holme, N., Fløjgaard, C. & Svenning, J.-C. 2010. Climate Change Risks and Conservation Implications for a Threatened Small-Range Mammal Species. *PLoS ONE*, 5, 1-12.
- Muscarella, R., Galante, P. J., Soley-Guardia, M., Boria, R. A., Kass, J. M., Uriarte, M., Anderson, R. P. & McPherson, J. 2014. ENMeval: An R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxentecological niche models. *Methods in Ecology and Evolution*, 5, 1198-1205.
- Naidoo, R., Balmford, A., Ferraro, P. J., Polasky, S., Ricketts, T. H. & Rouget, M. 2006. Integrating economic costs into conservation planning. *Trends Ecol Evol*, 21, 681-7.
- Nakicenovic, N., Swart, R., Alcamo, J., Davis, G., Vries, B. d., Fenhann, J., Gaffin, S., Gregory, K., Griibler, A., Jung, T. Y., Kram, T., Emilio Lebre La Rovere, Michaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H., Price, L., Riahi, K., Roehrl, A., Rogner, H.-H., Sankovski, A., Schlesinger, M., Priyadarshi Shukla, Smith, S., Rooijen, S. v., Victor, N. & Dadi, Z. 2000. *Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, UK, .
- Newbold, T. 2009. *The value of species distribution models as a tool for conservation and ecology in Egypt and Britain*. Ph.D. thesis, University of Nottingham, UK.

- Newbold, T., Gilbert, F., Zalat, S., El-Gabbas, A. & Reader, T. 2009. Climate-based models of spatial patterns of species richness in Egypt's butterfly and mammal fauna. *Journal of Biogeography*, 36, 2085-2095.
- Newbold, T. 2010. Applications and limitations of museum data for conservation and ecology, with particular attention to species distribution models. *Progress in Physical Geography*, 34, 3-22.
- Newbold, T., Reader, T., El-Gabbas, A., Berg, W., Shohdi, W. M., Zalat, S., El Din, S. B. & Gilbert, F. 2010. Testing the accuracy of species distribution models using species records from a new field survey. *Oikos*, 119, 1326-1334.
- Novoa, A., Rodríguez, R., Richardson, D. & González, L. 2013. Soil quality: a key factor in understanding plant invasion? The case of *Carpobrotus edulis* (L.) N.E.Br. *Biological Invasions*, 16, 429-443.
- NRL 2015. National Red List. <http://www.nationalredlist.org/>. Downloaded on 30 December 2015.
- Okigbo, R. N., Eme, U. E. & Ogbogu, S. 2008. Biodiversity and conservation of medicinal and aromatic plants in Africa. *Biotechnology and Molecular Biology Reviews*, 3, 127-134.
- Oliver, T., Roy, D. B., Hill, J. K., Brereton, T. & Thomas, C. D. 2010. Heterogeneous landscapes promote population stability. *Ecology Letters*, 13, 473-484.
- Ortega-Huerta, M. A. & Peterson, A. T. 2004. Modelling spatial patterns of biodiversity for conservation prioritization in North-eastern Mexico. *Diversity and Distributions*, 10, 39-54.
- Park, T. 1948. Experimental studies of interspecies competition. 1. Competition between populations of the flour beetles, *Tribolium confusum* Duval and *Tribolium castaneum* Herbst. *Ecological Monographs*, 18, 265-307.
- Parmesan, C., Ryrholm, N., Stefanescu, C., Hillk, J. K., Thomas, C. D., Descimon, H., Huntley, B., Kaila, L., Kullberg, J., Tammaru, T., Tennent, W. J., Thomas, J. A. & Warren, M. 1999. Poleward shifts in geographical ranges of butterfly species associated with regional warming. *Nature*, 399, 579-583.
- Parmesan, C. & Yohe, G. 2003. Globally coherent fingerprint of climate change impacts across natural systems. *Nature*, 421, 37-42.
- Pawar, S., Koo, M. S., Kelley, C., Ahmed, M. F., Chaudhuri, S. & Sarkar, S. 2007. Conservation assessment and prioritization of areas in Northeast India: Priorities for amphibians and reptiles. *Biological Conservation*, 136, 346-361.
- Pearce, J. & Ferrier, S. 2000. Evaluating the predictive performance of habitat models developed using logistic regression. *Ecological Modelling*, 133, 225-245.
- Pearson, R. G., Dawson, T. P., Berry, P. M. & Harrison, P. A. 2002. Species: A spatial evaluation of climate impact on the envelope of species. *Ecological Modelling*, 154, 289-300.
- Pearson, R. G. & Dawson, T. P. 2003. Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? *Global Ecology & Biogeography*, 12, 361-371.
- Pearson, R. G., Thuiller, W., Araújo, M. B., Martinez-Meyer, E., Brotons, L., McClean, C., Miles, L., Segurado, P., Dawson, T. P. & Lees, D. C. 2006. Model-based uncertainty in species range prediction. *Journal of Biogeography*, 33, 1704-1711.
- Pearson, R. G. 2007. Species' Distribution Modeling for Conservation Educators and Practitioners. Synthesis. American Museum of Natural History.
- Pearson, R. G., Raxworthy, C. J., Nakamura, M. & Townsend Peterson, A. 2007. Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *Journal of Biogeography*, 34, 102-117.
- Pearson, R. G., Stanton, J. C., Shoemaker, K. T., Aiello-Lammens, M., Ersts, P. J., Horning, N., Fordham, D. A., Raxworthy, C. J., Ryu, H. Y., McNees, J. & Akçakaya, H. R. 2014. Life history and spatial traits predict extinction risk due to climate change. *Nature Climate Change*, 4.
- Pena, J. C. d. C., Kamino, L. H. Y., Rodrigues, M., Mariano-Neto, E. & de Siqueira, M. F. 2014. Assessing the conservation status of species with limited

- available data and disjunct distribution. *Biological Conservation*, 170, 130-136.
- Perrings, C., Williamson, M., Barbier, E. B., Delfino, D., Dalmazzone, S., Shogren, J., Simmons, P. & Watkinson, A. 2002. Biological Invasion Risks and the Public Good: an Economic Perspective. *Conservation Ecology*, 6, 1.
- Peterson, A. T., Ortega-Huerta, M. A., Bartley, J., Sánchez-Cordero, V., Soberón, J., Buddemeier, R. H. & Stockwell, D. R. B. 2002. Future projections for Mexican faunas under global climate change scenarios. *Nature*, 416, 626-629.
- Peterson, A. T. 2003. Predicting the Geography of Species' Invasions via Ecological Niche Modeling. *The Quarterly Review Of Biology*, 78, 419-433.
- Peterson, A. T. & Robins, C. R. 2003. Using Ecological-Niche Modeling to Predict Barred Owl Invasions with Implications for Spotted Owl Conservation. *Conservation Biology*, 7, 1161-1165.
- Peterson, A. T. & Shaw, J. 2003. Lutzomyia vectors for cutaneous leishmaniasis in Southern Brazil: ecological niche models, predicted geographic distributions, and climate change effects. *International Journal for Parasitology*, 33, 919-931.
- Peterson, A. T., Soberón, J., Pearson, R. G., Anderson, R. P., Martínez-Meyer, E., Nakamura, M. & Araujo, M. B. 2011. *Ecological Niches and Geographic Distributions*, Princeton University Press.
- Phillips, S. J., Anderson, R. P. & Schapire, R. E. 2006. Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, 190, 231-259.
- Phillips, S. J. & Dudík, M. 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography*, 31, 161-175.
- Phillips, S. J., Dudík, M., Elith, J., Graham, C. H., Lehmann, A., Leathwick, J. & Ferrier, S. 2009. Phillips_Sample selection bias and presence-only distribution models- implications for background and pseudo-absence data. *Ecological Applications*, 19.
- Phillips, S. J. & Elith, J. 2010. POC plots: calibrating species distribution models with presence-only data. *Ecology*, 91, 2476-2484.
- Pimentel, D., Zuniga, R. & Morrison, D. 2005. Update on the environmental and economic costs associated with alien-invasive species in the United States. *Ecological Economics*, 52, 273-288.
- Pimm, S. L., Russell, G. J., Gittleman, J. L. & Brooks, T. M. 1995. The Future of Biodiversity. *Science*, 269, 347-350.
- Pineda, E. & Lobo, J. M. 2009. Assessing the accuracy of species distribution models to predict amphibian species richness patterns. *Journal of Animal Ecology*, 78, 182-190.
- Polasky, S. 2008. Why conservation planning needs socioeconomic data. *Proc Natl Acad Sci U S A*, 105, 6505-6.
- Pressey, R. L., Humphries, C. J., Margules, C. R., Vane-Wright, R. I. & Williams, P. 1993. Beyond Opportunism: Key Principles for Systematic Reserve Selection. *Trends In Ecology & Evolution*, 8, 124-128.
- Pressey, R. L., Cabeza, M., Watts, M. E., Cowling, R. M. & Wilson, K. A. 2007. Conservation planning in a changing world. *Trends Ecol Evol*, 22, 583-92.
- Pulliam, H. R. 2000. On the relationship between niche and distribution. *Ecology Letters*, 3, 349-361.
- Radosavljevic, A. & Anderson, R. P. 2014. Making better Maxent models of species distributions: complexity, overfitting and evaluation. *Journal of Biogeography*, 41, 629-643.
- Rafferty, N. E. & Ives, A. R. 2011. Effects of experimental shifts in flowering phenology on plant-pollinator interactions. *Ecology Letters*, 14, 69-74.
- Rafieian-Kopae, M. 2012. Medicinal plants and the human needs. *Journal of HerbMed Pharmacology*, 1, 1-2.
- Rands, M. R. W., Adams, W. M., Bennun, L., Butchart, S. H. M., Clements, A., Coomes, D., Entwistle, A., Hodge, I., Kapos, V., Scharlemann, J. P. W., Sutherland, W. J. & Vira, B. 2010. Biodiversity Conservation: Challenges Beyond 2010. *Science*, 329, 1298-1303.

- Rangel, T. F. L. V. B., Bini, L. M., Diniz-Filho, J. A. F., Pinto, M. P., Carvalho, P. & Bastos, R. P. 2007. Human development and biodiversity conservation in Brazilian Cerrado. *Applied Geography*, 27, 14-27.
- Raxworthy, C. J., Martinez-Meyer, E., Horning, N., Nussbaum, R. A., Schneider, G. E., Ortega-Huerta, M. A. & Peterson, A. T. 2003. Predicting distributions of known and unknown reptile species in Madagascar. *Nature*, 426, 837-841.
- Regos, A., D'Amen, M., Herrando, S., Guisan, A. & Brotons, L. 2015. Fire management, climate change and their interacting effects on birds in complex Mediterranean landscapes: dynamic distribution modelling of an early-successional species—the near-threatened Dartford Warbler (*Sylvia undata*). *Journal of Ornithology*, 156, 275–286.
- Richardson, D. M. & Wilgen, B. W. v. 2004. Invasive alien plants in South Africa: how well do we understand the ecological impacts? *South African Journal of Science*, 100, 45-52.
- Richardson, D. M. & Thuiller, W. 2007. Home away from home - objective mapping of high-risk source areas for plant introductions. *Diversity and Distributions*, 13, 299-312.
- Ricketts, T. H., Dinerstein, E., Boucher, T., Brooks, T. M., Butchart, S. H., Hoffmann, M., Lamoreux, J. F., Morrison, J., Parr, M., Pilgrim, J. D., Rodrigues, A. S., Sechrest, W., Wallace, G. E., Berlin, K., Bielby, J., Burgess, N. D., Church, D. R., Cox, N., Knox, D., Loucks, C., Luck, G. W., Master, L. L., Moore, R., Naidoo, R., Ridgely, R., Schatz, G. E., Shire, G., Strand, H., Wettengel, W. & Wikramanayake, E. 2005. Pinpointing and preventing imminent extinctions. *PNAS*, 102, 18497-501.
- Robinson, T. P., van Klinken, R. D. & Metternicht, G. 2010. Comparison of alternative strategies for invasive species distribution modeling. *Ecological Modelling*, 221, 2261-2269.
- Rodrigues, A. S., Pilgrim, J. D., Lamoreux, J. F., Hoffmann, M. & Brooks, T. M. 2006. The value of the IUCN Red List for conservation. *Trends in Ecology and Evolution*, 21, 71-6.
- Rodríguez, J. P., Brotons, L., Bustamante, J. & Seoane, J. 2007. The application of predictive modelling of species distribution to biodiversity conservation. *Diversity and Distributions*, 13, 243-251.
- Root, T. L., Price, J. T., Hall, K. R., Schneider, S. H., Rosenzweig, C. & Pounds, J. A. 2003. Fingerprints of global warming on wild animals and plants. *Nature*, 421, 57-60.
- Ross, I. A. 2005. *Medicinal plants of the world (volume 3): chemical constituents, traditional and modern medicinal uses*, New Jersey: Humana Press Inc.
- Rushton, S. P., Ormerod, S. J. & Kerby, G. 2004. New paradigms for modelling species distributions? *Journal of Applied Ecology*, 41, 193–200.
- Sala, O. E., Chapin, F. S., Armesto, J. J., Berlow, E., Bloomfield, J., Dirzo, R., Huber-Sanwald, E., Huenneke, L. F., Jackson, R. B., Kinzig, A., Leemans, R., Lodge, D. M., Mooney, H. A., Oesterheld, M. n., Poff, N. L., Sykes, M. T., Walker, B. H., Walker, M. & Wall, D. H. 2000. Global Biodiversity Scenarios for the Year 2100. *Science*, 287.
- Sarkar, S., Aggarwal, A., Garson, J., Margules, C. R. & Zeidler, J. 2002. Place prioritization for biodiversity content. *Journal of Biosciences*, 27, 339–346.
- Sarkar, S. & Garson, J. 2004. Multiple Criterion Synchronisation for Conservation Area Network Design: The Use of Non-dominated Alternative Sets. *Conservation and Society*, 2, 433-448.
- Saupe, E. E., Papes, M., Selden, P. A. & Vetter, R. S. 2011. Tracking a Medically Important Spider: Climate Change, Ecological Niche Modeling, and the Brown Recluse (*Loxosceles reclusa*). *PLoS One*, 6, e17731.
- Schatz, G. E., Birkinshaw, C., Lowry, P. P., Randriantafika, F. & Ratovoson, F. 2000. The endemic plant families of Madagascar project: integrating taxonomy and conservation. *Diversity and endemism in Madagascar. Memoires de la Societe de Biogeographie, Paris*, 11-24.

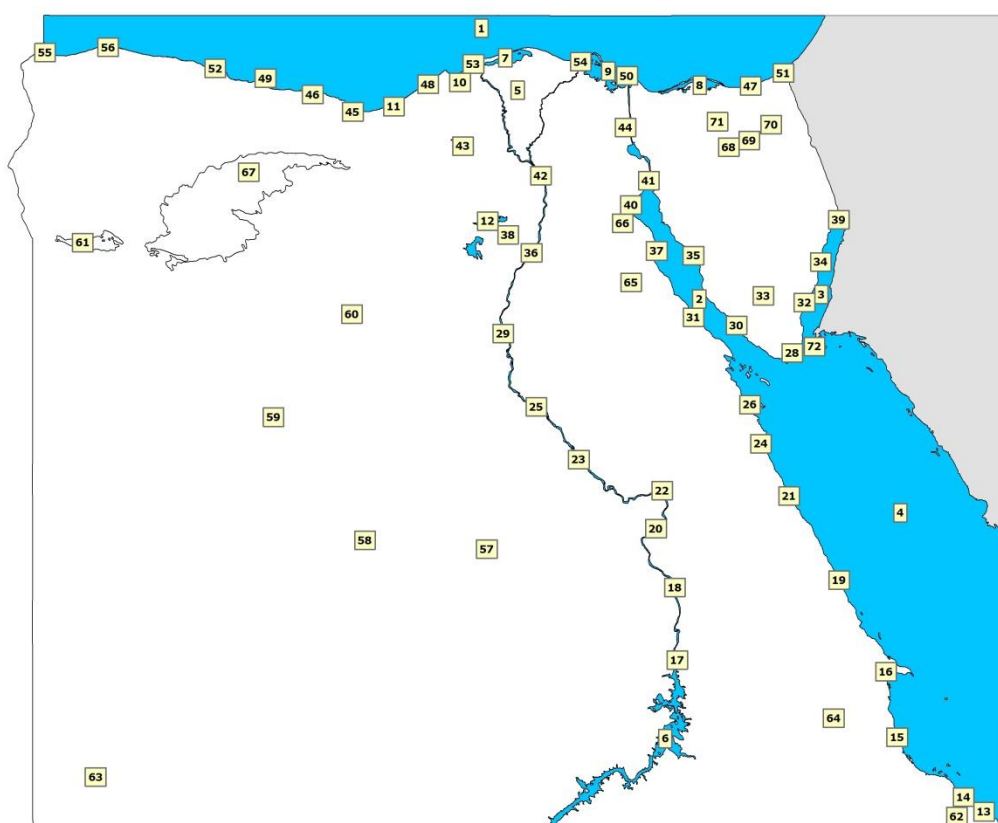
- Schipper, J., Chanson, J. S., Chiozza, F., Cox, N. A., et al. 2008. The Status of the World's Land and Marine Mammals: Diversity, Threat, and Knowledge. *Science*, 322.
- Sciberras, M., Jenkins, S. R., Kaiser, M. J., Hawkins, S. J. & Pullin, A. S. 2013. Evaluating the biological effectiveness of fully and partially protected marine areas. *Environmental Evidence*, 2, 1-31.
- Seiferling, I. S., Proulx, R., Peres-Neto, P. R., Fahrig, L. & Messier, C. 2012. Measuring protected-area isolation and correlations of isolation with land-use intensity and protection status. *Conservation Biology*, 26, 610-618.
- Serra-Diaz, J. M., Ninyerola, M. & Lloret, F. 2012. Coexistence of *Abies alba* (Mill.) – *Fagus sylvatica* (L.) and climate change impact in the Iberian Peninsula: A climatic-niche perspective approach. *Flora - Morphology, Distribution, Functional Ecology of Plants*, 207, 10-18.
- Shcheglovitova, M. & Anderson, R. P. 2013. Estimating optimal complexity for ecological niche models: A jackknife approach for species with small sample sizes. *Ecological Modelling*, 269, 9-17.
- Sinclair, S. J., White, M. D. & Newell, G. R. 2010. How Useful Are Species Distribution Models for Managing Biodiversity under Future Climates? *Ecology and Society*, 15.
- Slater, H. & Michael, E. 2012. Predicting the current and future potential distributions of lymphatic filariasis in Africa using maximum entropy ecological niche modelling. *PLoS One*, 7, e32202.
- Smith, J. B., Schneider, S. H., Oppenheimer, M., Yohe, G. W., Hare, W., Mastrandrea, M. D., Patwardhan, A., Burton, I., Corfee-Morlot, J., Magadza, C. H., Fussler, H. M., Pittock, A. B., Rahman, A., Suarez, A. & van Ypersele, J. P. 2009. Assessing dangerous climate change through an update of the Intergovernmental Panel on Climate Change (IPCC) "reasons for concern". *Proceedings of the National Academy of Sciences U S A*, 106, 4133-4137.
- Soberón, J. & Peterson, A. T. 2005. Interpretation of models of fundamental ecological niches and species' distributional areas. *Biodiversity Informatics*, 2, 1-10.
- Soberón, J. 2007. Grinnellian and Eltonian niches and geographic distributions of species. *Ecology Letters*, 10, 1115-1123.
- Soberón, J. & Nakamura, M. 2009. Niches and distributional areas: concepts, methods, and assumptions. *Proceedings of the National Academy of Sciences U S A*, 106, 19644-19650.
- Soultan, A. A. 2011. *Identifying the current and future distribution of antelopes in Egypt under different scenarios of climate change*. M.Sc. thesis, University of East Anglia, UK.
- Spasojevic, M. J., Grace, J. B., Harrison, S., Damschen, E. I. & Salguero-Gómez, R. 2014. Functional diversity supports the physiological tolerance hypothesis for plant species richness along climatic gradients. *Journal of Ecology*, 102, 447-455.
- Srujana, T. S., Konduri, R. B. & Rao, B. S. S. 2012. Phytochemical investigation and biological activity of leaves extract of plant *Boswellia serrata*. *The Pharma Innovation*, 1, 22-46.
- Stanton, J. C., Pearson, R. G., Horning, N., Ersts, P. & Reşit Akçakaya, H. 2012. Combining static and dynamic variables in species distribution models under climate change. *Methods in Ecology and Evolution*, 3, 349-357.
- Stanton, J. C., Shoemaker, K. T., Pearson, R. G. & Akçakaya, H. R. 2015. Warning times for species extinctions due to climate change. *Global Change Biology*, 21, 1066-77.
- Stockwell, D. R. B. 2006. Improving ecological niche models by data mining large environmental datasets for surrogate models. *Ecological Modelling*, 192, 188-196.
- Stuart, S. N., Chanson, J. S., Cox, N. A., Young, B. E., Rodrigues, A. S. L., Fischman, D. L. & Waller, R. W. 2004. Status and Trends of Amphibian Declines and Extinctions Worldwide. *Science*, 306.

- Syfert, M. M., Smith, M. J. & Coomes, D. A. 2013. The Effects of Sampling Bias and Model Complexity on the Predictive Performance of MaxEnt Species Distribution Models. *PLoS ONE*, 8, e55158.
- Syfert, M. M., Joppa, L., Smith, M. J., Coomes, D. A., Bachman, S. P. & Brummitt, N. A. 2014. Using species distribution models to inform IUCN Red List assessments. *Biological Conservation*, 177, 174-184.
- Thalmann, D. J. K., Kikodze, D., Khutsishvili, M., Kharazishvili, D., Guisan, A., Broennimann, O. & Müller-Schärer, H. 2015. Areas of high conservation value in Georgia: present and future threats by invasive alien plants. *Biological Invasions*, 17, 1041-1054.
- Thomas, C. D. & Lennon, J. J. 1999. Birds extend their ranges northwards. *Nature*, 399, 312.
- Thomas, C. D., Cameron, A., Green, R. E., Bakkenes, M., Beaumont, L. J., Collingham, Y. C., Erasmus, B. F. N., Siqueira, M. F. d., Grainger, A., Hannah, L., Hughes, L., Huntley, B., Albert S. van Jaarsveld, Midgley, G. F., Miles, L., Ortega-Huerta, M. A., Peterson, A. T., Phillips, O. L. & Williams, S. E. 2004. Extinction risk from climate change. *Nature*, 427, 145-148.
- Thomas, C. D., Gillingham, P. K., Bradbury, R. B., Roy, D. B., Anderson, B. J., Baxter, J. M., Bourn, N. A., Crick, H. Q., Findon, R. A., Fox, R., Hodgson, J. A., Holt, A. R., Morecroft, M. D., O'Hanlon, N. J., Oliver, T. H., Pearce-Higgins, J. W., Procter, D. A., Thomas, J. A., Walker, K. J., Walmsley, C. A., Wilson, R. J. & Hill, J. K. 2012. Protected areas facilitate species' range expansions. *PNAS*, 109, 14063-14068.
- Thomas, C. d. & Gillingham, p. k. 2015. The performance of protected reas for biodiversity under climate change. *Biological Journal of the Linnean Society*, 115, 718-730.
- Thuiller, W. 2004. Patterns and uncertainties of species' range shifts under climate change. *Global Change Biology*, 10, 2020-2027.
- Thuiller, W., Lavorel, S., Araujo, M. B., Sykes, M. T. & Prentice, I. C. 2005. Climate change threats to plant diversity in Europe. *PNAS*, 102, 8245-8250.
- Thuiller, W., Richardson, D. M., Rouget, M., Proches, S. & Wilson, J. R. U. 2006. Interactions Between Environment, Species Traits, and Human Uses Describe Patterns of Plant Invasions. *Ecology*, 87, 1755-1769.
- Thuiller, W. 2007. Climate change and the ecologist. *Nature*, 448, 550-552.
- Thuiller, W., Lafourcade, B., Engler, R. & Araújo, M. B. 2009. BIOMOD - a platform for ensemble forecasting of species distributions. *Ecography*, 32, 369-373.
- Traba, J., García de la Morena, E. L., Morales, M. B. & Suárez, F. 2007. Determining high value areas for steppe birds in Spain: hot spots, complementarity and the efficiency of protected areas. *Biodiversity and Conservation*, 16, 3255-3275.
- Trethowan, P. D., Robertson, M. P. & McConnachie, A. J. 2011. Ecological niche modelling of an invasive alien plant and its potential biological control agents. *South African Journal of Botany*, 77, 137-146.
- Turner, J., Connolley, W. M., Lachlan-Cope, T. A. & Marshall, G. J. 2006. The performance of the Hadley Centre Climate Model (HadCM3) in high southern latitudes. *International Journal of Climatology*, 26, 91-112.
- Uehara-Prado, M., Brown, K. S. & Freitas, A. V. L. 2007. Species richness, composition and abundance of fruit-feeding butterflies in the Brazilian Atlantic Forest: comparison between a fragmented and a continuous landscape. *Global Ecology and Biogeography*, 0, 061120101210014-???
- Urban, M. C. 2015. Accelerating extinction risk from climate change. *Science*, 348, 571-573.
- Urban, M. C., Bocedi, G., Hendry, A. P., Mihoub, J. B., Pe'er, G., Singer, A., Bridle, J. R., Crozier, L. G., De Meester, L., Godsoe, W., Gonzalez, A., Hellmann, J. J., Holt, R. D., Huth, A., Johst, K., Krug, C. B., Leadley, P. W., Palmer, S. C., Pantel, J. H., Schmitz, A., Zollner, P. A. & Travis, J. M. 2016. Improving the forecast for biodiversity under climate change. *Science*, 353.

- van Proosdij, A. S. J., Sosef, M. S. M., Wieringa, J. J. & Raes, N. 2015. Minimum required number of specimen records to develop accurate species distribution models. *Ecography*, 38, 001–011.
- van Rheede van Oudtshoorn, K. & van Rooyen, M. W. 1999. *Dispersal Biology of Desert Plants*, Springer-Verlag, Berlin Heidelberg.
- Vandermeer, J. H. 1972. Niche Theory. *Annual Review of Ecology and Systematics*, 3, 107–132.
- VanDerWal, J., Shoo, L. P., Graham, C. & Williams, S. E. 2009. Selecting pseudo-absence data for presence-only distribution modeling: How far should you stray from what you know? *Ecological Modelling*, 220, 589–594.
- Walther, G.-R., Post, E., Convey, P., Menzel, A., Parmesan, C., Beebee, T. J. C., Fromentin, J.-M., Hoegh-Guldberg, O. & Bairlein, F. 2002. Ecological responses to recent climate change. *Nature*, 416.
- Warren, D. L. & Seifert, S. N. 2011. Warren_Ecological niche modeling in Maxent-the importance of model complexity and the performance of model selection criteria. *Ecological Applications*, 21, 335–342.
- Warren, D. L., Wright, A. N., Seifert, S. N., Shaffer, H. B. & Franklin, J. 2013. Incorporating model complexity and spatial sampling bias into ecological niche models of climate change risks faced by 90 California vertebrate species of concern. *Diversity and Distributions*, 20, 334–343.
- Watson, J. E., Dudley, N., Segan, D. B. & Hockings, M. 2014. The performance and potential of protected areas. *Nature*, 515, 67–73.
- WCS 2005. Last of the Wild Project, Version 2, 2005 (LWP-2): Global Human Influence Index (HII) Dataset (Geographic). Palisades, NY: Wildlife Conservation Society - WCS and Center for International Earth Science Information Network - CIESIN. NASA Socioeconomic Data and Applications Center (SEDAC).
- White, A. E. 2016. Geographical Barriers and Dispersal Propensity Interact to Limit Range Expansions of Himalayan Birds. *The American Naturalist*, 188, 99–112.
- Whitfield, J. 2005. Biogeography: Is Everything Everywhere? *SCIENCE*, 310, 960–961.
- Williams, J. C., ReVelle, C. S. & Levin, S. A. 2005. Spatial attributes and reserve design models: A review. *Environmental Modeling & Assessment*, 10, 163–181.
- Williams, P. H. 2001. WORLDMAP Version 4. Priority areas for biodiversity. <http://www.nhm.ac.uk/science/projects/worldmap>.
- Williamson, M. & Fitter, A. 1996. The Varying Success of Invaders. *Ecology*, 77, 1661–1666.
- Willis, F., Moat, J. & Paton, A. 2003. Defining a role for herbarium data in Red List assessments: a case study of *Plectranthus* from eastern and southern tropical Africa. *Biodiversity and Conservation*, 12, 1537–1552.
- Wilson, K. A., Underwood, E. C., Morrison, S. A., Klausmeyer, K. R., Murdoch, W. W., Reyers, B., Wardell-Johnson, G., Marquet, P. A., Rundel, P. W., McBride, M. F., Pressey, R. L., Bode, M., Hoekstra, J. M., Andelman, S., Looker, M., Rondinini, C., Kareiva, P., Shaw, M. R. & Possingham, H. P. 2007. Conserving Biodiversity Efficiently: What to Do, Where, and When. *PLoS One*, 5, e223.
- Wisz, M. S. & Guisan, A. 2009. Do pseudo-absence selection strategies influence species distribution models and their predictions? An information-theoretic approach based on simulated data. *BMC Ecol*, 9, 8.
- Wisz, M. S., Pottier, J., Kissling, W. D., Pellissier, L., Lenoir, J., Damgaard, C. F., Dormann, C. F., Forchhammer, M. C., Grytnes, J. A., Guisan, A., Heikkinen, R. K., Høye, T. T., Kuhn, I., Luoto, M., Maiorano, L., Nilsson, M. C., Normand, S., Ockinger, E., Schmidt, N. M., Termansen, M., Timmermann, A., Wardle, D. A., Aastrup, P. & Svenning, J. C. 2013. The role of biotic interactions in shaping distributions and realised assemblages of species: implications for species distribution modelling. *Biological Reviews*, 88, 15–30.

- Wright, A. N., Schwartz, M. W., Hijmans, R. J. & Shaffer, H. B. 2016. Advances in climate models from CMIP3 to CMIP5 do not change predictions of future habitat suitability for California reptiles and amphibians. *Climate Change*, 134.
- Wulff, A. S., Hollingsworth, P. M., Ahrends, A., Jaffre, T., Veillon, J. M., L'Huillier, L. & Fogliani, B. 2013. Conservation priorities in a biodiversity hotspot: analysis of narrow endemic plant species in New Caledonia. *PLoS One*, 8, e73371.
- Yackulic, C. B., Chandler, R., Zipkin, E. F., Royle, J. A., Nichols, J. D., Campbell Grant, E. H., Veran, S. & O'Hara, R. B. 2013. Presence-only modelling using MAXENT: when can we trust the inferences? *Methods in Ecology and Evolution*, 4, 236-243.
- Young, A. M. & Larson, B. M. 2011. Clarifying debates in invasion biology: a survey of invasion biologists. *Environmental Research*, 111, 893-8.
- Zamin, T. J., Baillie, J. E., Miller, R. M., Rodriguez, J. P., Ardid, A. & Collen, B. 2010. National red listing beyond the 2010 target. *Conservation Biology*, 24, 1012-20.
- Zhang, M.-G., Zhou, Z.-K., Chen, W.-Y., Slik, J. W. F., Cannon, C. H. & Raes, N. 2012. Using species distribution modeling to improve conservation and land use planning of Yunnan, China. *Biological Conservation*, 153, 257-264.
- Zhang, M.-G., Zhou, Z.-K., Chen, W.-Y., Cannon, C. H., Raes, N., Slik, J. W. F. & Bradley, B. 2014. Major declines of woody plant species ranges under climate change in Yunnan, China. *Diversity and Distributions*, 20, 405-415.
- Zhang, X. C. & Nearing, M. A. 2005. Impact of climate change on soil erosion, runoff, and wheat productivity in central Oklahoma. *Catena*, 61, 185-195.
- Zhu, M., Xi, X., Hctor, T. S. & Volk, M. 2015. Integrating conservation costs into sea level rise adaptive conservation prioritization. *Global Ecology and Conservation*, 4, 48-62.

9 Appendices



1	The Mediterranean Sea
2	The Suez Gulf
3	The Aqaba Gulf
4	The Red Sea
5	The Nile Delta
6	Lake Nasser
7	Lake Brullus
8	Lake Bardawil
9	Lake Manzala
10	Lake Idku
11	Lake Mariut
12	Lake Qarun
13	Halayeb
14	Abu Ramad
15	Al-Shalatein
16	Berenice
17	Aswan
18	Edfu
19	Mersa Alam
20	Luxor
21	El-Quseir
22	Qena
23	Sohag
24	Safaga

25	Assiut
26	Hurghada
27	Ras Mohamed
28	Sharm El-Sheikh
29	El-Minia
30	El-Tur
31	Ras Gharib
32	Dahab
33	Saint-Katherine
34	Nuweiba
35	Abu Zneima
36	Beni Suef
37	Ras Zaafarana
38	Fayoum
39	Taba
40	Ain Sukhna
41	Suez
42	The greater Cairo
43	Wadi El-Natrun
44	Ismailia
45	El-Alamein
46	El-Dabaa
47	El-Arish
48	Alexandria

49	Ras El-Hekma
50	Port-Said
51	Rafah
52	Mersa Matruh
53	Rosetta
54	Damietta
55	Sallum
56	Sidi Barrani
57	Kharga oasis
58	Dakhla oasis
59	Farafra oasis
60	Bahariya oasis
61	Siwa oasis
62	Gebel Elba area
63	El-Gilf El-Kebir
64	Gebel Abraq area
65	Gebel El-Gallala El-Qibliya
66	Gebel El-Gallala El-Bahariya
67	Qattara Depression
68	Gebel Yillaq
69	El-Hassana
70	Gebel El-Hallal
71	Gebel El-Maghara
72	Tiran & Sanafir islands

Appendix 1 : Egypt's political border and all cities and geographical regions mentioned in this study (El-Gabbas *et al.*, 2016).

Appendix 2: List of the plant species used in this study, together with assessments of their status and distribution within Egypt, their world distribution (according to a standard scheme: see Leach et al 2013, El-Gabbas et al 2016), the number of records in the database, and the mean AUC of the Species Distribution Models created using MaxEnt and k-fold cross-validation (k=10).

Species	Native to Egypt?	World distribution	Distribution within Egypt	Mean AUC	Number of records
<i>Acacia pachyceras</i>	native	restricted	localized	0.982	11
<i>Acacia tortilis</i>	native	narrow	widespread	0.890	242
<i>Achillea fragrantissima</i>	native	restricted	widespread	0.926	239
<i>Achillea santolina</i>	native	narrow	widespread	0.980	13
<i>Adonis dentata</i>	native	narrow	narrow	0.972	33
<i>Aerva javanica</i>	native	widespread	widespread	0.911	175
<i>Agathophora alopecuroides</i>	native	narrow	narrow	0.891	26
<i>Alhagi graecorum</i>	native	narrow	widespread	0.806	100
<i>Anabasis articulata</i>	native	narrow	widespread	0.924	126
<i>Anagallis arvensis</i>	native	widespread	widespread	0.889	119
<i>Anastatica hierochuntica</i>	native	narrow	widespread	0.841	31
<i>Andrachne aspera</i>	native	narrow	widespread	0.941	31
<i>Artemisia judaica</i>	native	narrow	widespread	0.930	684
<i>Artemisia monosperma</i>	native	restricted	narrow	0.946	115
<i>Asclepias sinaica</i>	native	near-endemic	narrow	0.973	31
<i>Asparagus stipularis</i>	native	narrow	widespread	0.987	20
<i>Atriplex halimus</i>	native	narrow	narrow	0.898	125
<i>Avena barbata</i>	native	narrow	widespread	0.914	22
<i>Ballota undulata</i>	native	restricted	narrow	0.929	124
<i>Bassia muricata</i>	native	narrow	widespread	0.853	83
<i>Calendula arvensis</i>	native	widespread	widespread	0.895	66
<i>Calotropis procera</i>	native	widespread	widespread	0.858	228
<i>Capparis spinosa</i>	native	narrow	localized	0.859	241
<i>Chenopodium album</i>	native	widespread	widespread	0.926	166
<i>Chenopodium murale</i>	native	widespread	widespread	0.880	319
<i>Chiliadenus montanus</i>	native	near-endemic	narrow	0.910	88
<i>Citrullus colocynthis</i>	native	narrow	widespread	0.879	168
<i>Cleome amblyocarpa</i>	native	narrow	widespread	0.916	71
<i>Colutea istria</i>	native	restricted	localized	0.910	24
<i>Cornulaca monacantha</i>	native	widespread	widespread	0.914	93
<i>Cymbopogon schoenanthus</i>	native	narrow	narrow	0.835	15
<i>Cynodon dactylon</i>	native	widespread	widespread	0.880	240
<i>Deverra tortuosa</i>	native	restricted	widespread	0.940	141
<i>Deverra triradiata</i>	native	restricted	narrow	0.832	64
<i>Diplotaxis acris</i>	native	narrow	narrow	0.916	60
<i>Diplotaxis eruroides</i>	native	widespread	widespread	0.898	12
<i>Diplotaxis harra</i>	native	restricted	narrow	0.911	147
<i>Echinops spinosus</i>	native	narrow	widespread	0.915	213

<i>Ephedra alata</i>	native	narrow	widespread	0.850	46
<i>Eruca sativa</i>	non-native	widespread	widespread	0.938	96
<i>Euphorbia peplis</i>	native	narrow	narrow	0.960	13
<i>Euphorbia retusa</i>	native	narrow	narrow	0.885	114
<i>Fagonia arabica</i>	native	restricted	widespread	0.910	294
<i>Fagonia glutinosa</i>	native	narrow	narrow	0.902	125
<i>Fagonia mollis</i>	native	near-endemic	narrow	0.924	698
<i>Farsetia aegyptia</i>	native	narrow	widespread	0.906	114
<i>Globularia arabica</i>	native	restricted	narrow	0.923	51
<i>Gypsophila capillaris</i>	native	narrow	localized	0.885	59
<i>Halocnemum strobilaceum</i>	native	widespread	widespread	0.897	53
<i>Haloxylon salicornicum</i>	native	narrow	widespread	0.943	242
<i>Haloxylon scoparium</i>	native	narrow	narrow	0.882	36
<i>Haplophyllum tuberculatum</i>	native	narrow	widespread	0.889	73
<i>Heliotropium arbainese</i>	native	narrow	widespread	0.877	146
<i>Herniaria hirsuta</i>	native	widespread	widespread	0.846	13
<i>Hyoscyamus muticus</i>	native	narrow	widespread	0.877	143
<i>Imperata cylindrica</i>	native	widespread	widespread	0.835	109
<i>Iphiona mucronata</i>	native	near-endemic	narrow	0.904	53
<i>Juncus rigidus</i>	native	narrow	widespread	0.855	235
<i>Lavandula pubescens</i>	native	restricted	narrow	0.986	15
<i>Lycium shawii</i>	native	restricted	widespread	0.905	161
<i>Malva parviflora</i>	native	widespread	widespread	0.866	165
<i>Melilotus indicus</i>	native	widespread	widespread	0.906	239
<i>Mesembryanthemum crystallinum</i>	native	widespread	widespread	0.934	38
<i>Mesembryanthemum forsskaolli</i>	native	restricted	widespread	0.833	13
<i>Mesembryanthemum nodiflorum</i>	native	narrow	narrow	0.912	79
<i>Moltkiopsis ciliata</i>	native	narrow	widespread	0.931	181
<i>Nitraria retusa</i>	native	narrow	widespread	0.920	100
<i>Noaea mucronata</i>	native	narrow	narrow	0.860	47
<i>Ochradenus baccatus</i>	native	narrow	widespread	0.898	137
<i>Orobanche cernua</i>	native	widespread	widespread	0.909	42
<i>Pancratium sickenbergeri</i>	native	near-endemic	narrow	0.930	42
<i>Panicum turgidum</i>	native	narrow	widespread	0.906	164
<i>Paronychia arabica</i>	native	narrow	narrow	0.888	169
<i>Paronychia argentea</i>	native	narrow	narrow	0.867	17
<i>Peganum harmala</i>	native	widespread	narrow	0.913	138
<i>Pergularia tomentosa</i>	native	narrow	widespread	0.850	362
<i>Phoenix dactylifera</i>	native	widespread	widespread	0.826	64
<i>Phragmites australis</i>	native	narrow	narrow	0.858	128
<i>Plantago afra</i>	native	narrow	widespread	0.908	43
<i>Plantago ovata</i>	native	narrow	widespread	0.904	36
<i>Pluchea dioscoridis</i>	native	narrow	widespread	0.802	62
<i>Polycarpea repens</i>	native	narrow	narrow	0.895	172
<i>Polycarpon succulentum</i>	native	restricted	widespread	0.908	94
<i>Pulicaria undulata</i>	native	narrow	widespread	0.890	271

<i>Reaumuria hirtella</i>	native	restricted	localized	0.948	109
<i>Reichardia tingitana</i>	native	widespread	widespread	0.902	120
<i>Retama raetam</i>	native	narrow	narrow	0.915	261
<i>Salvia aegyptiaca</i>	native	narrow	widespread	0.911	69
<i>Salvia lanigera</i>	native	narrow	narrow	0.877	44
<i>Senecio glaucus</i>	native	narrow	widespread	0.914	159
<i>Seriphidium herba-album</i>	native	narrow	widespread	0.940	267
<i>Silene succulenta</i>	native	restricted	localized	0.857	25
<i>Silene villosa</i>	native	narrow	widespread	0.908	51
<i>Sisymbrium irio</i>	native	widespread	widespread	0.880	56
<i>Solanum elaeagnifolium</i>	non-native	widespread	narrow	0.989	24
<i>Solanum nigrum</i>	native	endemic	localized	0.883	199
<i>Stachys aegyptiaca</i>	native	near-endemic	narrow	0.950	168
<i>Stipagrostis scoparia</i>	native	restricted	widespread	0.930	49
<i>Tamarix aphylla</i>	native	narrow	widespread	0.823	86
<i>Tamarix nilotica</i>	native	narrow	widespread	0.853	332
<i>Tephrosia purpurea</i>	native	near-endemic	widespread	0.881	78
<i>Teucrium leucocladum</i>	native	near-endemic	narrow	0.943	66
<i>Teucrium polium</i>	native	narrow	narrow	0.868	133
<i>Thymelaea hirsuta</i>	native	narrow	widespread	0.920	61
<i>Tribulus terrestris</i>	native	widespread	widespread	0.869	65
<i>Trifolium resupinatum</i>	native	narrow	widespread	0.930	126
<i>Trigonella stellata</i>	native	narrow	widespread	0.922	62
<i>Urginea maritima</i>	native	narrow	narrow	0.918	24
<i>Urtica urens</i>	native	widespread	widespread	0.919	34
<i>Vicia sativa</i>	native	widespread	localized	0.851	68
<i>Zilla spinosa</i>	native	narrow	widespread	0.919	632
<i>Zygophyllum album</i>	native	narrow	widespread	0.920	115
<i>Zygophyllum coccineum</i>	native	near-endemic	widespread	0.870	488
<i>Zygophyllum dumosum</i>	native	near-endemic	narrow	0.971	27

Appendix 3: Preliminary species classification based on IUCN Red List categories according to current range size (first based on EOO_{records} alone, and then on AOO_{records} alone under three different assumptions about the minimum distance among 'locations'). These are preliminary because a lack of data means there is no evidence for 'continuing decline' or 'extreme fluctuations'.

Species	EOO	AOO >20 km ²	AOO >50 km ²	AOO >100 km ²
<i>Acacia pachyceras</i>	LC	VU	EN	EN
<i>Acacia tortilis</i>	LC	LC	LC	LC
<i>Achillea fragrantissima</i>	LC	LC	LC	LC
<i>Achillea santolina</i>	LC	VU	VU	EN
<i>Adonis dentata</i>	LC	LC	LC	VU
<i>Aerva javanica</i>	LC	LC	LC	LC
<i>Agathophora alopecuroides</i>	LC	LC	LC	VU
<i>Alhagi graecorum</i>	LC	LC	LC	LC
<i>Anabasis articulata</i>	LC	LC	LC	LC
<i>Anagallis arvensis</i>	LC	LC	LC	LC
<i>Anastatica hierochuntica</i>	LC	LC	LC	LC
<i>Andrachne aspera</i>	LC	LC	LC	VU
<i>Artemisia judaica</i>	LC	LC	LC	LC
<i>Artemisia monosperma</i>	LC	LC	LC	LC
<i>Asclepias sinaica</i>	LC	VU	VU	VU
<i>Asparagus stipularis</i>	LC	VU	VU	EN
<i>Atriplex halimus</i>	LC	LC	LC	LC
<i>Avena barbata</i>	LC	LC	VU	EN
<i>Ballota undulata</i>	LC	LC	LC	LC
<i>Bassia muricata</i>	LC	LC	LC	LC
<i>Calendula arvensis</i>	LC	LC	LC	LC
<i>Calotropis procera</i>	LC	LC	LC	LC
<i>Capparis spinosa</i>	LC	LC	LC	LC
<i>Chenopodium album</i>	LC	LC	LC	LC
<i>Chenopodium murale</i>	LC	LC	LC	LC
<i>Chiliadenus montanus</i>	LC	LC	LC	LC
<i>Citrullus colocynthis</i>	LC	LC	LC	LC
<i>Cleome amblyocarpa</i>	LC	LC	LC	LC
<i>Colutea istria</i>	LC	LC	VU	VU
<i>Cornulaca monacantha</i>	LC	LC	LC	LC
<i>Cymbopogon schoenanthus</i>	LC	VU	VU	VU
<i>Cynodon dactylon</i>	LC	LC	LC	LC
<i>Deverra tortuosa</i>	LC	LC	LC	LC
<i>Deverra triradiata</i>	LC	LC	LC	VU
<i>Diplotaxis acris</i>	LC	LC	LC	LC
<i>Diplotaxis eruroides</i>	LC	VU	VU	VU
<i>Diplotaxis harra</i>	LC	LC	LC	LC
<i>Echinops spinosus</i>	LC	LC	LC	LC
<i>Ephedra alata</i>	LC	LC	LC	LC
<i>Eruca sativa</i>	LC	LC	LC	LC
<i>Euphorbia peplis</i>	LC	VU	EN	EN

<i>Euphorbia retusa</i>	LC	LC	LC	LC
<i>Fagonia arabica</i>	LC	LC	LC	LC
<i>Fagonia glutinosa</i>	LC	LC	LC	LC
<i>Fagonia mollis</i>	LC	LC	LC	LC
<i>Farsetia aegyptia</i>	LC	LC	LC	LC
<i>Globularia arabica</i>	LC	LC	LC	LC
<i>Gypsophila capillaris</i>	LC	LC	LC	LC
<i>Halocnemum strobilaceum</i>	LC	LC	LC	LC
<i>Haloxylon salicornicum</i>	LC	LC	LC	LC
<i>Haloxylon scoparium</i>	LC	LC	LC	VU
<i>Haplophyllum tuberculatum</i>	LC	LC	LC	LC
<i>Heliotropium arbainense</i>	LC	LC	LC	LC
<i>Herniaria hirsuta</i>	LC	VU	VU	EN
<i>Hyoscyamus muticus</i>	LC	LC	LC	LC
<i>Imperata cylindrica</i>	LC	LC	LC	LC
<i>Iphiona mucronata</i>	LC	LC	LC	VU
<i>Juncus rigidus</i>	LC	LC	LC	LC
<i>Lavandula pubescens</i>	VU	VU	EN	EN
<i>Lycium shawii</i>	LC	LC	LC	LC
<i>Malva parviflora</i>	LC	LC	LC	LC
<i>Melilotus indicus</i>	LC	LC	LC	LC
<i>Mesembryanthemum crystallinum</i>	LC	LC	LC	VU
<i>Mesembryanthemum forsskaolii</i>	LC	VU	VU	VU
<i>Mesembryanthemum nodiflorum</i>	LC	LC	LC	LC
<i>Moltkiopsis ciliata</i>	LC	LC	LC	LC
<i>Nitraria retusa</i>	LC	LC	LC	LC
<i>Noaea mucronata</i>	LC	LC	LC	VU
<i>Ochradenus baccatus</i>	LC	LC	LC	LC
<i>Orobanche cernua</i>	LC	LC	LC	VU
<i>Pancratium sickenbergeri</i>	LC	LC	LC	VU
<i>Panicum turgidum</i>	LC	LC	LC	LC
<i>Paronychia arabica</i>	LC	LC	LC	LC
<i>Paronychia argentea</i>	LC	LC	VU	VU
<i>Peganum harmala</i>	LC	LC	LC	LC
<i>Pergularia tomentosa</i>	LC	LC	LC	LC
<i>Phoenix dactylifera</i>	LC	LC	LC	LC
<i>Phragmites australis</i>	LC	LC	LC	LC
<i>Plantago afra</i>	LC	LC	LC	VU
<i>Plantago ovata</i>	LC	LC	LC	VU
<i>Pluchea dioscoridis</i>	LC	LC	LC	LC
<i>Polycarpaea repens</i>	LC	LC	LC	LC
<i>Polycarpon succulentum</i>	LC	LC	LC	LC
<i>Pulicaria undulata</i>	LC	LC	LC	LC
<i>Reaumuria hirtella</i>	LC	LC	LC	VU
<i>Reichardia tingitana</i>	LC	LC	LC	LC
<i>Retama raetam</i>	LC	LC	LC	LC

<i>Salvia aegyptiaca</i>	LC	LC	LC	VU
<i>Salvia lanigera</i>	LC	LC	LC	LC
<i>Senecio glaucus</i>	LC	LC	LC	LC
<i>Seriphidium herba-alba</i>	LC	LC	LC	VU
<i>Silene succulenta</i>	LC	LC	VU	VU
<i>Silene villosa</i>	LC	LC	LC	VU
<i>Sisymbrium irio</i>	LC	LC	LC	LC
<i>Solanum elaeagnifolium</i>	VU	EN	EN	EN
<i>Solanum nigrum</i>	LC	LC	LC	LC
<i>Stachys aegyptiaca</i>	LC	LC	LC	VU
<i>Stipagrostis scoparia</i>	LC	LC	LC	VU
<i>Tamarix aphylla</i>	LC	LC	LC	LC
<i>Tamarix nilotica</i>	LC	LC	LC	LC
<i>Tephrosia purpurea</i>	LC	LC	LC	LC
<i>Teucrium leucocladum</i>	LC	LC	LC	VU
<i>Teucrium polium</i>	LC	LC	LC	LC
<i>Thymelaea hirsuta</i>	LC	LC	LC	VU
<i>Tribulus terrestris</i>	LC	LC	LC	VU
<i>Trifolium resupinatum</i>	LC	LC	LC	LC
<i>Trigonella stellata</i>	LC	LC	LC	LC
<i>Urginea maritima</i>	LC	LC	VU	EN
<i>Urtica urens</i>	LC	LC	LC	VU
<i>Vicia sativa</i>	LC	LC	LC	LC
<i>Zilla spinosa</i>	LC	LC	LC	LC
<i>Zygophyllum album</i>	LC	LC	LC	LC
<i>Zygophyllum coccineum</i>	LC	LC	LC	LC
<i>Zygophyllum dumosum</i>	LC	LC	VU	EN

Appendix 4: IUCN Red List assessment based on current records, and, global and national status for each species (before our study).

Species	EOO records (km ²)	AOO records (km ²)	> 20 km	>50 km	>100 km	Global IUCN status	National IUCN status (Egypt)
<i>Acacia pachyceras</i>	21270	40	VUB2(a)	ENB2(a)	ENB2(a)	Not assessed	Not assessed
<i>Acacia tortilis</i>	1162997	744	LC	LC	LC	Not assessed	Not assessed
<i>Achillea fragrantissima</i>	270837	448	LC	LC	LC	Not assessed	Not assessed
<i>Achillea santolina</i>	111185	56	VUB2(a)	VUB2(a)	ENB2(a)	Not assessed	Not assessed
<i>Adonis dentata</i>	190751	104	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Aerva javanica</i>	640164	460	LC	LC	LC	Not assessed	Not assessed
<i>Agathophora alopecuroides</i>	200269	84	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Alhagi graecorum</i>	811639	392	LC	LC	LC	Not assessed	Not assessed
<i>Anabasis articulata</i>	430092	396	LC	LC	LC	Not assessed	Not assessed
<i>Anagallis arvensis</i>	760880	284	LC	LC	LC	Not assessed	Not assessed
<i>Anastatica hierochuntica</i>	418562	104	LC	LC	LC	Not assessed	Not assessed
<i>Andrachne aspera</i>	442148	92	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Artemisia judaica</i>	376669	620	LC	LC	LC	Not assessed	Not assessed
<i>Artemisia monosperma</i>	330417	300	LC	LC	LC	Not assessed	Not assessed
<i>Asclepias sinaica</i>	28886	64	VUB2(a)	VUB2(a)	VUB2(a)	Not assessed	Not assessed
<i>Asparagus stipularis</i>	95950	44	VUB2(a)	VUB2(a)	ENB2(a)	Not assessed	Not assessed
<i>Atriplex halimus</i>	478178	324	LC	LC	LC	Not assessed	Not assessed
<i>Avena barbata</i>	104122	80	LC	VUB2(a)	ENB2(a)	Not assessed	Not assessed
<i>Ballota undulata</i>	245203	264	LC	LC	LC	Not assessed	Not assessed
<i>Bassia muricata</i>	441809	212	LC	LC	LC	Not assessed	Not assessed
<i>Calendula arvensis</i>	666373	220	LC	LC	LC	Not assessed	Not assessed
<i>Calotropis procera</i>	706885	456	LC	LC	LC	Not assessed	Not assessed

<i>Capparis spinosa</i>	703474	540	LC	LC	LC	Not assessed	Not assessed
<i>Chenopodium album</i>	672812	416	LC	LC	LC	Not assessed	Not assessed
<i>Chenopodium murale</i>	827203	832	LC	LC	LC	Not assessed	Not assessed
<i>Chiliadenus montanus</i>	181487	208	LC	LC	LC	Not assessed	Not assessed
<i>Citrullus colocynthis</i>	1095042	560	LC	LC	LC	Not assessed	Not assessed
<i>Cleome amblyocarpa</i>	374194	204	LC	LC	LC	Not assessed	Not assessed
<i>Colutea istria</i>	297815	80	LC	VUB2(a)	VUB2(a)	Not assessed	VU
<i>Cornulaca monacantha</i>	620168	240	LC	LC	LC	Not assessed	Not assessed
<i>Cymbopogon schoenanthus</i>	339998	48	VUB2(a)	VUB2(a)	VUB2(a)	Not assessed	Not assessed
<i>Cynodon dactylon</i>	829680	624	LC	LC	LC	Not assessed	Not assessed
<i>Deverra tortuosa</i>	364913	416	LC	LC	LC	Not assessed	Not assessed
<i>Deverra triradiata</i>	310714	192	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Diplotaxis acris</i>	303063	188	LC	LC	LC	Not assessed	Not assessed
<i>Diplotaxis eruroides</i>	435010	40	VUB2(a)	VUB2(a)	VUB2(a)	Not assessed	Not assessed
<i>Diplotaxis harra</i>	433791	368	LC	LC	LC	Not assessed	Not assessed
<i>Echinops spinosus</i>	689673	460	LC	LC	LC	Not assessed	Not assessed
<i>Ephedra alata</i>	445717	152	LC	LC	LC	LC	Not assessed
<i>Eruca sativa</i>	407014	252	LC	LC	LC	Not assessed	Not assessed
<i>Euphorbia peplis</i>	71525	24	VUB2(a)	ENB2(a)	ENB2(a)	Not assessed	Not assessed
<i>Euphorbia retusa</i>	612728	268	LC	LC	LC	Not assessed	Not assessed
<i>Fagonia arabica</i>	665194	732	LC	LC	LC	Not assessed	Not assessed
<i>Fagonia glutinosa</i>	313347	316	LC	LC	LC	Not assessed	Not assessed
<i>Fagonia mollis</i>	432495	552	LC	LC	LC	Not assessed	Not assessed
<i>Farsetia aegyptia</i>	488726	336	LC	LC	LC	Not assessed	Not assessed
<i>Globularia arabica</i>	530016	148	LC	LC	LC	Not assessed	Not assessed
<i>Gypsophila capillaris</i>	384699	168	LC	LC	LC	Not assessed	Not assessed
<i>Halocnemum strobilaceum</i>	289611	184	LC	LC	LC	Not assessed	Not assessed
<i>Haloxylon salicornicum</i>	312109	460	LC	LC	LC	Not assessed	Not assessed
<i>Haloxylon scoparium</i>	385802	108	LC	LC	VUB2(a)	Not assessed	Not assessed

<i>Haplophyllum tuberculatum</i>	602861	192	LC	LC	LC	Not assessed	Not assessed
<i>Heliotropium arbainese</i>	542344	312	LC	LC	LC	Not assessed	Not assessed
<i>Herniaria hirsuta</i>	96971	48	VUB2(a)	VUB2(a)	ENB2(a)	Not assessed	Not assessed
<i>Hyoscyamus muticus</i>	698566	448	LC	LC	LC	Not assessed	Not assessed
<i>Imperata cylindrica</i>	773361	372	LC	LC	LC	Not assessed	Not assessed
<i>Iphiona mucronata</i>	385745	164	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Juncus rigidus</i>	836760	596	LC	LC	LC	LC	Not assessed
<i>Lavandula pubescens</i>	17588	44	VUB1(a); ENB2(a)	VUB1(a); ENB2(a)	VUB1(a); ENB2(a)	Not assessed	Not assessed
<i>Lycium shawii</i>	468015	600	LC	LC	LC	Not assessed	Not assessed
<i>Malva parviflora</i>	854372	564	LC	LC	LC	Not assessed	Not assessed
<i>Melilotus indicus</i>	736230	628	LC	LC	LC	Not assessed	Not assessed
<i>Mesembryanthemum crystallinum</i>	486322	152	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Mesembryanthemum forsskalii</i>	291418	52	VUB2(a)	VUB2(a)	VUB2(a)	Not assessed	Not assessed
<i>Mesembryanthemum nodiflorum</i>	432349	232	LC	LC	LC	Not assessed	Not assessed
<i>Moltkiopsis ciliata</i>	389468	384	LC	LC	LC	Not assessed	Not assessed
<i>Nitraria retusa</i>	509591	344	LC	LC	LC	Not assessed	Not assessed
<i>Noaea mucronata</i>	372234	136	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Ochradenus baccatus</i>	414153	452	LC	LC	LC	Not assessed	Not assessed
<i>Orobanche cernua</i>	316167	164	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Pancratium sickenbergeri</i>	317658	140	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Panicum turgidum</i>	854530	476	LC	LC	LC	Not assessed	Not assessed
<i>Paronychia arabica</i>	623301	440	LC	LC	LC	Not assessed	Not assessed
<i>Paronychia argentea</i>	551188	68	LC	VUB2(a)	VUB2(a)	Not assessed	Not assessed
<i>Peganum harmala</i>	351830	356	LC	LC	LC	Not assessed	Not assessed
<i>Pergularia tomentosa</i>	985392	680	LC	LC	LC	Not assessed	Not assessed
<i>Phoenix dactylifera</i>	748862	232	LC	LC	LC	Not assessed	Not assessed
<i>Phragmites australis</i>	775300	440	LC	LC	LC	LC	Not assessed
<i>Plantago afra</i>	176343	120	LC	LC	VUB2(a)	Not assessed	Not assessed

<i>Plantago ovata</i>	152940	132	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Pluchea dioscoridis</i>	525265	188	LC	LC	LC	Not assessed	Not assessed
<i>Polycarpaea repens</i>	453199	524	LC	LC	LC	Not assessed	Not assessed
<i>Polycarpon succulentum</i>	480797	228	LC	LC	LC	Not assessed	Not assessed
<i>Pulicaria undulata</i>	642183	732	LC	LC	LC	Not assessed	Not assessed
<i>Reaumuria hirtella</i>	190737	300	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Reichardia tingitana</i>	476684	388	LC	LC	LC	Not assessed	Not assessed
<i>Retama raetam</i>	485490	660	LC	LC	LC	Not assessed	Not assessed
<i>Salvia aegyptiaca</i>	338688	136	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Salvia lanigera</i>	329066	116	LC	LC	LC	Not assessed	Not assessed
<i>Senecio glaucus</i>	535142	376	LC	LC	LC	Not assessed	Not assessed
<i>Seriphidium herba-alba</i>	298231	392	LC	LC	VUB2(a)	Not found	Not assessed
<i>Silene succulenta</i>	221092	80	LC	VUB2(a)	VUB2(a)	Not assessed	Not assessed
<i>Silene villosa</i>	248423	120	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Sisymbrium irio</i>	321706	200	LC	LC	LC	Not assessed	Not assessed
<i>Solanum elaeagnifolium</i>	7498	52	VUB1(a); ENB2(a)	VUB1(a); ENB2(a)	VUB1(a); ENB2(a)	Not assessed	Not assessed
<i>Solanum nigrum</i>	859531	552	LC	LC	LC	Not found	Not assessed
<i>Stachys egyptiaca</i>	274388	348	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Stipagrostis scoparia</i>	333812	140	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Tamarix aphylla</i>	672548	292	LC	LC	LC	Not assessed	Not assessed
<i>Tamarix nilotica</i>	861719	980	LC	LC	LC	LC	Not assessed
<i>Tephrosia purpurea</i>	793145	232	LC	LC	LC	Not assessed	Not assessed
<i>Teucrium leucocladum</i>	130794	208	LC	LC	VUB2(a)	Not assessed	VU
<i>Teucrium polium</i>	396664	332	LC	LC	LC	Not assessed	Not assessed
<i>Thymelaea hirsuta</i>	292766	176	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Tribulus terrestris</i>	532121	200	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Trifolium resupinatum</i>	561346	340	LC	LC	LC	Not assessed	Not assessed
<i>Trigonella stellata</i>	254151	216	LC	LC	LC	Not assessed	Not assessed

<i>Urginea maritima</i>	395417	64	LC	VUB2(a)	ENB2(a)	Not assessed	Not assessed
<i>Urtica urens</i>	248801	128	LC	LC	VUB2(a)	Not assessed	Not assessed
<i>Vicia sativa</i>	643569	228	LC	LC	LC	Not assessed	Not assessed
<i>Zilla spinosa</i>	562613	896	LC	LC	LC	Not assessed	VU
<i>Zygophyllum album</i>	556293	372	LC	LC	LC	Not assessed	Not assessed
<i>Zygophyllum coccineum</i>	734834	804	LC	LC	LC	Not assessed	Not assessed
<i>Zygophyllum dumosum</i>	61718	72	LC	VUB2(a)	ENB2(a)	Not assessed	VU

Appendix 5: Species classification based on IUCN Red List categories according to predicted future changes in range sizes assuming unlimited and no dispersal.

Definitions are: LC (loss <15%), NT (loss >15%), VU (loss >30%), EN (loss >50%), CR (loss >80%).

Unlimited dispersal based on 10 years								No dispersal based on 10 years						
species	current	A2 2020	A2 2050	A2 2080	B2 2020	B2 2050	B2 2080	current	A2 2020	A2 2050	A2 2080	B2 2020	B2 2050	B2 2080
<i>Acacia pachyceras</i>	LC	LC	LC	LC	LC	LC	LC	LC	NT	LC	LC	LC	LC	LC
<i>Acacia tortilis</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Achillea fragrantissima</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Achillea santolina</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Adonis dentata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Aerva javanica</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Agathophora alopecuroides</i>	LC	LC	LC	LC	NT	LC	NT	LC	LC	LC	NT	NT	LC	NT
<i>Alhagi graecorum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Anabasis articulata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Anagallis arvensis</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Anastatica hierochuntica</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Andrachne aspera</i>	LC	LC	LC	NT	LC	LC	LC	LC	LC	LC	NT	LC	LC	LC
<i>Artemisia judaica</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Artemisia monosperma</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Asclepias sinaica</i>	LC	LC	LC	LC	LC	LC	NT	LC	LC	LC	LC	LC	LC	LC
<i>Asparagus stipularis</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Atriplex halimus</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Avena barbata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Ballota undulata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Bassia muricata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Calendula arvensis</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Calotropis procera</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC

<i>Capparis spinosa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Chenopodium album</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Chenopodium murale</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Chiliadenus montanus</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Citrullus colocynthis</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Cleome amblyocarpa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Colutea istria</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Cornulaca monacantha</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Cymbopogon schoenanthus</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Cynodon dactylon</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Deverra tortuosa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	NT	LC	LC
<i>Deverra triradiata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Diploaxis acris</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Diploaxis eruroides</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Diploaxis harra</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Echinops spinosus</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Ephedra alata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Eruca sativa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Euphorbia peplis</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Euphorbia retusa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Fagonia arabica</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Fagonia glutinosa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Fagonia mollis</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Farsetia aegyptia</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Globularia arabica</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Gypsophila capillaris</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Halocnemum strobilaceum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Haloxylon salicornicum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Haloxylon scoparium</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Haplophyllum tuberculatum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC

<i>Heliotropium arbainese</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Herniaria hirsuta</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	NT	LC	LC	LC
<i>Hyoscyamus muticus</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Imperata cylindrica</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Iphiona mucronata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Juncus rigidus</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Lavandula pubescens</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Lycium shawii</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Malva parviflora</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Melilotus indicus</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Mesembryanthemum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Mesembryanthemum forsskaolii</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Mesembryanthemum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Moltkiopsis ciliata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Nitraria retusa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Noaea mucronata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Ochradenus baccatus</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Orobancha cernua</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Pancratium sickenbergeri</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Panicum turgidum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Paronychia arabica</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Paronychia argentea</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Peganum harmala</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Pergularia tomentosa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Phoenix dactylifera</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Phragmites australis</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Plantago afra</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Plantago ovata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Pluchea dioscoridis</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Polycarpaea repens</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC

<i>Polycarpon succulentum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Pulicaria undulata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Reaumuria hirtella</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Reichardia tingitana</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Retama raetam</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Salvia aegyptiaca</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Salvia lanigera</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Senecio glaucus</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Seriphidium herba-album</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Silene succulenta</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Silene villosa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Sisymbrium irio</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Solanum elaeagnifolium</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Solanum nigrum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Stachys aegyptiaca</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Stipagrostis scoparia</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Tamarix aphylla</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Tamarix nilotica</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Tephrosia purpurea</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Teucrium leucocladum</i>	LC	LC	LC	LC	LC	LC	NT	LC	LC	LC	LC	LC	LC	LC
<i>Teucrium polium</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Thymelaea hirsuta</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Tribulus terrestris</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Trifolium resupinatum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Trigonella stellata</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Urginea maritima</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Urtica urens</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Vicia sativa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Zilla spinosa</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Zygophyllum album</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC

<i>Zygophyllum coccineum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC
<i>Zygophyllum dumosum</i>	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC	LC

Appendix 6: Comparison between Egyptian and global (GBIF & Kew) data in terms of the number of records and range size (EOO and AOO).

Species	Egypt records	GBIF records	Kew records	World EOO km ²	World AOO km ²	Egypt EOO records km ²	Egypt AOO records km ²	#records egypt/world (as a %)	AOO egypt/world (as a %)
<i>Acacia pachyceras</i>	11	129	129	2209193	340	21270	40	8.5	11.8
<i>Acacia tortilis</i>	242	1193	900	101107692	1920	1162997	744	26.9	38.8
<i>Achillea fragrantissima</i>	239	295	295	1050120	912	270837	448	81.0	49.1
<i>Achillea santolina</i>	13	171	171	9559108	544	111185	56	7.6	10.3
<i>Adonis dentata</i>	33	454	454	80534398	1024	190751	104	7.3	10.2
<i>Aerva javanica</i>	175	769	900	143932840	2516	640164	460	19.4	18.3
<i>Agathophora alopecuroides</i>	26	302	302	150021	744	200269	84	8.6	11.3
<i>Alhagi graecorum</i>	100	342	342	1059563	968	811639	392	29.2	40.5
<i>Anabasis articulata</i>	126	1473	899	6660620	1780	430092	396	14.0	22.2
<i>Anagallis arvensis</i>	119	90083	900	135020785	2512	760880	284	13.2	11.3
<i>Anastatica hierochuntica</i>	31	181	181	15958520	512	418562	104	17.1	20.3
<i>Andrachne aspera</i>	31	175	175	18643132	528	442148	92	17.7	17.4
<i>Artemisia judaica</i>	684	41	41	2279387	112	376669	620	1668.3	553.6
<i>Artemisia monosperma</i>	115	1063	900	92505	844	330417	300	12.8	35.5
<i>Asclepias sinaica</i>	31	13	13	93124	52	28886	64	238.5	123.1
<i>Asparagus stipularis</i>	20	482	482	3332829	1140	95950	44	4.1	3.9
<i>Atriplex halimus</i>	125	3870	900	223788817	2192	478178	324	13.9	14.8
<i>Avena barbata</i>	22	67084	900	179538655	2420	104122	80	2.4	3.3
<i>Ballota undulata</i>	124	1460	900	29891	1336	245203	264	13.8	19.8
<i>Bassia muricata</i>	83	250	250	1697049	536	441809	212	33.2	39.6
<i>Calendula arvensis</i>	66	14204	900	177469566	2360	666373	220	7.3	9.3
<i>Calotropis procera</i>	228	1265	881	238659918	2344	706885	456	25.9	19.5
<i>Capparis spinosa</i>	241	3077	900	363876327	2268	703474	540	26.8	23.8
<i>Chenopodium album</i>	166	169708	900	79848414	2708	672812	416	18.4	15.4
<i>Chenopodium murale</i>	319	11675	900	162152543	2540	827203	832	35.4	32.8
<i>Chiliadenus montanus</i>	88	7	7	7750	24	181487	208	1257.1	866.7
<i>Citrullus colocynthis</i>	168	1139	900	231615704	2676	1095042	560	18.7	20.9
<i>Cleome amblyocarpa</i>	71	136	136	4263972	424	374194	204	52.2	48.1
<i>Colutea istria</i>	24	122	122	8516539	204	297815	80	19.7	39.2
<i>Cornulaca monacantha</i>	93	35	35	3609009	76	620168	240	265.7	315.8
<i>Cymbopogon schoenanthus</i>	15	235	235	51907235	620	339998	48	6.4	7.7
<i>Cynodon dactylon</i>	240	44461	900	123196220	2400	829680	624	26.7	26.0

<i>Deverra tortuosa</i>	141	480	480	769755	1396	364913	416	29.4	29.8
<i>Deverra triradiata</i>	64	135	135	1056170	420	310714	192	47.4	45.7
<i>Diplotaxis acris</i>	60	323	323	447258	768	303063	188	18.6	24.5
<i>Diplotaxis eruroides</i>	12	9543	900	7058719	2520	435010	40	1.3	1.6
<i>Diplotaxis harra</i>	147	1514	900	22978989	1956	433791	368	16.3	18.8
<i>Echinops spinosus</i>	213	82	82	4390755	220	689673	460	259.8	209.1
<i>Ephedra alata</i>	46	174	174	12369689	320	445717	152	26.4	47.5
<i>Eruca sativa</i>	96	1143	900	178025828	2632	407014	252	10.7	9.6
<i>Euphorbia peplis</i>	13	1647	900	190783979	1772	71525	24	1.4	1.4
<i>Euphorbia retusa</i>	114	73	72	3193945	184	612728	268	158.3	145.7
<i>Fagonia arabica</i>	294	338	338	5872275	724	665194	732	87.0	101.1
<i>Fagonia glutinosa</i>	125	236	236	5868354	568	313347	316	53.0	55.6
<i>Fagonia mollis</i>	698	515	515	73863	1428	432495	552	135.5	38.7
<i>Farsetia aegyptia</i>	114	246	246	9837472	776	488726	336	46.3	43.3
<i>Globularia arabica</i>	51	120	120	1351725	308	530016	148	42.5	48.1
<i>Gypsophila capillaris</i>	59	13	13	662478	44	384699	168	453.8	381.8
<i>Halocnemum strobilaceum</i>	53	301	301	23901121	324	289611	184	17.6	56.8
<i>Haloxylon salicornicum</i>	242	289	289	1841850	712	312109	460	83.7	64.6
<i>Haloxylon scoparium</i>	36	188	188	3807403	408	385802	108	19.1	26.5
<i>Haplophyllum tuberculatum</i>	73	460	459	10624233	1244	602861	192	15.9	15.4
<i>Heliotropium arbainense</i>	146	121	125	1056217	400	542344	312	116.8	78.0
<i>Herniaria hirsuta</i>	13	8283	900	140356576	2848	96971	48	1.4	1.7
<i>Hyoscyamus muticus</i>	143	20	20	7292772	52	698566	448	715.0	861.5
<i>Imperata cylindrica</i>	109	17589	900	87264395	2120	773361	372	12.1	17.5
<i>Iphiona mucronata</i>	53	29	29	91718	68	385745	164	182.8	241.2
<i>Juncus rigidus</i>	235	1053	900	36431782	1472	836760	596	26.1	40.5
<i>Lavandula pubescens</i>	15	81	81	1377915	240	17588	44	18.5	18.3
<i>Lycium shawii</i>	161	492	491	16203262	1204	468015	600	32.8	49.8
<i>Malva parviflora</i>	165	8144	900	100472074	2656	854372	564	18.3	21.2
<i>Melilotus indicus</i>	239	8866	900	95821907	2516	736230	628	26.6	25.0
<i>Mesembryanthemum crystallinum</i>	38	4312	900	23028255	1680	486322	152	4.2	9.0
<i>Mesembryanthemum forsskalii</i>	13	97	97	6329	232	291418	52	13.4	22.4
<i>Mesembryanthemum nodiflorum</i>	79	2958	900	340774273	2568	432349	232	8.8	9.0
<i>Moltkiopsis ciliata</i>	181	193	193	4157744	388	389468	384	93.8	99.0
<i>Nitraria retusa</i>	100	191	191	7519281	444	509591	344	52.4	77.5
<i>Noaea mucronata</i>	47	945	900	4952575	1860	372234	136	5.2	7.3
<i>Ochradenus baccatus</i>	137	580	579	6131238	1320	414153	452	23.7	34.2

<i>Orobanche cernua</i>	42	882	881	75697183	2352	316167	164	4.8	7.0
<i>Pancratium sickenbergeri</i>	42	155	155	15897	228	317658	140	27.1	61.4
<i>Panicum turgidum</i>	164	469	469	17153398	1136	854530	476	35.0	41.9
<i>Paronychia arabica</i>	169	330	330	8912796	680	623301	440	51.2	64.7
<i>Paronychia argentea</i>	17	6134	900	5749439	2644	551188	68	1.9	2.6
<i>Peganum harmala</i>	138	1584	900	312336506	2604	351830	356	15.3	13.7
<i>Pergularia tomentosa</i>	362	231	231	17120467	688	985392	680	156.7	98.8
<i>Phoenix dactylifera</i>	64	1119	898	168401537	1484	748862	232	7.1	15.6
<i>Phragmites australis</i>	128	315892	900	98919561	2860	775300	440	14.2	15.4
<i>Plantago afra</i>	43	6469	900	167327158	2348	176343	120	4.8	5.1
<i>Plantago ovata</i>	36	2997	900	37661642	2460	152940	132	4.0	5.4
<i>Pluchea dioscoridis</i>	62	412	412	86071134	876	525265	188	15.0	21.5
<i>Polycarpaea repens</i>	172	95	95	8085756	232	453199	524	181.1	225.9
<i>Polycarpon succulentum</i>	94	451	451	1104536	616	480797	228	20.8	37.0
<i>Pulicaria undulata</i>	271	73	73	14954994	212	642183	732	371.2	345.3
<i>Reaumuria hirtella</i>	109	741	741	168880	1588	190737	300	14.7	18.9
<i>Reichardia tingitana</i>	120	3978	900	44196498	2052	476684	388	13.3	18.9
<i>Retama raetam</i>	261	2226	899	80981078	1484	485490	660	29.0	44.5
<i>Salvia aegyptiaca</i>	69	623	623	29666098	1548	338688	136	11.1	8.8
<i>Salvia lanigera</i>	44	718	718	23278347	1744	329066	116	6.1	6.7
<i>Senecio glaucus</i>	159	4447	900	53759840	1740	535142	376	17.7	21.6
<i>Seriphidium herba-alba</i>	267	3646	900	10363491	2692	298231	392	29.7	14.6
<i>Silene succulenta</i>	25	452	452	1109210	464	221092	80	5.5	17.2
<i>Silene villosa</i>	51	79	79	5920415	256	248423	120	64.6	46.9
<i>Sisymbrium irio</i>	56	57426	900	108372728	1128	321706	200	6.2	17.7
<i>Solanum elaeagnifolium</i>	24	3131	900	98519030	2408	7498	52	2.7	2.2
<i>Solanum nigrum</i>	199	99111	900	149248658	2608	859531	552	22.1	21.2
<i>Stachys aegyptiaca</i>	168	60	60	3958	180	274388	348	280.0	193.3
<i>Stipagrostis scoparia</i>	49	124	124	1794927	232	333812	140	39.5	60.3
<i>Tamarix aphylla</i>	86	723	723	449551512	1880	672548	292	11.9	15.5
<i>Tamarix nilotica</i>	332	437	437	15101202	1160	861719	980	76.0	84.5
<i>Tephrosia purpurea</i>	78	1889	900	322695798	2388	793145	232	8.7	9.7
<i>Teucrium leucocladum</i>	66	45	45	31039	112	130794	208	146.7	185.7
<i>Teucrium polium</i>	133	11262	900	7098126	2712	396664	332	14.8	12.2
<i>Thymelaea hirsuta</i>	61	6167	900	3512758	2156	292766	176	6.8	8.2
<i>Tribulus terrestris</i>	65	7430	900	82149153	2528	532121	200	7.2	7.9

<i>Trifolium resupinatum</i>	126	5119	900	109333406	2764	561346	340	14.0	12.3
<i>Trigonella stellata</i>	62	708	708	5729368	1592	254151	216	8.8	13.6
<i>Urginea maritima</i>	24	6538	900	50292519	2088	395417	64	2.7	3.1
<i>Urtica urens</i>	34	47085	900	162616140	2448	248801	128	3.8	5.2
<i>Vicia sativa</i>	68	187754	900	122615999	2520	643569	228	7.6	9.0
<i>Zilla spinosa</i>	632	391	391	1255856	872	562613	896	161.6	102.8
<i>Zygophyllum album</i>	115	116	116	6483466	256	556293	372	99.1	145.3
<i>Zygophyllum coccineum</i>	488	53	53	3535638	184	734834	804	920.8	437.0
<i>Zygophyllum dumosum</i>	27	943	900	21049	1600	61718	72	3.0	4.5

Appendix 7: Species classification based on IUCN Red List categories according to predicted future changes in range sizes assuming unlimited dispersal.

Definitions are: LC (loss <15%), NT (loss >15%), VU (loss >30%), EN (loss >50%), CR (loss >80%).

Species	Current model	A2 2020	A2 2050	A2 2080	B2 2020	B2 2050	B2 2080
<i>Acacia pachyceras</i>	LC	LC	LC	LC	LC	LC	LC
<i>Acacia tortilis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Achillea fragrantissima</i>	LC	LC	LC	NT	LC	LC	LC
<i>Achillea santolina</i>	LC	LC	LC	LC	LC	LC	LC
<i>Adonis dentata</i>	LC	LC	NT	LC	LC	NT	LC
<i>Aerva javanica</i>	LC	LC	LC	LC	LC	LC	LC
<i>Agathophora alopecuroides</i>	LC	VU	LC	VU	VU	LC	VU
<i>Alhagi graecorum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Anabasis articulata</i>	LC	LC	LC	NT	LC	LC	VU
<i>Anagallis arvensis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Anastatica hierochuntica</i>	LC	LC	LC	VU	LC	LC	NT
<i>Andrachne aspera</i>	LC	LC	VU	CR	NT	VU	VU
<i>Artemisia judaica</i>	LC	LC	LC	LC	LC	LC	NT
<i>Artemisia monosperma</i>	LC	LC	LC	LC	LC	LC	LC
<i>Asclepias sinaica</i>	LC	NT	LC	VU	NT	LC	EN
<i>Asparagus stipularis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Atriplex halimus</i>	LC	LC	NT	LC	LC	LC	LC
<i>Avena barbata</i>	LC	LC	NT	LC	VU	LC	LC
<i>Ballota undulata</i>	LC	LC	LC	LC	LC	LC	NT
<i>Bassia muricata</i>	LC	LC	LC	LC	LC	LC	LC
<i>Calendula arvensis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Calotropis procera</i>	LC	LC	LC	LC	LC	LC	LC
<i>Capparis spinosa</i>	LC	LC	LC	LC	LC	LC	LC
<i>Chenopodium album</i>	LC	LC	LC	LC	LC	LC	LC
<i>Chenopodium murale</i>	LC	LC	LC	LC	LC	LC	LC
<i>Chiladenus montanus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Citrullus colocynthis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Cleome amblyocarpa</i>	LC	LC	LC	LC	LC	LC	LC
<i>Colutea istria</i>	LC	LC	LC	NT	NT	LC	NT
<i>Cornulaca monacantha</i>	LC	LC	LC	LC	LC	LC	LC
<i>Cymbopogon schoenanthus</i>	LC	VU	LC	LC	LC	VU	LC
<i>Cynodon dactylon</i>	LC	LC	LC	LC	LC	LC	LC
<i>Deverra tortuosa</i>	LC	VU	LC	NT	VU	LC	LC
<i>Deverra triradiata</i>	LC	LC	LC	LC	LC	NT	LC
<i>Diploaxis acris</i>	LC	LC	LC	LC	LC	LC	LC
<i>Diploaxis erucoides</i>	LC	LC	LC	VU	LC	LC	LC
<i>Diploaxis harra</i>	LC	LC	LC	LC	LC	LC	LC
<i>Echinops spinosus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Ephedra alata</i>	LC	LC	LC	LC	NT	LC	LC
<i>Eruca sativa</i>	LC	LC	LC	LC	LC	LC	LC
<i>Euphorbia peplis</i>	LC	LC	LC	LC	LC	LC	LC

<i>Euphorbia retusa</i>	LC	LC	LC	NT	LC	LC	LC
<i>Fagonia arabica</i>	LC	LC	LC	LC	LC	LC	LC
<i>Fagonia glutinosa</i>	LC	LC	LC	VU	LC	LC	LC
<i>Fagonia mollis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Farsetia aegyptia</i>	LC	LC	LC	NT	LC	LC	LC
<i>Globularia arabica</i>	LC	LC	NT	VU	NT	LC	LC
<i>Gypsophila capillaris</i>	LC	LC	LC	LC	LC	LC	LC
<i>Halocnemum strobilaceum</i>	LC	LC	LC	LC	LC	LC	VU
<i>Haloxyton salicornicum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Haloxyton scoparium</i>	LC	LC	LC	LC	LC	LC	LC
<i>Haplophyllum tuberculatum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Heliotropium arbainense</i>	LC	LC	LC	LC	LC	LC	LC
<i>Herniaria hirsuta</i>	LC	LC	LC	VU	LC	LC	LC
<i>Hyoscyamus muticus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Imperata cylindrica</i>	LC	LC	LC	LC	LC	LC	LC
<i>Iphiona mucronata</i>	LC	LC	LC	LC	LC	LC	LC
<i>Juncus rigidus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Lavandula pubescens</i>	LC	LC	NT	LC	LC	LC	LC
<i>Lycium shawii</i>	LC	LC	LC	LC	LC	LC	LC
<i>Malva parviflora</i>	LC	LC	LC	LC	LC	LC	LC
<i>Melilotus indicus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Mesembryanthemum crystallinum</i>	LC	LC	LC	VU	LC	NT	LC
<i>Mesembryanthemum forsskaolii</i>	LC	LC	LC	LC	LC	LC	LC
<i>Mesembryanthemum nodiflorum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Moltkiopsis ciliata</i>	LC	LC	LC	VU	LC	LC	VU
<i>Nitraria retusa</i>	LC	LC	LC	LC	LC	LC	LC
<i>Noaea mucronata</i>	LC	LC	LC	LC	LC	LC	LC
<i>Ochradenus baccatus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Orobanche cernua</i>	LC	LC	NT	LC	LC	LC	LC
<i>Pancratium sickenbergeri</i>	LC	LC	LC	LC	LC	LC	LC
<i>Panicum turgidum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Paronychia arabica</i>	LC	LC	LC	LC	LC	LC	LC
<i>Paronychia argentea</i>	LC	LC	LC	LC	LC	VU	LC
<i>Peganum harmala</i>	LC	LC	LC	LC	LC	LC	LC
<i>Pergularia tomentosa</i>	LC	LC	LC	LC	LC	LC	LC
<i>Phoenix dactylifera</i>	LC	LC	LC	LC	LC	LC	LC
<i>Phragmites australis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Plantago afra</i>	LC	LC	LC	NT	LC	LC	LC
<i>Plantago ovata</i>	LC	LC	LC	VU	LC	LC	LC
<i>Pluchea dioscoridis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Polycarpaea repens</i>	LC	LC	LC	LC	LC	LC	LC
<i>Polycarpon succulentum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Pulicaria undulata</i>	LC	LC	LC	LC	LC	LC	LC
<i>Reaumuria hirtella</i>	LC	LC	LC	LC	LC	LC	LC
<i>Reichardia tingitana</i>	LC	LC	LC	LC	LC	LC	LC
<i>Retama raetam</i>	LC	LC	LC	LC	NT	LC	LC

<i>Salvia aegyptiaca</i>	LC	LC	VU	NT	LC	LC	NT
<i>Salvia lanigera</i>	LC	LC	LC	LC	LC	LC	LC
<i>Senecio glaucus</i>	LC	LC	LC	NT	LC	LC	LC
<i>Seriphidium herba-alba</i>	LC	LC	LC	LC	LC	LC	LC
<i>Silene succulenta</i>	LC	LC	LC	LC	LC	LC	LC
<i>Silene villosa</i>	LC	LC	LC	VU	LC	LC	VU
<i>Sisymbrium irio</i>	LC	NT	NT	VU	NT	NT	NT
<i>Solanum elaeagnifolium</i>	LC	LC	LC	LC	LC	LC	LC
<i>Solanum nigrum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Stachys aegyptiaca</i>	LC	LC	NT	NT	LC	LC	LC
<i>Stipagrostis scoparia</i>	LC	LC	LC	LC	LC	LC	LC
<i>Tamarix aphylla</i>	LC	LC	LC	LC	LC	LC	LC
<i>Tamarix nilotica</i>	LC	LC	LC	LC	LC	LC	LC
<i>Tephrosia purpurea</i>	LC	LC	LC	LC	LC	LC	LC
<i>Teucrium leucocladum</i>	LC	LC	LC	LC	LC	LC	EN
<i>Teucrium polium</i>	LC	LC	LC	LC	LC	NT	LC
<i>Thymelaea hirsuta</i>	LC	LC	LC	LC	LC	LC	VU
<i>Tribulus terrestris</i>	LC	LC	LC	LC	LC	LC	LC
<i>Trifolium resupinatum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Trigonella stellata</i>	LC	LC	LC	LC	LC	LC	NT
<i>Urginea maritima</i>	LC	LC	LC	LC	LC	LC	LC
<i>Urtica urens</i>	LC	LC	LC	LC	LC	LC	NT
<i>Vicia sativa</i>	LC	LC	NT	LC	LC	LC	LC
<i>Zilla spinosa</i>	LC	LC	LC	LC	LC	LC	LC
<i>Zygophyllum album</i>	LC	LC	LC	NT	LC	LC	LC
<i>Zygophyllum coccineum</i>	LC	LC	NT	LC	LC	LC	LC
<i>Zygophyllum dumosum</i>	LC	LC	LC	LC	LC	LC	LC

Appendix 8: Species classification based on IUCN Red List categories according to predicted future changes in range sizes assuming no dispersal.

Definitions are: LC (loss <15%), NT (loss >15%), VU (loss >30%), EN (loss >50%), CR (loss >80%).

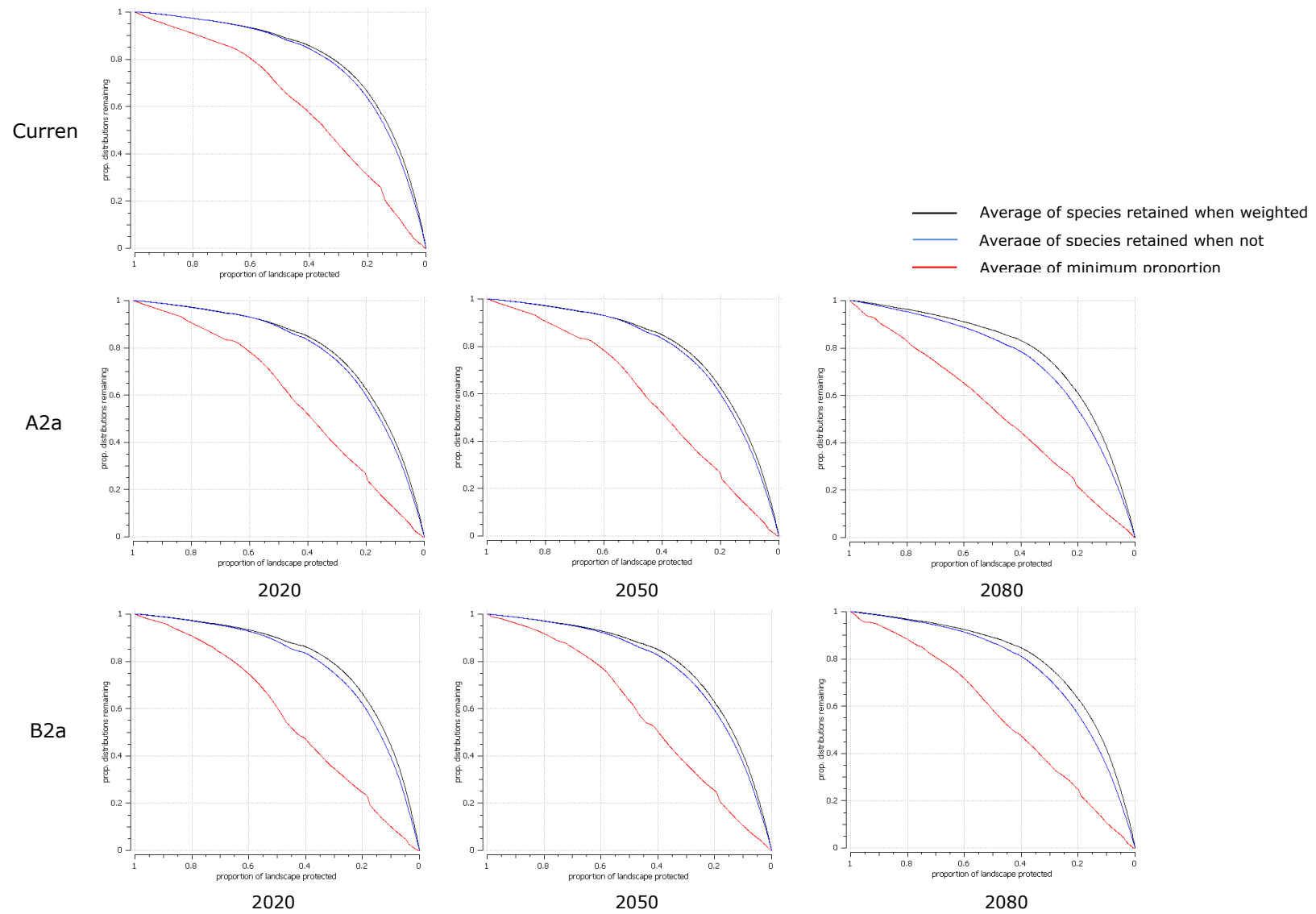
Species	Current model	A2 2020	A2 2050	A2 2080	B2 2020	B2 2050	B2 2080
<i>Acacia pachyceras</i>	LC	EN	LC	LC	NT	LC	LC
<i>Acacia tortilis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Achillea fragrantissima</i>	LC	LC	LC	LC	NT	LC	LC
<i>Achillea santolina</i>	LC	LC	LC	LC	LC	LC	LC
<i>Adonis dentata</i>	LC	LC	NT	LC	LC	NT	LC
<i>Aerva javanica</i>	LC	LC	LC	LC	LC	LC	LC
<i>Agathophora alopecuroides</i>	LC	VU	LC	CR	VU	LC	VU
<i>Alhagi graecorum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Anabasis articulata</i>	LC	NT	LC	NT	NT	LC	VU
<i>Anagallis arvensis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Anastatica hierochuntica</i>	LC	LC	LC	VU	LC	LC	NT
<i>Andrachne aspera</i>	LC	NT	VU	CR	NT	VU	NT
<i>Artemisia judaica</i>	LC	NT	LC	LC	NT	LC	LC
<i>Artemisia monosperma</i>	LC	LC	LC	LC	LC	LC	LC
<i>Asclepias sinaica</i>	LC	NT	LC	VU	NT	LC	VU
<i>Asparagus stipularis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Atriplex halimus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Avena barbata</i>	LC	NT	NT	VU	VU	LC	LC
<i>Ballota undulata</i>	LC	LC	LC	LC	LC	LC	LC
<i>Bassia muricata</i>	LC	LC	LC	LC	LC	LC	LC
<i>Calendula arvensis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Calotropis procera</i>	LC	LC	LC	LC	LC	LC	LC
<i>Capparis spinosa</i>	LC	LC	LC	LC	NT	LC	LC
<i>Chenopodium album</i>	LC	LC	LC	LC	LC	LC	LC
<i>Chenopodium murale</i>	LC	LC	LC	LC	LC	LC	LC
<i>Chiliadenus montanus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Citrullus colocynthis</i>	LC	NT	LC	LC	NT	LC	LC
<i>Cleome amblyocarpa</i>	LC	LC	LC	NT	LC	LC	LC
<i>Colutea istria</i>	LC	NT	LC	VU	NT	LC	NT
<i>Cornulaca monacantha</i>	LC	LC	LC	LC	LC	LC	LC
<i>Cymbopogon schoenanthus</i>	LC	LC	VU	LC	LC	VU	LC
<i>Cynodon dactylon</i>	LC	LC	LC	LC	LC	LC	LC
<i>Deverra tortuosa</i>	LC	NT	VU	LC	VU	VU	LC
<i>Deverra triradiata</i>	LC	LC	LC	LC	NT	LC	LC
<i>Diploaxis acris</i>	LC	LC	LC	LC	LC	LC	LC
<i>Diploaxis eruroides</i>	LC	LC	LC	NT	LC	LC	LC
<i>Diploaxis harra</i>	LC	LC	LC	LC	NT	LC	LC
<i>Echinops spinosus</i>	LC	NT	LC	LC	NT	LC	LC
<i>Ephedra alata</i>	LC	VU	LC	LC	VU	LC	LC
<i>Eruca sativa</i>	LC	NT	LC	LC	NT	LC	LC
<i>Euphorbia peplis</i>	LC	LC	LC	LC	LC	LC	LC

<i>Euphorbia retusa</i>	LC	LC	LC	LC	LC	LC	LC
<i>Fagonia arabica</i>	LC	LC	LC	LC	LC	LC	LC
<i>Fagonia glutinosa</i>	LC	NT	LC	VU	VU	LC	NT
<i>Fagonia mollis</i>	LC	NT	LC	LC	NT	LC	LC
<i>Farsetia aegyptia</i>	LC	NT	LC	LC	NT	LC	LC
<i>Globularia arabica</i>	LC	LC	NT	VU	NT	LC	LC
<i>Gypsophila capillaris</i>	LC	NT	LC	LC	NT	LC	LC
<i>Halocnemum strobilaceum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Haloxylon salicornicum</i>	LC	NT	LC	LC	NT	LC	NT
<i>Haloxylon scoparium</i>	LC	LC	LC	LC	LC	LC	LC
<i>Haplophyllum tuberculatum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Heliotropium arbainense</i>	LC	LC	LC	LC	LC	LC	LC
<i>Herniaria hirsuta</i>	LC	VU	LC	VU	VU	NT	LC
<i>Hyoscyamus muticus</i>	LC	NT	LC	LC	NT	LC	LC
<i>Imperata cylindrica</i>	LC	LC	LC	LC	NT	LC	LC
<i>Iphiona mucronata</i>	LC	LC	LC	LC	NT	LC	LC
<i>Juncus rigidus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Lavandula pubescens</i>	LC	LC	LC	LC	LC	LC	LC
<i>Lycium shawii</i>	LC	NT	LC	LC	NT	LC	LC
<i>Malva parviflora</i>	LC	LC	LC	LC	LC	LC	LC
<i>Melilotus indicus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Mesembryanthemum crystallinum</i>	LC	LC	LC	NT	LC	NT	LC
<i>Mesembryanthemum forsskaolii</i>	LC	LC	LC	LC	LC	LC	LC
<i>Mesembryanthemum nodiflorum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Moltkiopsis ciliata</i>	LC	VU	LC	LC	VU	LC	LC
<i>Nitraria retusa</i>	LC	LC	LC	LC	LC	LC	LC
<i>Noaea mucronata</i>	LC	LC	LC	LC	LC	LC	LC
<i>Ochradenus baccatus</i>	LC	LC	LC	LC	LC	LC	LC
<i>Orobancha cernua</i>	LC	NT	NT	LC	NT	NT	LC
<i>Pancratium sickenbergeri</i>	LC	LC	NT	LC	LC	LC	LC
<i>Panicum turgidum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Paronychia arabica</i>	LC	LC	LC	LC	NT	LC	LC
<i>Paronychia argentea</i>	LC	NT	LC	LC	LC	LC	LC
<i>Peganum harmala</i>	LC	LC	LC	LC	LC	LC	LC
<i>Pergularia tomentosa</i>	LC	LC	LC	LC	NT	LC	LC
<i>Phoenix dactylifera</i>	LC	LC	LC	LC	LC	LC	LC
<i>Phragmites australis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Plantago afra</i>	LC	LC	LC	LC	LC	LC	LC
<i>Plantago ovata</i>	LC	NT	LC	VU	NT	LC	LC
<i>Pluchea dioscoridis</i>	LC	LC	LC	LC	LC	LC	LC
<i>Polycarpaea repens</i>	LC	NT	LC	LC	NT	LC	LC
<i>Polycarpon succulentum</i>	LC	NT	LC	LC	NT	LC	LC
<i>Pulicaria undulata</i>	LC	LC	LC	LC	LC	LC	LC
<i>Reaumuria hirtella</i>	LC	LC	LC	NT	NT	LC	LC
<i>Reichardia tingitana</i>	LC	LC	LC	LC	NT	LC	LC
<i>Retama raetam</i>	LC	NT	LC	LC	NT	NT	LC

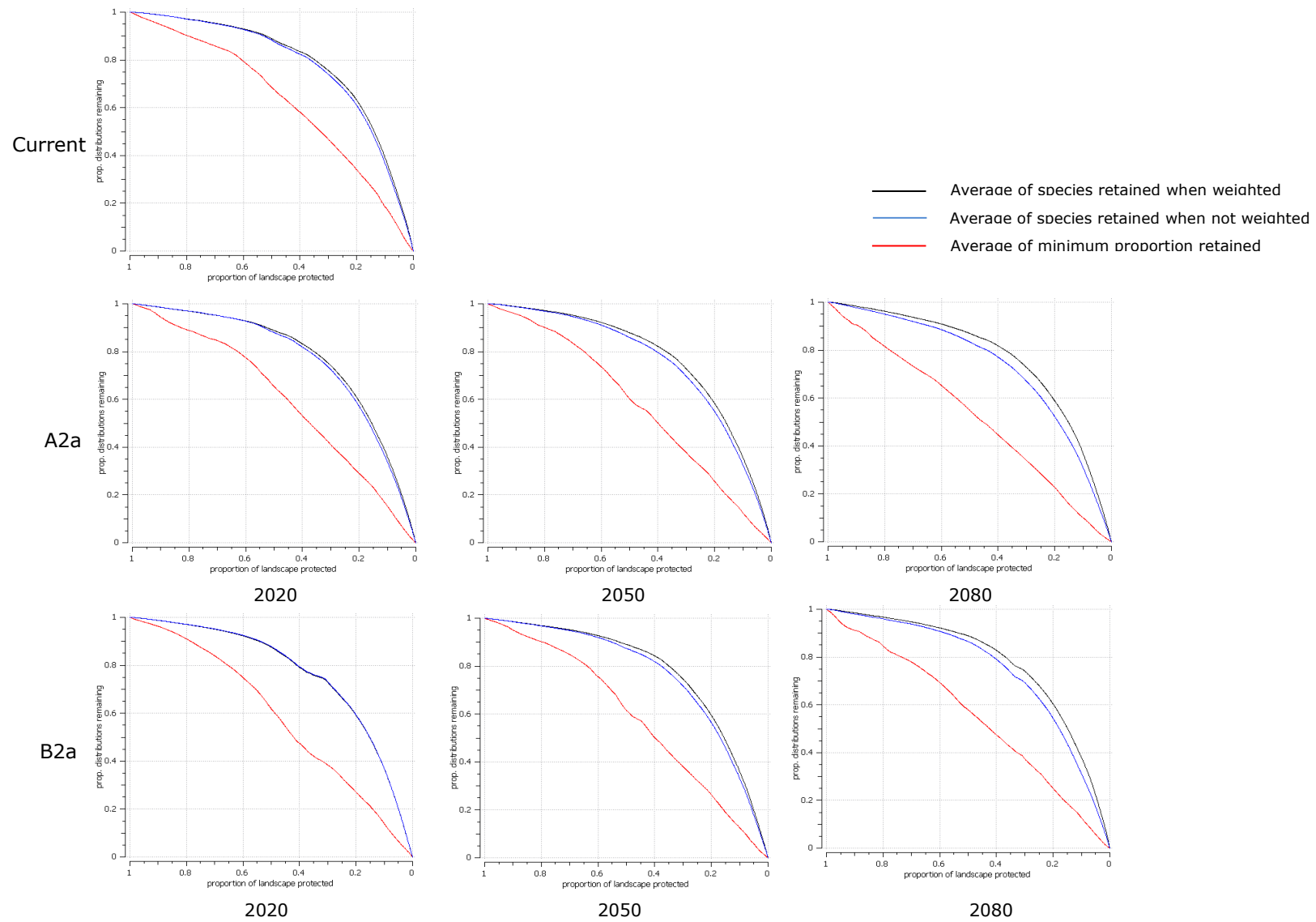
<i>Salvia aegyptiaca</i>	LC	LC	LC	LC	LC	LC	LC
<i>Salvia lanigera</i>	LC	LC	LC	LC	LC	LC	LC
<i>Senecio glaucus</i>	LC	NT	LC	NT	LC	LC	LC
<i>Seriphidium herba-alba</i>	LC	LC	LC	LC	LC	LC	LC
<i>Silene succulenta</i>	LC	LC	LC	LC	LC	LC	LC
<i>Silene villosa</i>	LC	LC	LC	VU	LC	LC	LC
<i>Sisymbrium irio</i>	LC	NT	NT	VU	VU	NT	NT
<i>Solanum elaeagnifolium</i>	LC	LC	LC	LC	LC	LC	LC
<i>Solanum nigrum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Stachys aegyptiaca</i>	LC	NT	NT	VU	NT	LC	NT
<i>Stipagrostis scoparia</i>	LC	LC	LC	LC	LC	LC	VU
<i>Tamarix aphylla</i>	LC	LC	LC	LC	LC	LC	LC
<i>Tamarix nilotica</i>	LC	LC	LC	LC	LC	LC	LC
<i>Tephrosia purpurea</i>	LC	LC	LC	LC	LC	LC	LC
<i>Teucrium leucocladum</i>	LC	NT	LC	LC	NT	LC	LC
<i>Teucrium polium</i>	LC	NT	LC	LC	LC	NT	LC
<i>Thymelaea hirsuta</i>	LC	LC	LC	LC	LC	LC	LC
<i>Tribulus terrestris</i>	LC	LC	LC	LC	LC	LC	LC
<i>Trifolium resupinatum</i>	LC	LC	LC	LC	LC	LC	LC
<i>Trigonella stellata</i>	LC	NT	LC	LC	VU	LC	NT
<i>Urginea maritima</i>	LC	LC	LC	LC	NT	LC	LC
<i>Urtica urens</i>	LC	LC	LC	LC	LC	LC	LC
<i>Vicia sativa</i>	LC	LC	LC	LC	LC	LC	LC
<i>Zilla spinosa</i>	LC	LC	LC	LC	NT	LC	LC
<i>Zygophyllum album</i>	LC	NT	LC	NT	NT	LC	LC
<i>Zygophyllum coccineum</i>	LC	NT	LC	LC	NT	LC	LC
<i>Zygophyllum dumosum</i>	LC	LC	LC	LC	LC	LC	LC

Appendix 9: How studies have used IUCN Red-List Categories and Criteria to choose the best grid-cell size.

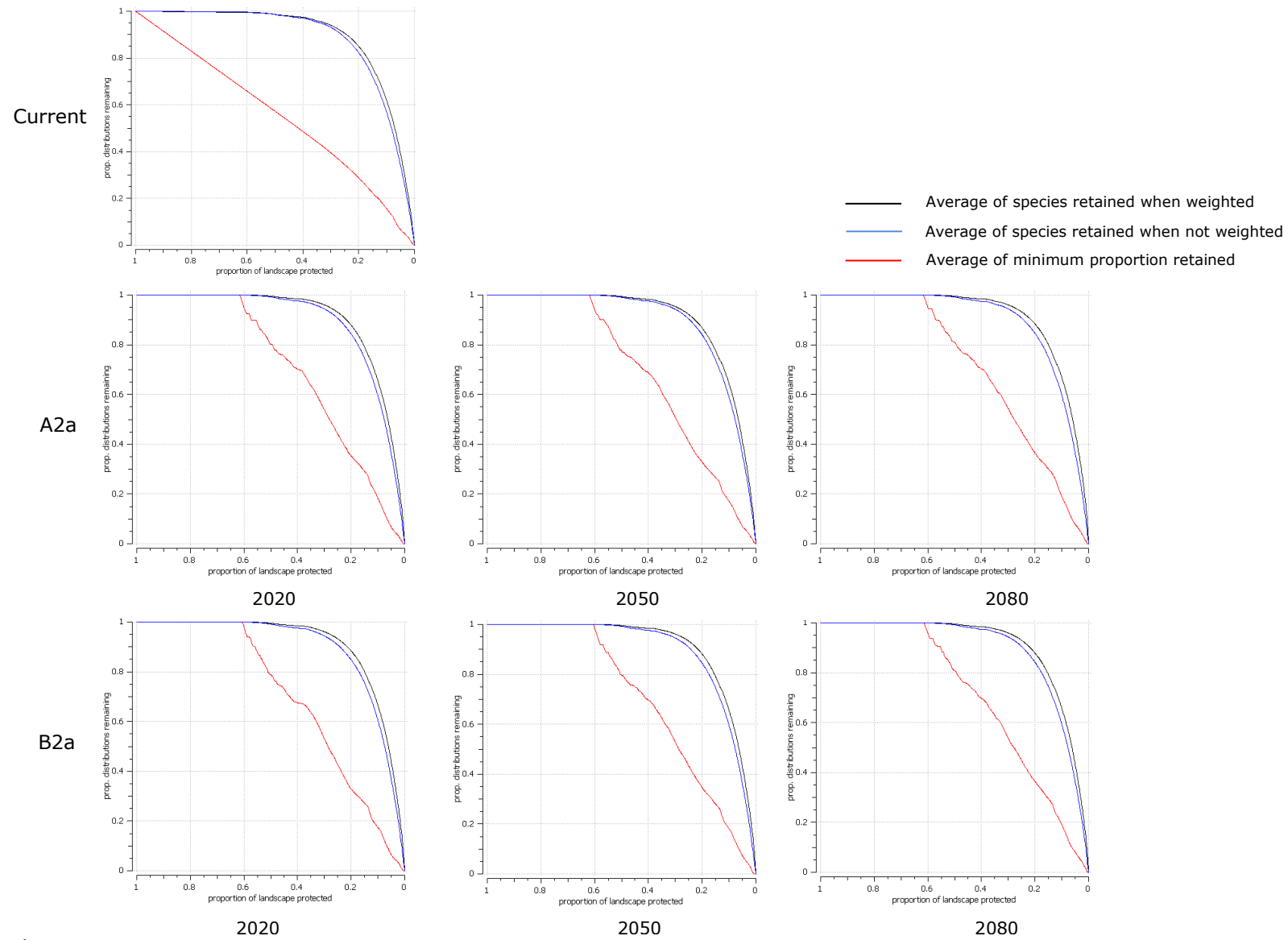
Sources	Kind of species	AOO	Locations	Decision	application of IUCN rules
IUCN Red List 2001	any	2 × 2 km	depends on threat event	'the appropriate scale [for calculating AOO] depends on the taxon in question and the comprehensiveness of the distribution data'	applied all the IUCN rules
Keith et al. 2000	plants	1 m ² to 0.01 ha	Not specified, presumably depends on pattern of records	"because the biologically appropriate scale for measuring area of occupancy does not match the implicit scale that is fixed in the current IUCN thresholds"	used the rules except the grid-cell size
Good <i>et al.</i> , 2006	plants	10 × 10 km	depends on pattern of records, various methods (same as 'subpopulations')	classification of species which are poorly sampled	used non-IUCN methods to measure AOO
Willis <i>et al.</i> 2003, Rivers <i>et al.</i> 2010, Rivers <i>et al.</i> 2011	plants	1/10th of the maximum distance between two points	depends on pattern of records, various methods (same as 'subpopulations')	assumes that the geographic extent of a species influences its subpopulation structure	used the rules except the grid-cell size
Sapir et al. 2003	plants	AOO fixed based on area of study (e.g. 0.05% to 0.005% of the area of study)	1 km ²	this method was applied to determine rare species for conservation in small regions	did not use IUCN rules because mainly interested in rarity, and Israel as a whole is too small
Callmender <i>et al.</i> 2007	plants	10 × 10 km, 1/10 th of maximum distance between records, 3 × 3 km	depends on 10 × 10 km	recommended 3 × 3 km because this gave the highest number of species classified as threatened	used the rules except the grid-cell size
Martín 2009	plants, vertebrates, arthropods, and molluscs	2 × 2 km	depends on the distance between the records	global assessment applied for endemic species	used the IUCN rules
Cardoso <i>et al.</i> 2011	invertebrates (arthropods and spiders)	Depends on habitat patches occupied by the species	depends on AOO	The current Criteria may not be suitable for assessing all invertebrate groups	used non-IUCN methods to measure AOO
Maes <i>et al.</i> 2012	butterflies	1×1 km, 5×5 km	NA	small grids recommended, which produce more threatened species	used the rules except for grid-cell size
This study	plants	2 × 2 for current records, and ~20 km ² for SDM models	depends on the distance between the records	the scale used is based on IUCN recommendations for the current assessments	IUNC rules applied except sub-Criteria because of lack of information



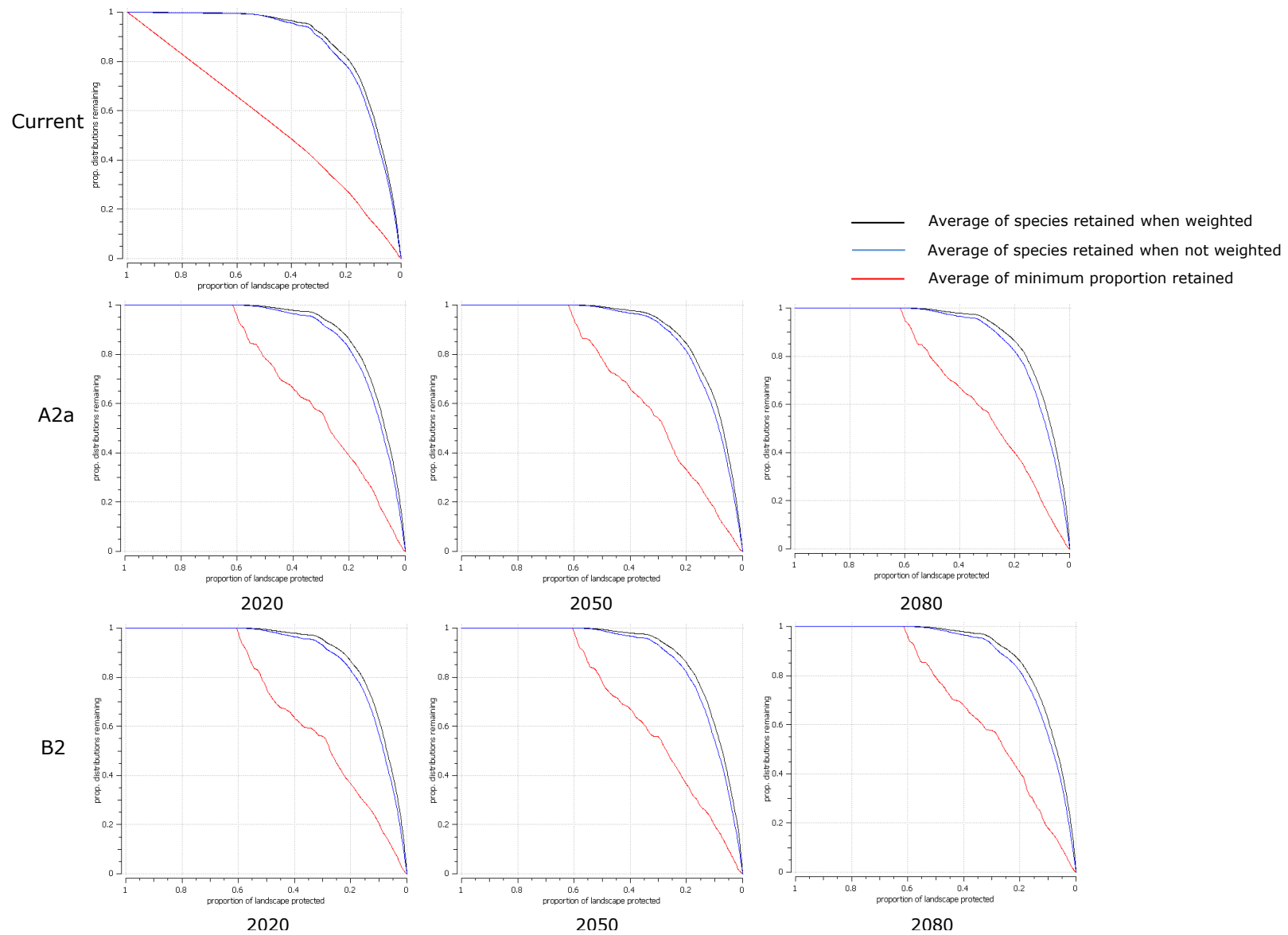
Appendix 10: The curve performance showing the proportion of species distribution preserved for Additive Benefit Function removal, comparing current and future times assuming unlimited dispersal.



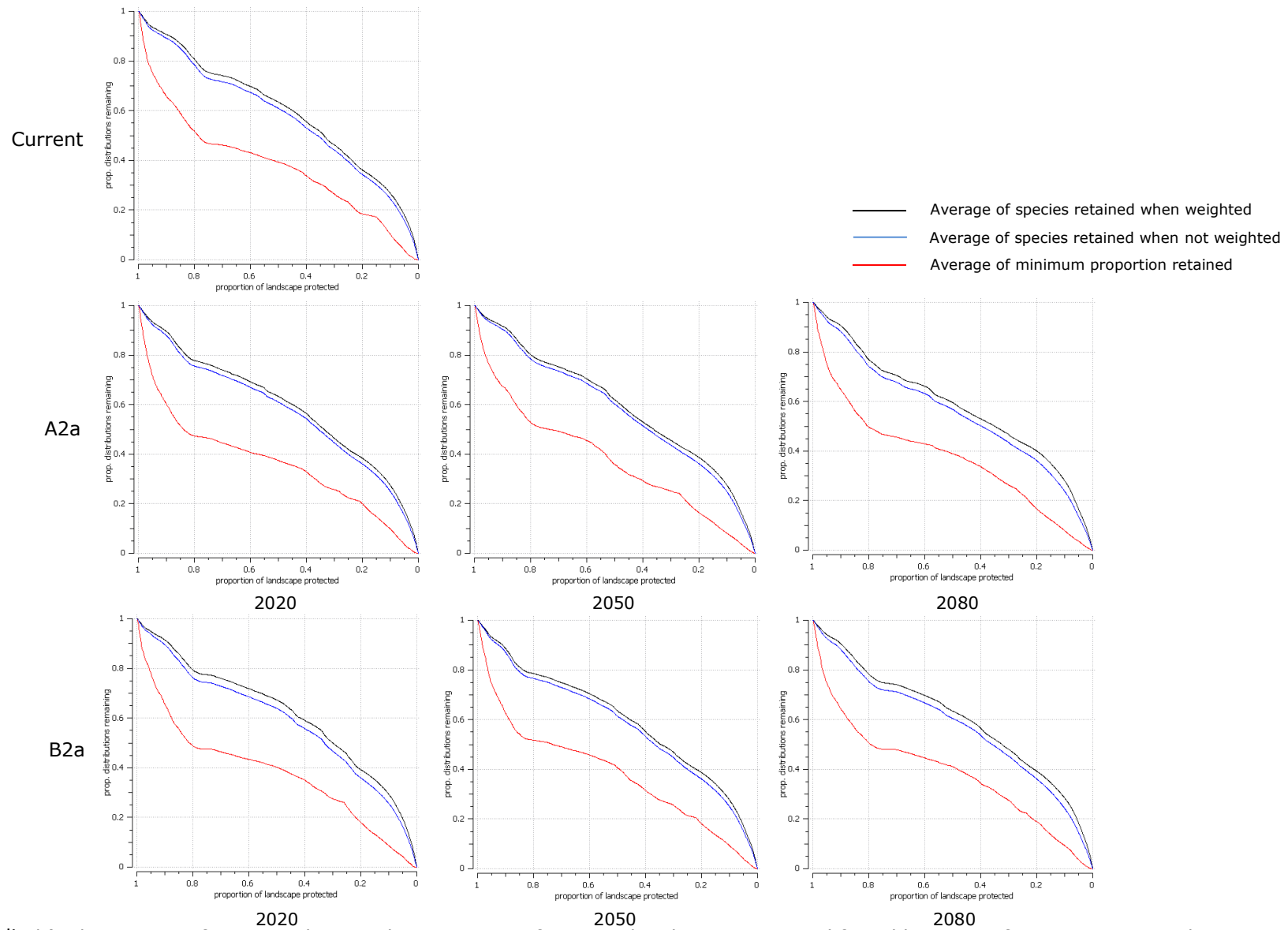
Appendix 11: The curve performance showing the proportion of species distribution preserved for Core – Area Zonation removal, comparing current and future times assuming unlimited dispersal.



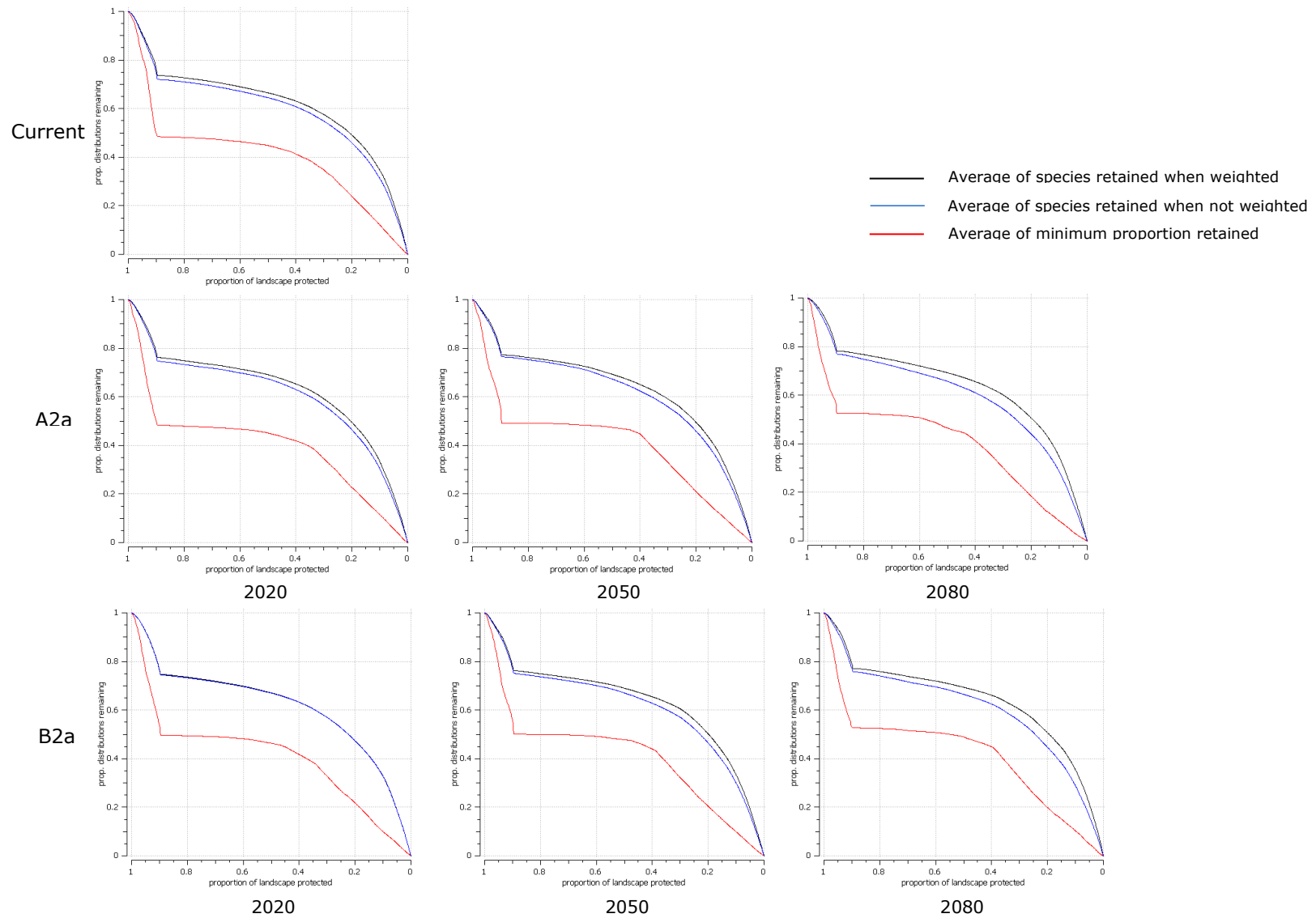
Appendix 12: The curve performance showing the proportion of species distribution preserved for Additive Benefit Function removal, comparing current and future times assuming no dispersal.



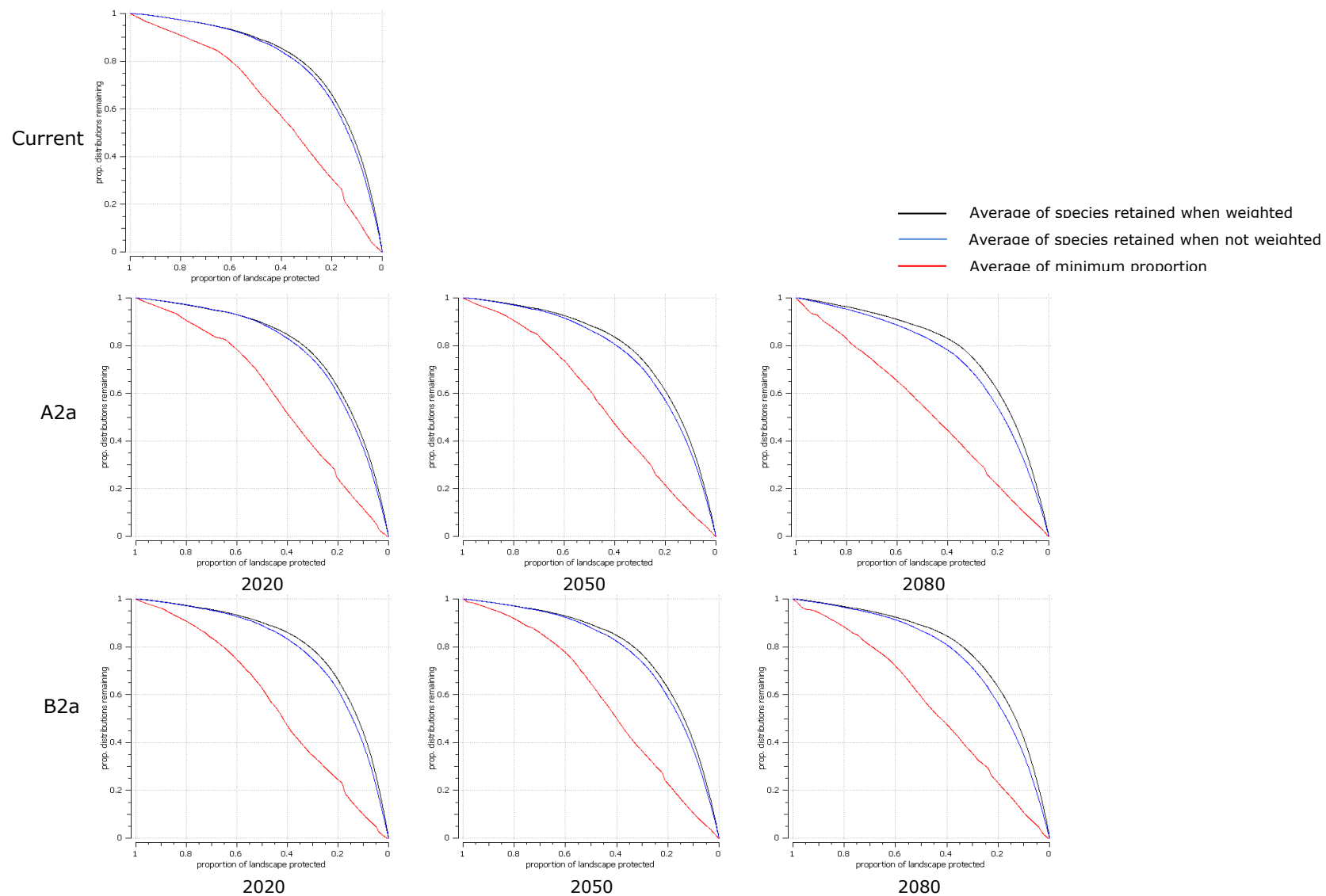
Appendix 13: The curve performance showing the proportion of species distribution preserved for Core – Area Zonation removal, comparing current and future times assuming no dispersal.



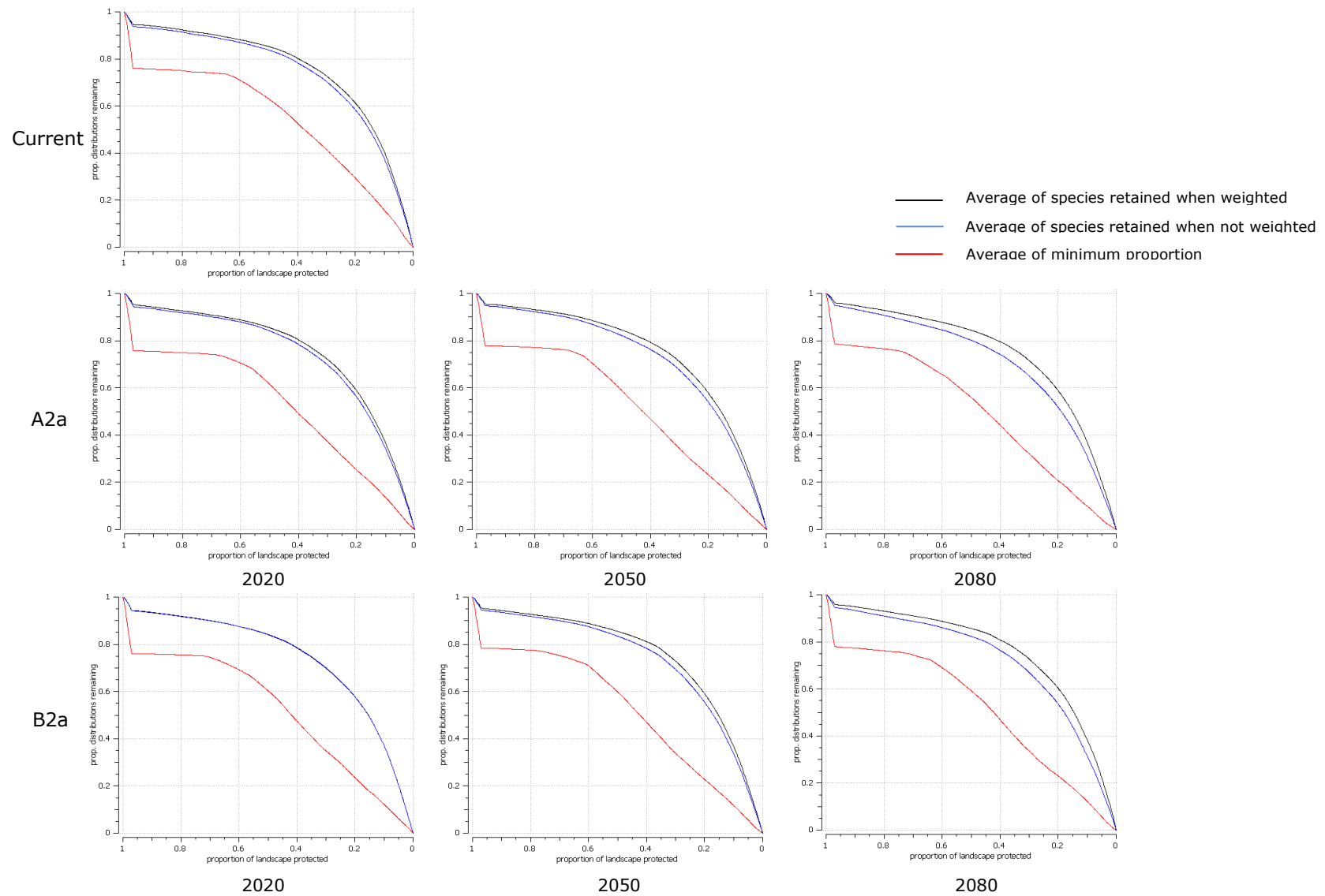
Appendix 14: The curve performance showing the proportion of species distribution preserved for Additive Benefit Function removal, comparing current and future times assuming unlimited dispersal using HII as a cost layer.



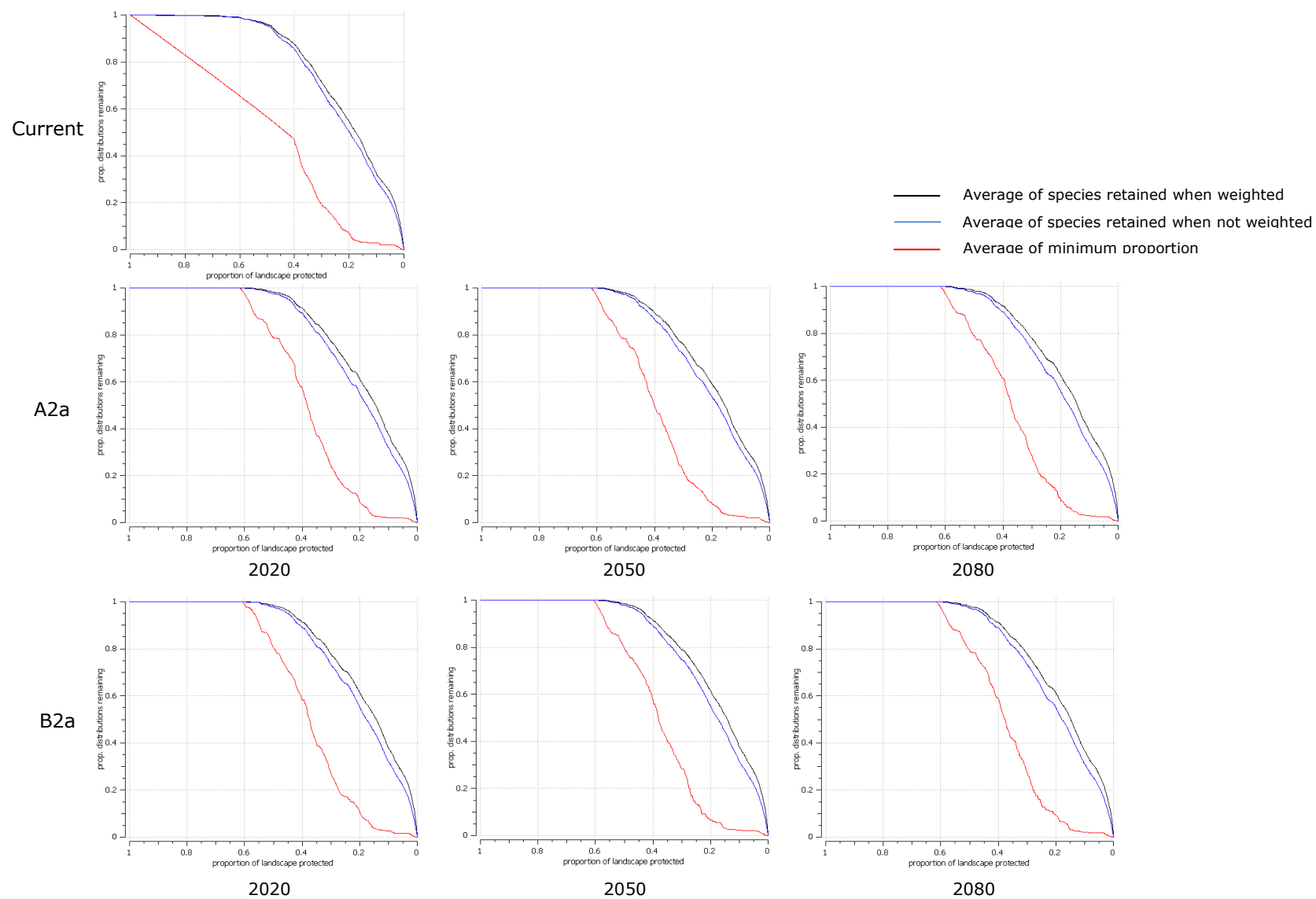
Appendix 15: The curve performance showing the proportion of species distribution preserved for Core – Area Zonation removal, comparing current and future times assuming unlimited dispersal using HII as a cost layer.



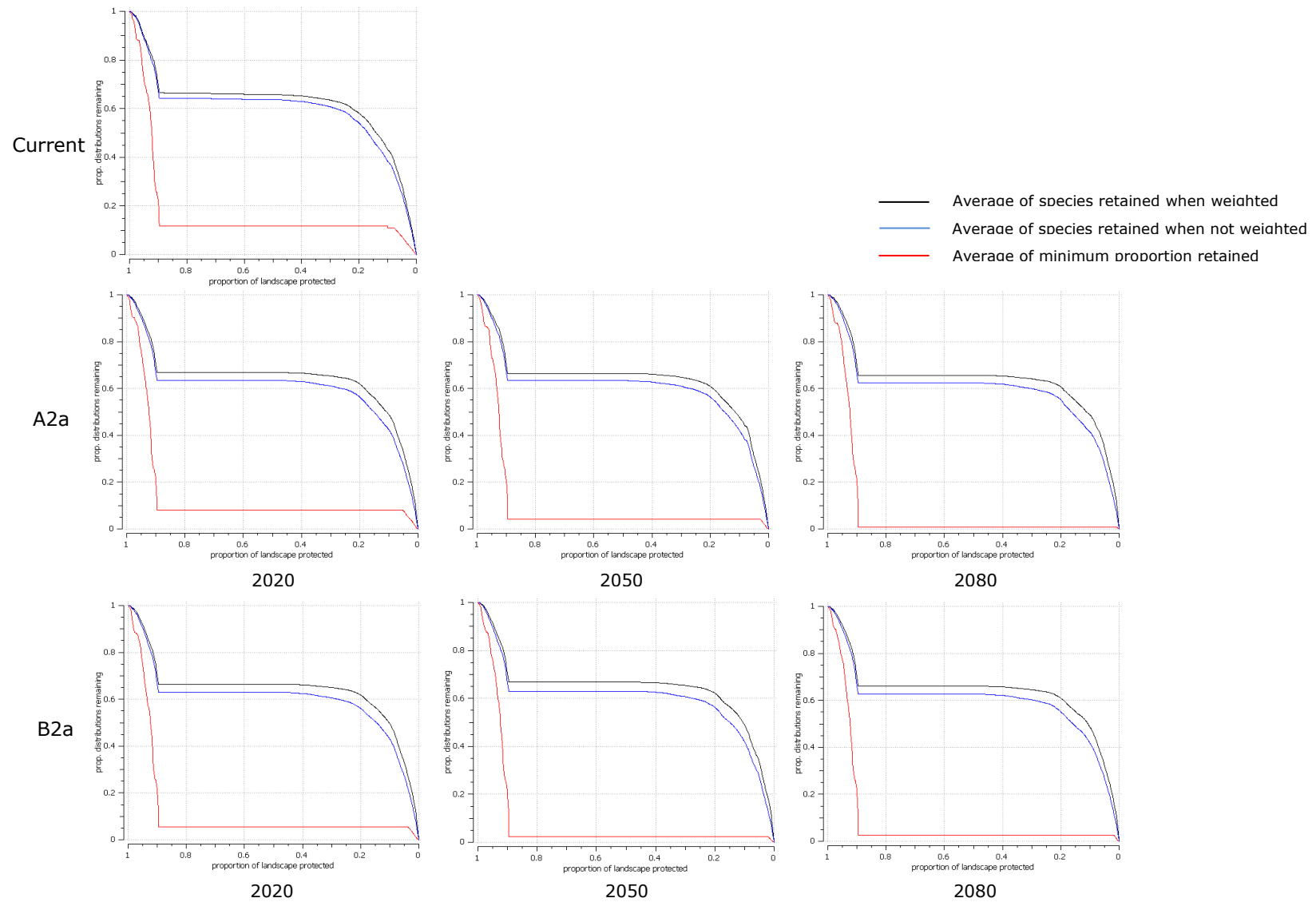
Appendix 16: The curve performance showing the proportion of species distribution preserved for Additive Benefit Function removal, comparing current and future times assuming unlimited dispersal using population density as a cost layer.



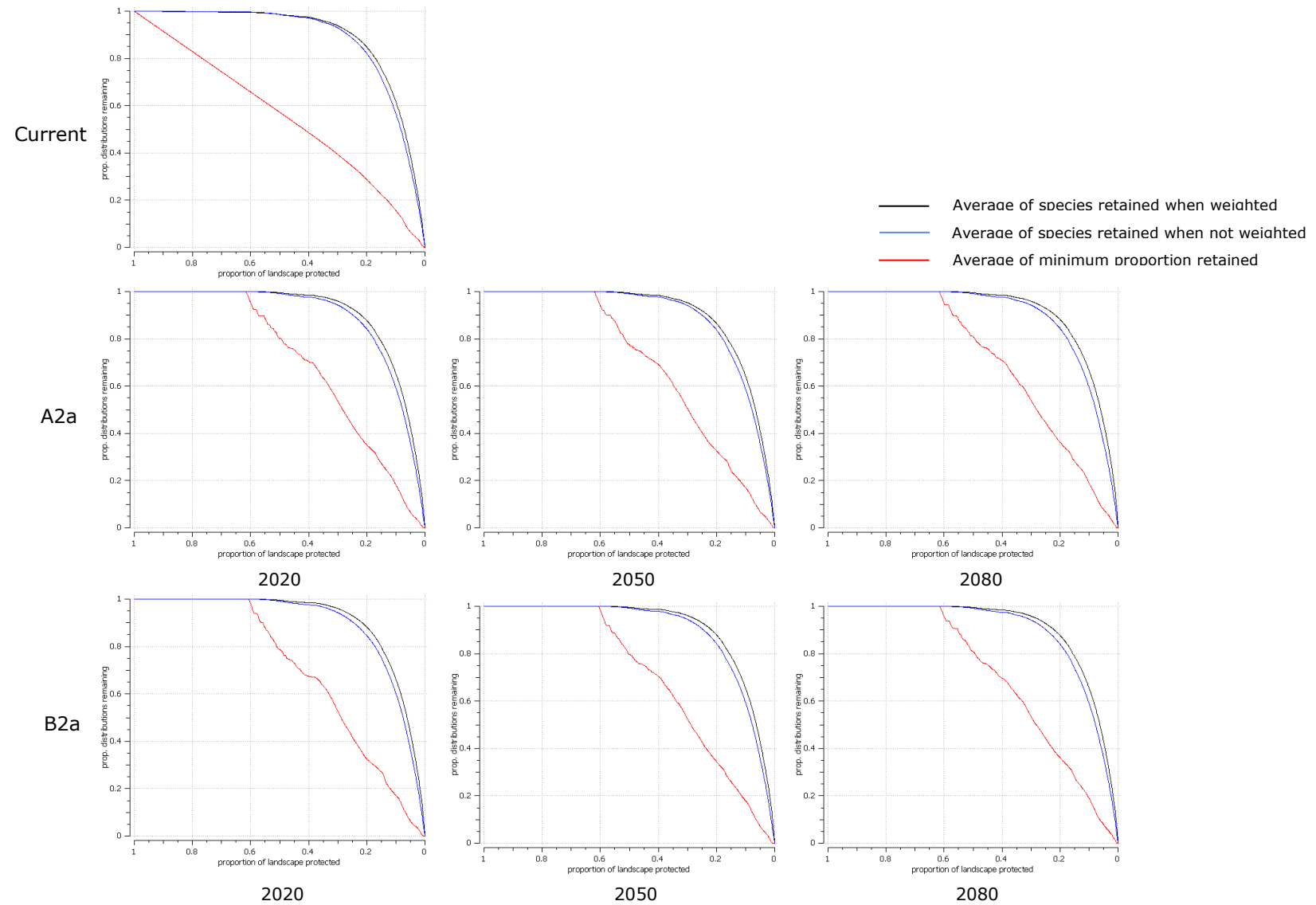
Appendix 17: The curve performance showing the proportion of species distribution preserved for Core – Area Zonation removal, comparing current and future times assuming unlimited dispersal using population density as a cost layer.



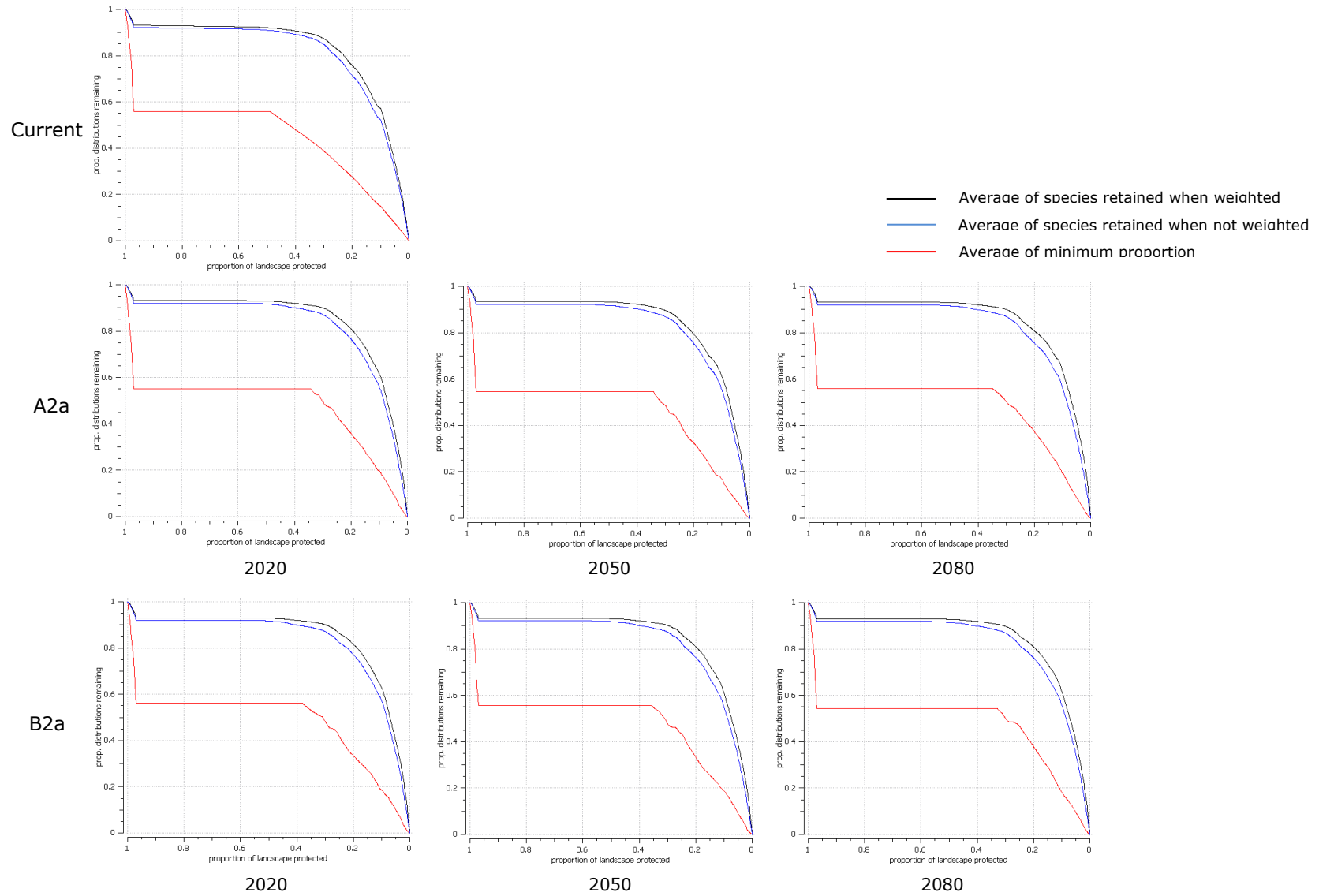
Appendix 18: The curve performance showing the proportion of species distribution preserved for Additive Benefit Function removal, comparing current and future times assuming no dispersal using HII as a cost layer.



Appendix 19: The curve performance showing the proportion of species distribution preserved for Core – Area Zonation removal, comparing current and future times assuming no dispersal using HII as a cost layer.



Appendix 20: The curve performance showing the proportion of species distribution preserved for Additive Benefit Function removal, comparing current and future times assuming no dispersal using population density as a cost layer.



Appendix 21: The curve performance showing the proportion of species distribution preserved for Core – Area Zonation removal, comparing current and future times assuming no dispersal using population density as a cost layer.