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Allowing for human socioeconomic impacts in the conservation of plants under climate change

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ABSTRACT

The impact of climate change on conservation planning is affected by the availability of data (especially in data-sparse countries) and socioeconomic impacts. We build models using MaxEnt for Egyptian medicinal plants as a model system, projecting them to different future times under two IPCC 4th assessment emission scenarios (A2a and B2a) assuming unlimited and no dispersal. We compare the effect of two indices of socioeconomic activity [Human Influence Index (HII) and human population density/km^2] as cost layers in spatial prioritization for conservation using zonation. We assess the efficacy of Egypt's network of Protected Areas (PAs) by comparing the predicted conservation value inside and outside each PA 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 before human socioeconomic impacts are included. The HII had a stronger impact than using human population density. The PA value excess (inside–outside) varied significantly with the type of cost and dispersal, but not with climate-change scenario or Zonation settings. We conclude that human socioeconomic impacts add new scope and insights for future conservation; and conservation planning without consideration of such impacts cannot be complete.

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KEYWORDS
Socioeconomic impact; conservation planning; Egypt; plants; species distribution models; Zonation

Introduction

Recent work shows that climate change is one of the main factors affecting the distribution of species and ecosystems (Alkemade et al. 2011); 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 (Araujo et al. 2011; Leach et al. 2013; El-Gabbas et al. 2016; Fois et al. 2018a). 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 modeling approaches have been used extensively for conservation and conservation planning (Araujo et al. 2011; Dobrovolski et al. 2014; Fois et al. 2018b). These 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. 2010, 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 analyzing 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. 2009). Spatial conservation prioritization can applied at different scales, national to global (Butchart et al. 2015; Di Minin et al. 2016, 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

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prioritization for conservation planning based only on biological data (Naidoo et al. 2006; Leach et al. 2013; El-Gabbas et al. 2016), which can undermine the conservation process if they do not take into consideration socioeconomic impacts (Knight et al. 2008; Faleiro et al. 2013). Recently, several studies have used socioeconomic data in conservation planning (Faleiro et al. 2013; Di Minin et al. 2017), especially in the Mediterranean basin (Petrosillo et al. 2010; Schmitz et al. 2012; Schmitz et al. 2017; Arnaiz-Schmitz et al. 2018) 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, based on the Convention on Biological Diversity report (CBD 2010).

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 (as a one sample *t*-test). We made this assessment with different assumptions about the pattern of human influence and plant dispersal abilities.

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), species with more than ten records but spatially very restricted records, and those with a mean area under the curve (AUC) of less than 0.7 to avoid inaccurate predictions (for more details see Franklin 2009; Kaky and Gilbert 2016). We ended up with 114 species of Egyptian medicinal plants, with 14,396 point records.

The environmental variables consisted of 23 descriptors, 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) (Supplementary Table S1). Normalized Difference Vegetation Index (NDVI) data for 7 years (2004–2010) 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) (Kaky and Gilbert 2017). A further environmental descriptor was a categorical habitat layer, derived from the Biomap project (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 remained for use after 12 were removed based on collinearity analysis using the Variance Inflation Factor (Supplementary Table S1), 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 Quadratic, Product, and Threshold (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 using AUC and the True skill statistic (TSS: see Kaky and Gilbert 2016). MaxEnt performance is good with presence-only data and small numbers of records (Elith et al. 2006), 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 ["high change–business as usual"] and B2a ["moderate change"]), 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; Hamann and Aitken 2013).

The A2a and B2a scenarios (see IPCC special reports; Hannah 2011; Phillips et al. 2017) have different assumptions about the amount of CO_2 emissions. The A2a scenario expects that the level of CO_2 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 CO_2 emission will not change much, because human population growth will be

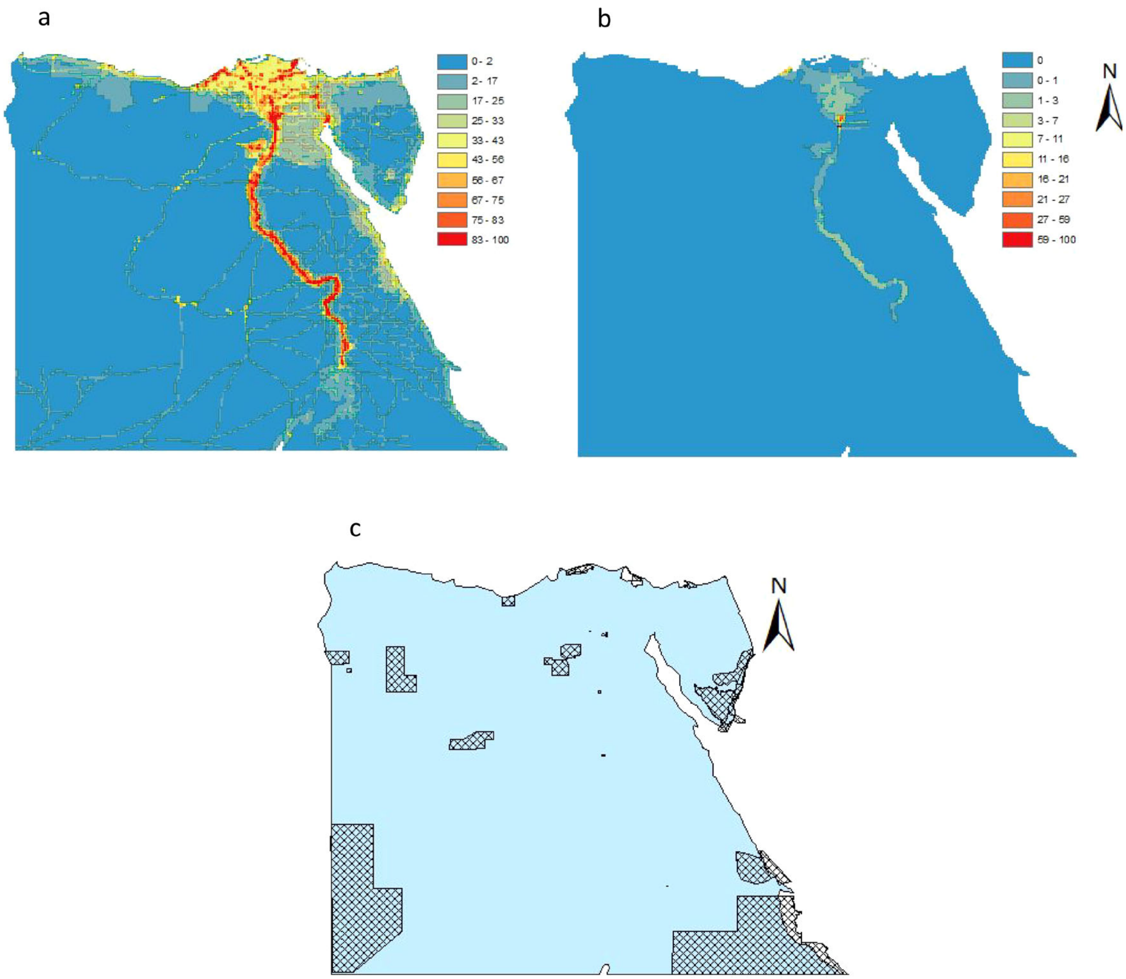

Figure 1. Cost layers used in Zonation and Egypt's protected areas. (a) the Human Influence Index; (b) Human Population density (both layers have been rescaled to be on the same range of 0–100); (c) Egypt's Protected Areas.

slower, with fewer changes in land-use, people are more environmentally conscious, and there is increasing invention in technology (Nakicenovic et al. 2000; 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 pixels by N pixels), 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 (*caz*), 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 (*abf*), 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 territory 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

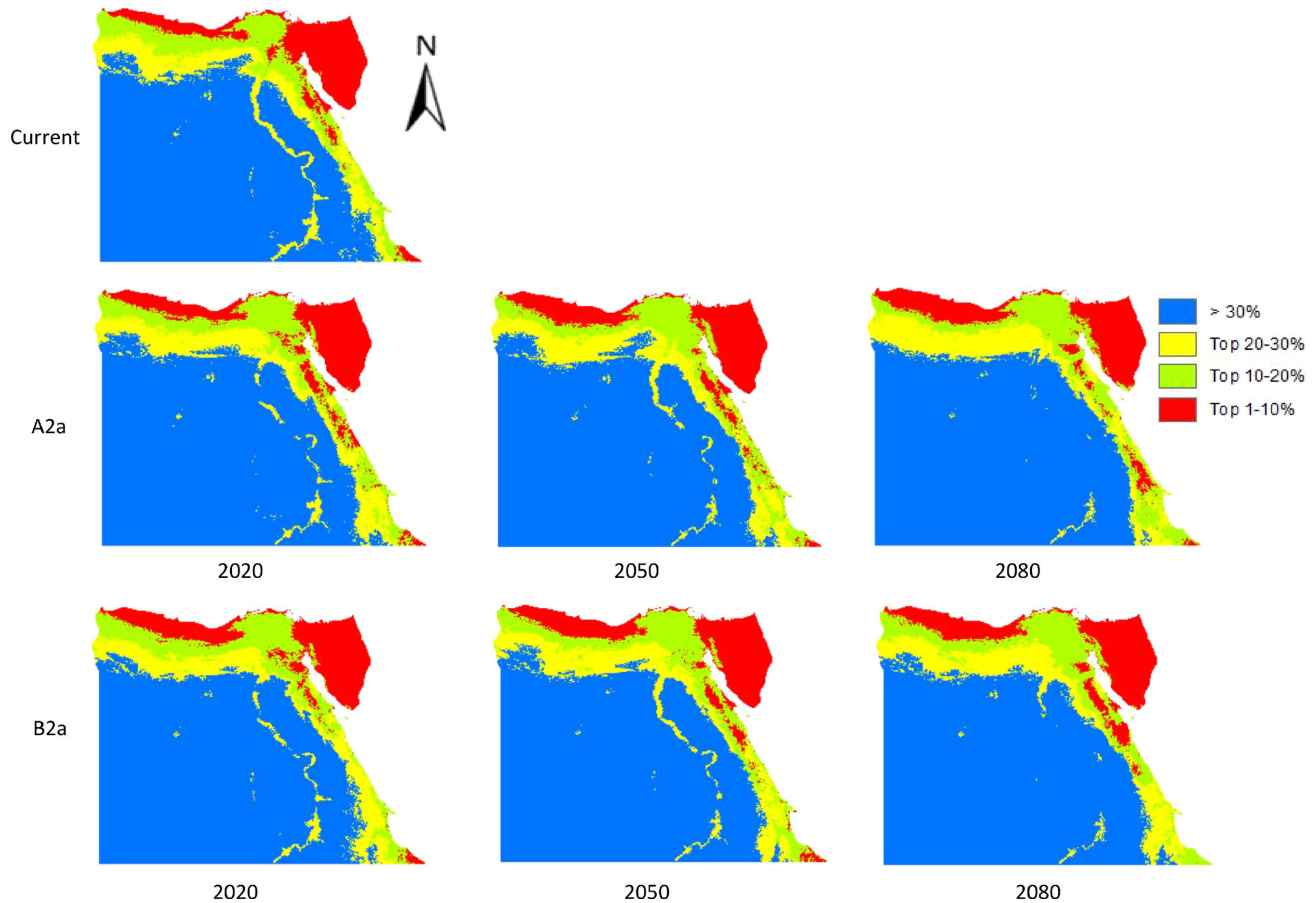

Figure 2. Conservation prioritization ranked values using the 'Additive Benefit Function' removal rule for current and future scenarios assuming unlimited dispersal without using cost layers. The colors run from red (high) to blue (low) conservation value.

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; for more details about the procedure, see Supplementary Figure S22).

Species were weighted by multiplying together scores representing national assessments of conservation status (IUCN assessments: Kaky and Gilbert 2017), the relative importance of Egypt's populations (world distribution), and the distribution of the species within Egypt (see Supplementary Table S2).

Human impacts were assessed using a 'cost layer'. Two types were used, the Human Influence Index (HII) for the years 1995–2004 (Figure 1a) and population density per km^2 in 2015 (Figure 1b), 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). For the HII layer we first reweighted the buffer around the roads to be zero, and then added a new buffer of 5 km to the main roads only, because after discussion with experts experienced with Egyptian conditions, the original 15-km buffer was not suitable for Egypt (Figure 1a). 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 *abf* 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 the *caz* removal rule, 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 (Figure 1c) was compared with these important locations visually and quantitatively for their effectiveness in conserving plants under the impact of future climate change. Designed by local biodiversity experts, PAs currently 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

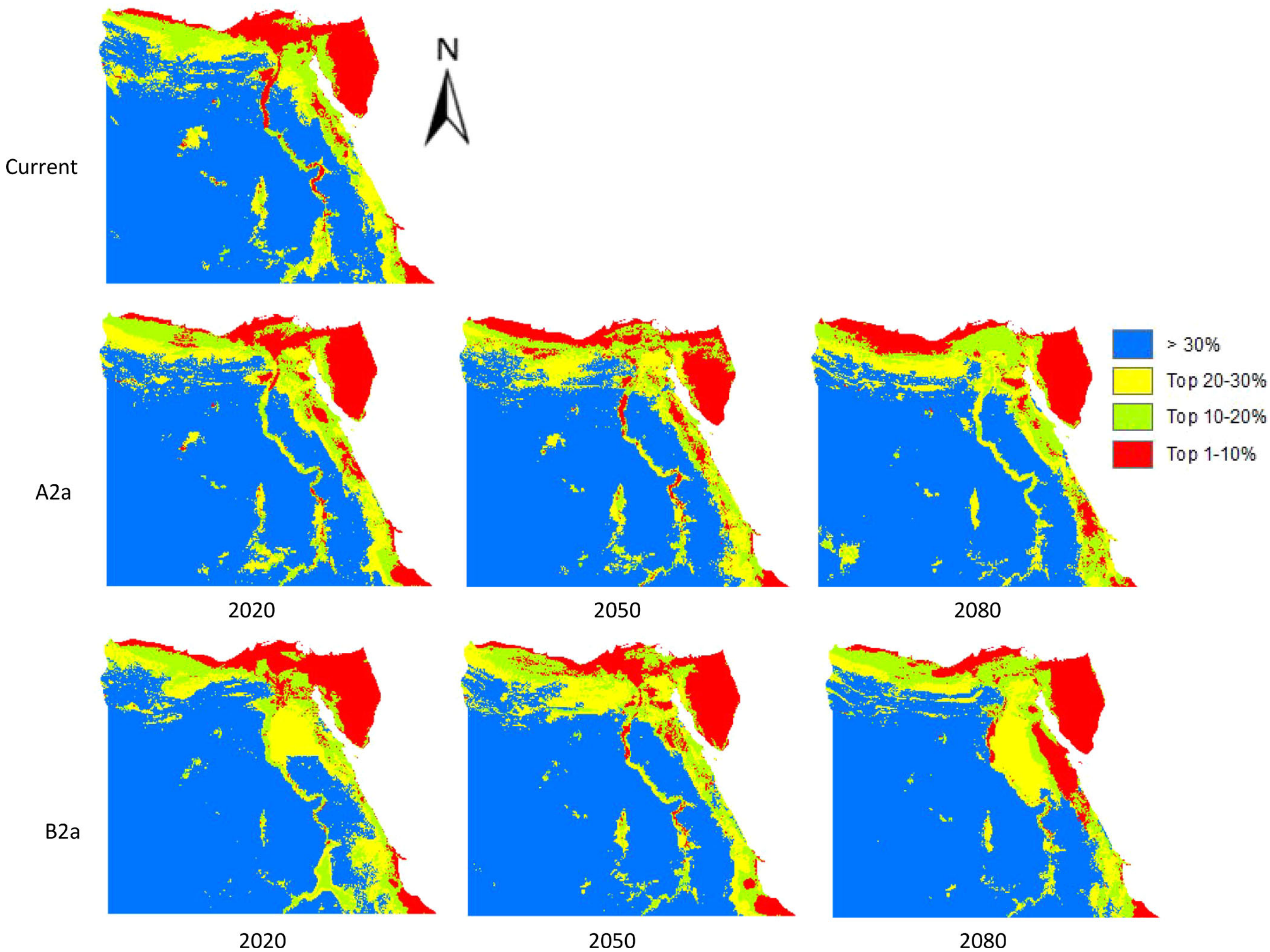

Figure 3. Conservation prioritization ranked values using the 'Core-Area Zonation' removal rule for current and future scenarios assuming unlimited dispersal without using cost layers. The colors run from red (high) to blue (low) conservation value.

conserved. We set the target as protection of 20% of the land, and compare each scenario and set of assumptions on the basis 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, HII, population density) and zonation setting (*abf*, *caz*). The paired difference inside-outside each PA was calculated, and this difference became the response variable of a Generalise Linear Model (GLM) with normal errors. In all, there were 2100 differences created.

Results

Under the assumption of unlimited dispersal, and using the *abf* removal rule, the best areas for conservation were the whole of Sinai, across the Mediterranean coast, the Suez Canal area, and the Red Sea coast (Figure 2). The map implies that by protecting 20% of the Egyptian territory, we can protect about 63% of the medicinal plant species (Supplementary Figure S9). 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 to 60% (A2a) or 56 to 62% (B2a) of the plant species (Supplementary Figure S9). Using the *caz* removal rule but still with unlimited dispersal, the best locations were the whole of Sinai, the Mediterranean coast, the Nile Delta, greater Cairo, and the Red Sea coastal area (Figure 3). About 61% of species are predicted to be conserved by protecting 20% of the land (Supplementary Figure S10). There were few predicted differences in the future under climate change for either scenario (Figure 3). 20% of the land was predicted to protect 51–57% (A2a) or 54–59% (B2a) of medicinal plant species (Supplementary Figure S10).

Under the no-dispersal assumption and using the *abf* removal rule, similar areas were prioritized but the conservation values increased, and 20% of the land protected 82% of the species (Supplementary Figures S1, S11). There were only trivial differences predicted in the future scenarios (Supplementary Figures S1, S11). Using the *caz* removal rule gave similar results, with about 79% of species protected in 20% of the land (Supplementary Figures S2, S12), and slightly higher conservation value under both scenarios for the Nile

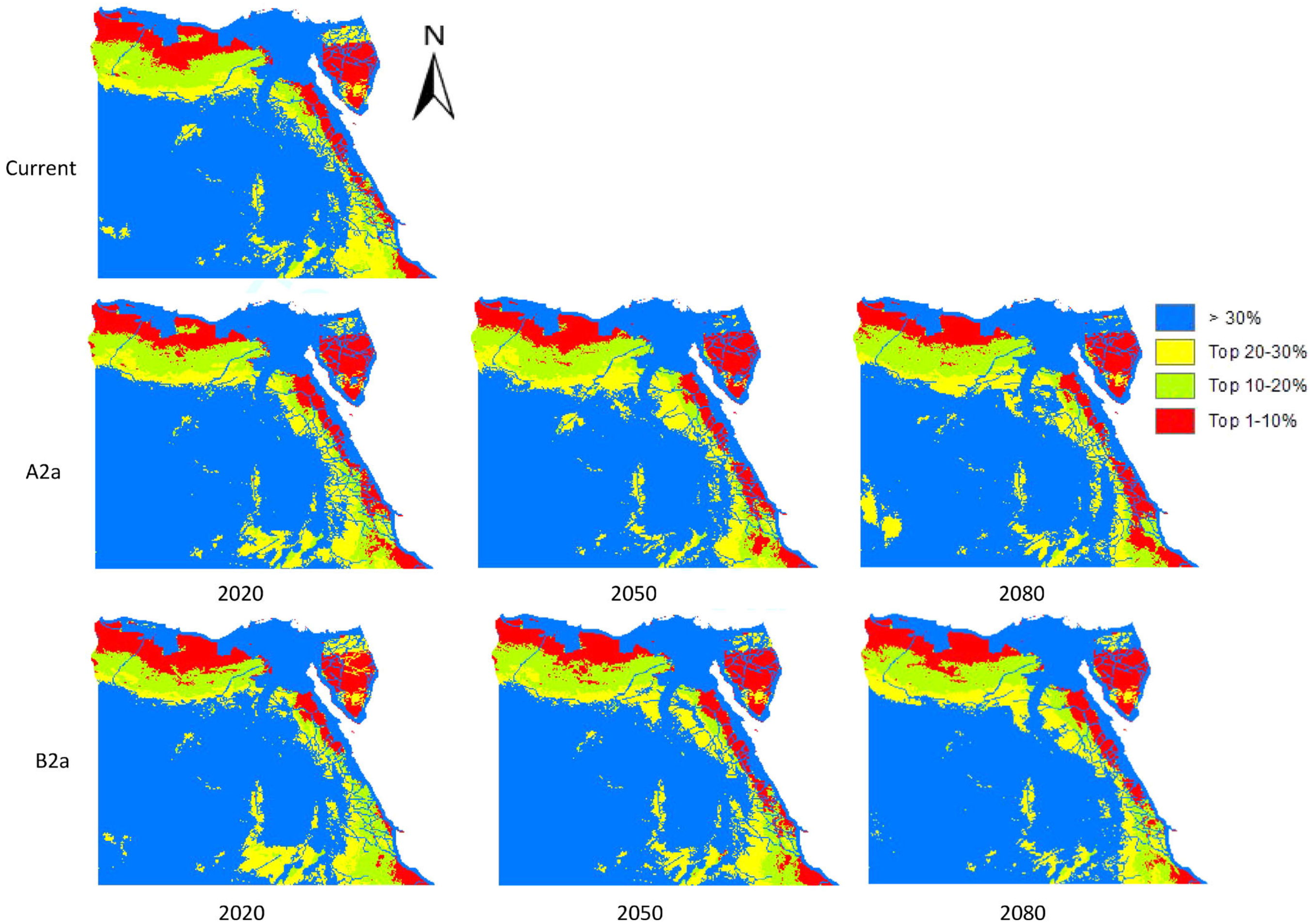

Figure 4. Conservation prioritization ranked values using the 'Additive Benefit Function' removal rule for current and future scenarios assuming unlimited dispersal and using the Human Influence Index as a cost layer. The colors run from red (high) to blue (low) conservation value.

Delta and slightly lower for the Red Sea coast. 20% of the land protected 81–83% across all scenarios (Supplementary Figures S2, S12).

Using the HII cost layer changed the results dramatically. Assuming unlimited dispersal and the *abf* removal rule, 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 4). 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 (Supplementary Figure S13). Using the *caz* removal rule the prioritization values increased across Sinai, Farafra oasis (Figure 5). The top 20% of the land was predicted to protect about 44–47% of the species under all scenarios (Supplementary Figure S14). Using the population density cost layer increased the Zonation rank scores significantly, again with only slight differences among scenarios and future times (Supplementary Figures S3, S4), and the top 20% of the land could protect 51–62% of the species (Supplementary Figures S15, S16).

Using the HII cost layer with no dispersal and the *abf* removal rule, the best areas for conservation were whole of Sinai, Qattara Depression, Siwa oasis, and areas from south of Ras Zaafarana to Halayeb excluding the Red Sea coastal areas. 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 (Supplementary Figures S5, S17). Using the *caz* removal rule gave similar results, 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 (Supplementary Figures S6, S18).

Using population density as a cost layer with no dispersal and the *abf* removal rule, 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 (Supplementary Figures S7, S19). Using the caz removal rule gave similar results, 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 (Supplementary Figures S8, S20). (Supplementary Figure S21 describes all the areas and region names mentioned in this study).

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

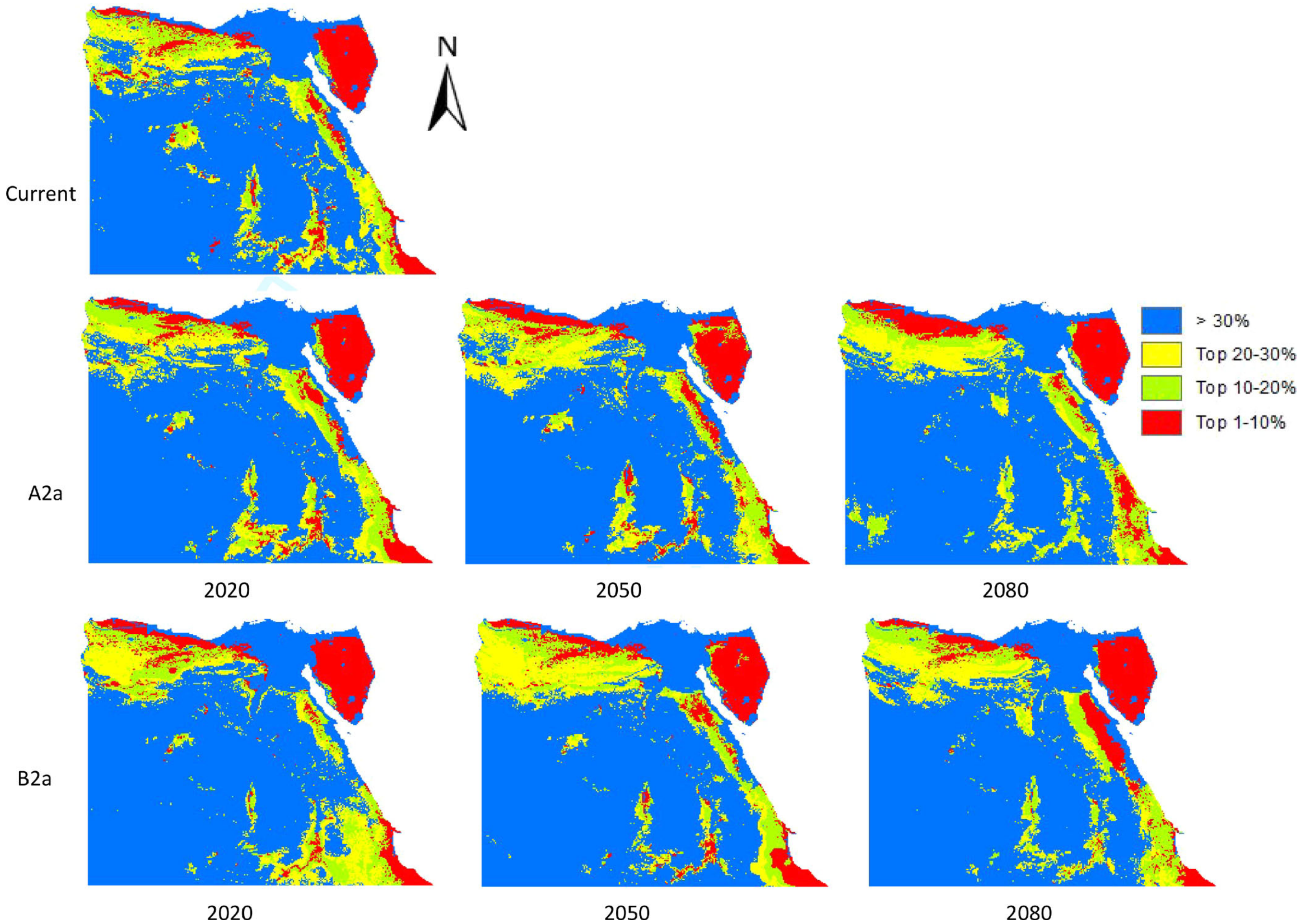

Figure 5. Conservation prioritization ranked values using the 'Core-Area Zonation' removal rule for current and future scenarios assuming unlimited dispersal and using the Human Influence Index cost layer. The colors run from red (high) to blue (low) conservation value.

Table 1. Final model of a GLM analyzing the difference in Zonation score inside–outside PAs (response variable) with various predictors; only significant terms are left in the model.

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	0.1	2	2070	3.66	<0.03

*Non-significant predictors that were removed were scenario (current, A2, B2), year (2020, 2050, 2080), and cell removal rule (*abf*, *caz*).

(Table 1, Figure 6a). The average difference for most PAs was positive, i.e. higher inside than outside (Figure 6b), but when using the HII cost layer (Figure 6c) the many positive differences were outweighed by the large negative differences of some PAs. There were no significant effects of climate-change scenario (A2, B2) or removal rule of Zonation (*abf*, *caz*).

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 (Moilanen et al. 2011; Schmitz et al. 2012; 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 (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

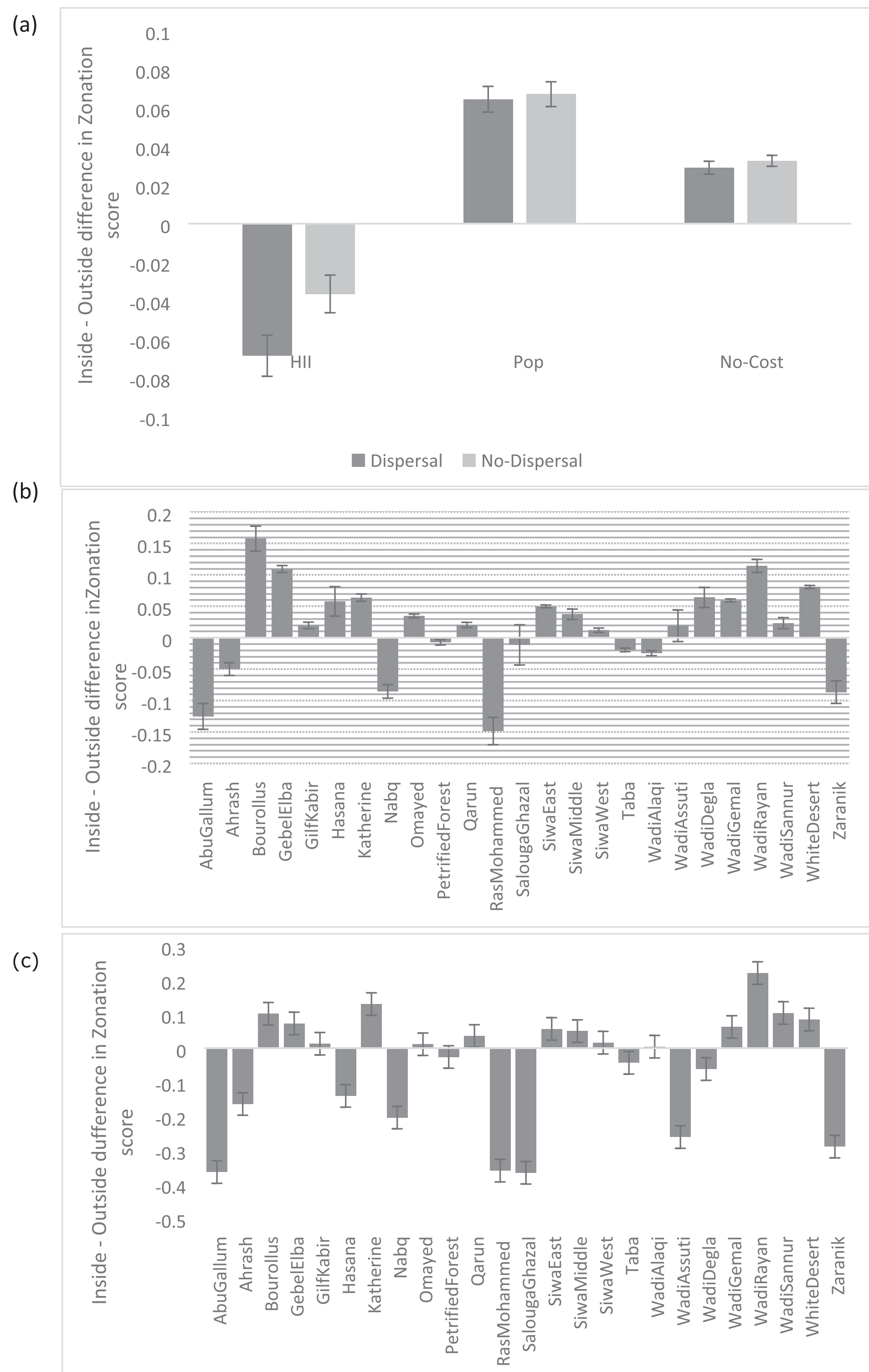

Figure 6. Mean difference between inside and outside PAs for conservation values derived from Zonation analyses: (a) for different cost layers (human influence index HII, population density Pop, and No-cost) and dispersal assumptions; (b) overall for each PA across all assumptions; (c) for each PA using the HII cost layer and across all other assumptions.

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 (Kaky and Gilbert 2017). 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 agrees 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 some of the PAs were ranked higher than inside, although there were substantial differences among PAs. Mismanagement of PAs can lead to loss species and failure to achieve conservation objectives (Schmitz et al. 2017), because the effective management of PAs is a key issue in mitigating biodiversity loss (Petrosillo et al. 2010; Semeraro et al. 2016). There is an association between increasing urban and industrial land use and the creation of PAs for conservation planning and to protect cultural landscapes (Arnaiz-Schmitz et al. 2018). However, several studies show that PAs may not mitigate the accelerated transformation of land uses, urbanization, and loss of landscape in urban-rural transitions (Schmitz et al. 2012, Amici et al. 2015; Schmitz et al. 2017). By changing and transforming land use, human activities lead to the loss of biodiversity and effects on ecosystem services (Slemp et al. 2012; Newbold et al. 2015). Urban expansion is one of the main factors in land-use change, biodiversity loss, and habitat loss (Newbold et al. 2015; Plieninger et al. 2016). For these reasons, allowing for human activities by using a cost layer changes substantially the optimal strategy in conservation planning.

In conclusion, our findings about PAs in Egypt support the idea of including socioeconomic information such as the HII in conservation planning. In assessing the best spatial conservation priorities, theoretically the use of such cost layers helps to decrease conflict between conservation and human land-use. The results highlight many currently unprotected locations that probably should be part of the Egyptian network of reserves. Of course, other human factors can play an important role in conservation planning, such as the cultural landscape of sacred sites (Avtzis et al. 2018). 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 also needed on the use of binarized distribution maps as input to Zonation analysis.

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