



Using species distribution models to assess the importance of Egypt's protected areas for the conservation of medicinal plants



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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 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.

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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 plants 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 health-care, 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: 41–45). 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, in prep.). Ideally the maps of

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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 differences 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.

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: 222–223). 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) (Table 1). Normalized Difference Vegetation Index (NDVI) data for seven years (2004–2010) 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 Table 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 3.3.3 k (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: 62–63), 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 Supplementary Table S1.)

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. 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

Table 1

Environmental variables used to build the models (highlighted variables were rejected after applying Variance Inflation Factor analysis to reduce 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

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. Results

In terms of mean AUC values, all models showed good performance (range 0.802–0.989) (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 [Supplementary Table S1](#)). 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 and 0.90, 55 species between 0.90 and 0.95, and 10 with very high AUC between 0.95 and 1 (Fig. 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 and 0.3, 14 species between 0.2 and 0.1, and the rest (96 species) less than 0.1 ([Supplementary Table S1](#)).

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

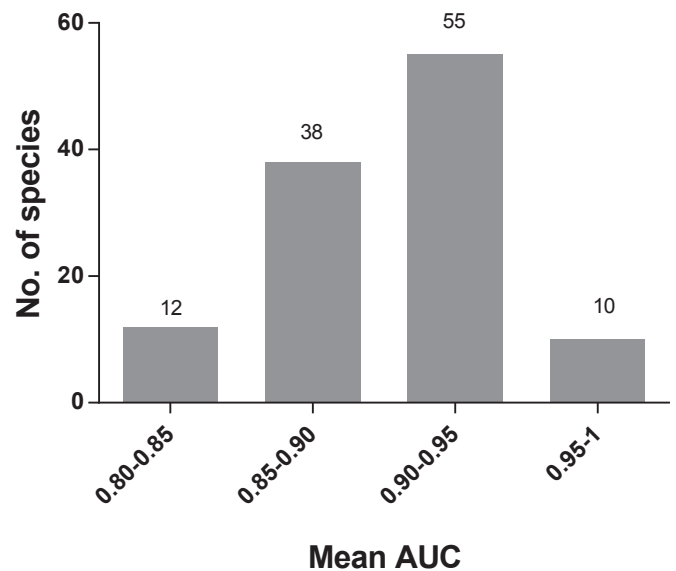


Fig. 1. Frequency distribution of the mean AUC values achieved in the distribution models of plant species.

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 (Fig. 2). Across all species, Bio6 was the highest for 36 species, followed by altitude (highest for 19 species), Bio3 and Bio8 (16 species) and Bio9 (see Fig. 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 (Fig. 4) match well with both types of species richness maps (Fig. 5A & B). Species richness is highest from the southwest to the northeast, especially North and

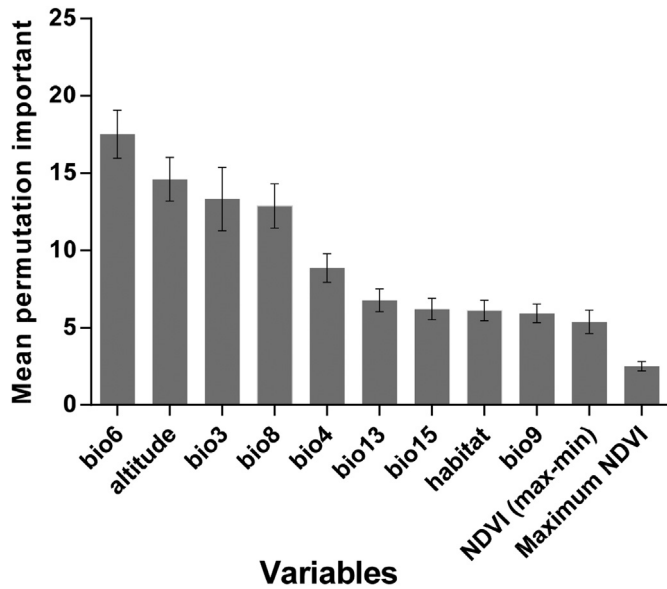


Fig. 2. Contribution to the final species distribution models made by each environmental predictor, illustrated by the mean permutation importance.

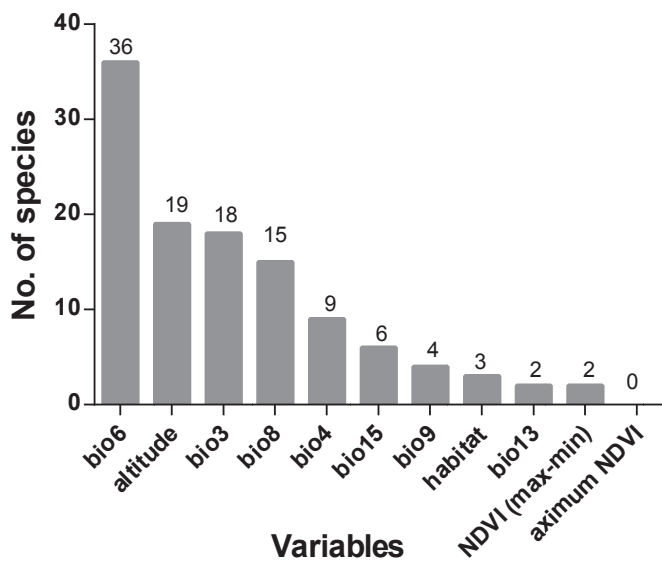


Fig. 3. Numbers of species where particular variables were the best predictor in species distribution models. One of the variables (ndvi_max) included in modelling was never the best predictor.

South Sinai, along the Mediterranean coast, and scattered areas of the Nile Delta. The probability species richness map (Fig. 5A) 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 (Supplementary Fig. S1).

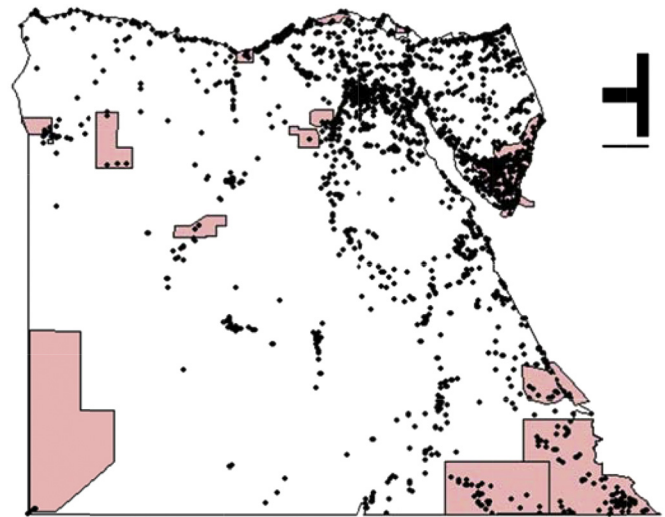


Fig. 4. Locations which Egyptian plants were sampled (square circle), and Protected Areas of Egypt (pink shading). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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-Natron, 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 (Supplementary Fig. S1).

The predicted species richness was significantly higher inside Protected Areas than outside for both the binary map (paired $t = 14.8$, $df = 24$, $p < 0.001$) (Supplementary Fig. S2A) and for the probability map (paired $t = 9.9$, $df = 24$, $p < 0.001$) (Supplementary Fig. S2B).

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 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

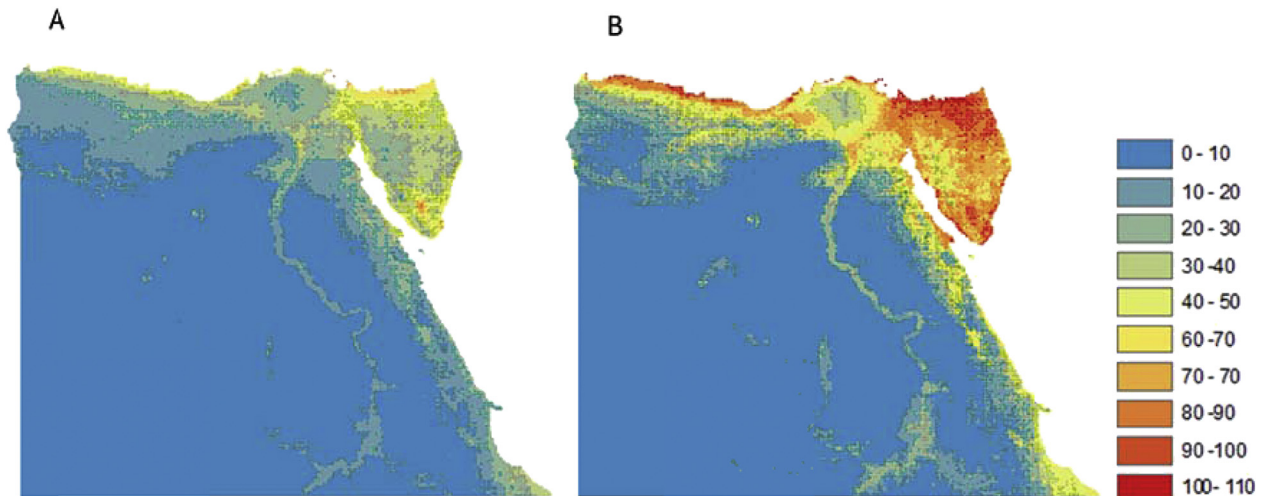


Fig. 5. Species richness for predicting current distributions: (A) probability richness map resulting from summing all individual species probability maps then rescaled to the same range as that of the binary map; (B) binary richness map, produced from adding all individual species thresholded maps. The colours range from blue to red, where blue indicates low and red high species richness. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 (Wisiz 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 and 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: 213–232), 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.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.jaridenv.2016.09.001>.

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