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Assessment of the extinction risks of medicinal plants in Egypt under climate change by integrating species distribution models and IUCN Red List criteria

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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. The use of species distribution models (SDMs) to predict habitat suitability, both currently and in the future under the effects of climate change, offers a potential solution for estimating extinction risk. With a set of validated observations, we used SDMs to make preliminary evaluations of the risk of extinction for 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. The IUCN assessments used the predicted distributions as well as the actual records to measure both 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, demonstrating the ability of SDMs to compensate for a lack of data. Most species could be classified as Least Concern (LC) at the current time, whilst in the future under climate change, many species face some risk of extinction, depending on assumptions. We conclude that it is possible to make regional risk assessments even in data-sparse countries, in order to plan conservation management in the future. Using species distribution modelling together with IUCN Red-List assessment is a good method for countries where data are sparse in order to conserve and protect threatened species.

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). The IUCN Categories and Criteria (IUCN, 2016) 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) and in management to prioritize conservation actions (Ricketts et al., 2005; Cassini, 2011).

In order to assess species (IUCN, 2016), the whole area encompassing validated records 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. 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. Where a taxon is affected by more than one threatening event, location should be defined by considering the most serious plausible threat." (IUCN, 2016).

The IUCN Red-List Categories and Criteria are designed to classify species under risk of extinction on a global scale (IUCN, 2016), but have developed to be applicable at national, local, and regional levels (IUCN, 2012). The first assessment of an entire group on a global scale was done for birds (Butchart et al., 2010), and Red Listing has also been applied successfully at national and regional scales (Zamin et al., 2010):

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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 decline and loss of species at risk of extinction by 2020, and to improve conservation planning (see CBD, 2010). One the main barriers to this effort is a lack of information. Most developing countries have few validated data, and even if available there is 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 worldwide (Parmesan and Yohe, 2003; Root et al., 2003; Hannah, 2011); others are, for example, human disturbance, invasive species, habitat loss and degradation, and changes in land-use (Chapin et al., 2000). As a result, there is now a huge effort being made to improve conservation planning by including possible changes in distributions. One simple way of trying to deal with this is to increase Protected Area coverage, which has gone from less than 2% of land cover in 1970 to about 15.4% in 2014 (Deguignet et al., 2014). A more sophisticated way 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 models (SDMs) use the environments of recorded locations to estimate the preferred environmental conditions of a species, and then map the distribution of this preferred environment in the area of interest. The risk of extinction under climate change is estimated from the estimated future changes in the distribution of the preferred environments. This is the procedure we have adopted here. SDMs are a very useful method of predicting distributions even when few data are available (Elith et al., 2006). There is strong evidence that even with few data, SDMs result in accurate portrayals of distributions (Elith and Leathwick, 2009). They use occurrence (presence/absence or just presence) data and associated environmental variables to predict distributions, which can then give a great deal of information useful for conservation planning, especially about possible future changes. SDMs provide estimates of the spatial variation of environmental suitability rather than the realised distribution (Marcer et al., 2013). Given certain assumptions, these 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).

SDMs only predict environmental suitability based on environmental factors 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, and SDMs can be used to estimate abundance (Anadon et al., 2010; Hwang and He, 2011) and changes in population size (He, 2012). 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.

Various studies have used SDMs to predict the range size of a species (i.e. the EOO) in order to apply IUCN Red-List assessments (Cardoso et al., 2011; Pena et al., 2014; Syfert et al., 2014; Keith et al., 2014; Stanton et al., 2015; Fois et al., 2016), but have mentioned small samples as a potential problem (Brummitt et al., 2008; Syfert et al., 2014). Currently, most data are presence-only, but several SDMs can use such data successfully to estimate the relative environmental suitability across the study area. This is potentially useful for measuring the EOO in IUCN assessments (see Merow et al., 2013; Syfert et al., 2014 for more details). Any SDM should take into account the accuracy of the data (for example, sampling bias, environmental predictors, algorithm used, etc.), because such factors impact the accuracy of the results (Elith and Leathwick, 2009). Some studies have used SDMs in applying IUCN Red-List criteria, but they have not always followed the full IUCN rules (Keith et al., 2000; Sapir et al., 2003; Good et al., 2006; Callmander et al., 2007; Rivers et al., 2010). Some explain that the IUCN Red-List criteria are not sufficient, especially for small organisms (Cardoso et al., 2011), and a comprehensive guide for applying the IUCN criteria under climate change has been lacking (IUCN, 2016). In this paper we try to avoid such shortcomings by respecting all the IUCN rules, using occurrence data obtained mainly from systematic surveys, taking care with the environmental variables, and using a single SDM approach consistently acknowledged to be among the best (MaxEnt).

Our study taxa are the medicinal plants of Egypt. 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., 2015), with only approximately 3% having been Red Listed by 2010, and only 5% by 2014 (Kew, 2010; Brummitt et al., 2015). There is no distribution map for most plants, and most countries do not have up-to-date checklists (Kew, 2010). In this study we take advantage of a validated dataset, and make preliminary national evaluations for 114 Egyptian medicinal plant species according to IUCN Red List Categories and Criteria. We do this by using SDMs for current conditions and then projecting them 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). The aim of the paper is therefore to test whether realistic IUCN assessments can be made by developing countries using SDMs as a substitute for the relative lack of data.

2. Methods

2.1. Occurrence data

Occurrence data for the 114 medicinal plant species (Table S1) used in this assessment were extracted from the databases of the Cairo-based BioMap project of 2004–8 (see Gilbert and Zalat, 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); unfortunately, non-medicinal plants do not have a validated dataset for comparison. 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 data come from recent systematic surveys with coordinates from hand-held GPS (of Sinai in particular), but the literature data derive 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). 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.

2.2. Species distribution models Using MaxEnt

MaxEnt version 3.3.3 k 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 assumed 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 equivalent to habitat suitability values. We did this after an exhaustive check to find the best combination of options, using the criteria of the highest Area Under the Curve (AUC) or True Skill Statistic (TSS), the standard measures of goodness-of-fit for SDMs (see Allouche et al., 2006). All mean values are given ± one SE.

2.3. Current and future environmental variables

The environmental variables consisted of 23 predictors. These included the standard set of 19 'Bio-layers', i.e. different measures of maximal, minimal and seasonality of temperature and precipitation data, created to represent biologically relevant environmental variables (Table S2). The Bio-layers along with altitude were 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). This was calculated from seven years of satellite imaging (Jan 2004–Dec 2010) to create layers of the maximum recorded NDVI (Max_NDVI), and the difference between the minimum and the maximum (NDVI_differences). A 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. This layer was a product of the Biomap project (for more details see Newbold et al., 2009). Eleven 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' in R (R Development Core Team, 2012) (see Table S2). VIF analysis sorts out the best set of uncorrelated predictor variables (see Bombi et al., 2012).

For each species, distributions were modelled for the 'current' time, assumed to be the year 2000, and then, as is standard in such studies, 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 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 involve different assumptions about the levels of CO_2 emissions, with A2 denoting large changes and B2 relatively small changes (Phillips et al., 2017; Hannah, 2011). The two extreme dispersal assumptions (see Peterson et al., 2002; Thuiller et al., 2005) assume species can perfectly (unlimited) or cannot at all (no-dispersal) track climate changes. These extremes were chosen because of the lack of information about true dispersal ranges in the species. We should see greater range changes 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 the HadCM3 is more highly correlated with the observed data than other similar models (Turner et al., 2006). Modelling used a grid-cell size of 2.5 arc-min ($\sim 4.6 \times 4.6$ km = ~ 20 km^2), which was chosen because of 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.

2.4. IUCN Red List assessments

The IUCN Red List Categories and Criteria (IUCN, 2016) were used to assess extinction risk under the impacts of climate change. There are several studies that have used these to assess plant species based on their distribution (e.g. (Keith et al., 2000; Callmander et al., 2007; Cardoso et al., 2011), but often they do not apply all the rules completely. For example, grid-size guidelines are often not followed (see Table S7). Here, we used the IUCN-recommended grid-cell size of 2 × 2 km in order to calculate the $EOO_{records}$ and $AOO_{records}$ from which the IUCN assessments for the current and future conditions were made. Estimates of predicted future changes (%) in range size under climate change used the same grid-cell size of 2 × 2 km, using the down-scaling process as recommended by IUCN (2016: 49–50). Each map was binarized (i.e. continuous predicted habitat suitabilities were turned into 1 [suitable] or 0 [unsuitable]) using the 10%-training-presence threshold rule (see Liu et al., 2005); we chose this threshold rule because this assumes that 90% of the training data are correctly classified, thus allowing for some georeferencing error with the data (Kaky and Gilbert, 2017): then EOO_{model} and AOO_{model} were calculated from the resulting set of 'presences'.

To estimate the number of "locations" (IUCN, 2016), we considered that over-collection by pharmaceutical companies is the biggest threat (GEF, 2000). The actions of such companies often destroy entire patches of plants (cf. Hoyle and 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), and therefore that in this case 'location' and 'subpopulation' are equivalent. Based on the assumed behaviour of collectors, we estimated the number of 'locations' (IUCN, 2016) on a national scale from the records by applying three different assumptions about the possible size gaps among the records (> 20, > 50 and > 100 km) that separate the subpopulations. In this way we assessed how many locations there were under each assumption. The number of locations was estimated in the same way for the SDMs of the future maps, but in fact this 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, we assessed the species based on two sub-criteria: (a) the small number of 'locations' (as previously described); and (b) 'continuing decline', an interpretation of the ongoing threat of over-collection implying a decline in the number of mature individuals - it is for this reason that our assessments are called 'preliminary'. It was enough if either metric (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 Fig. 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,

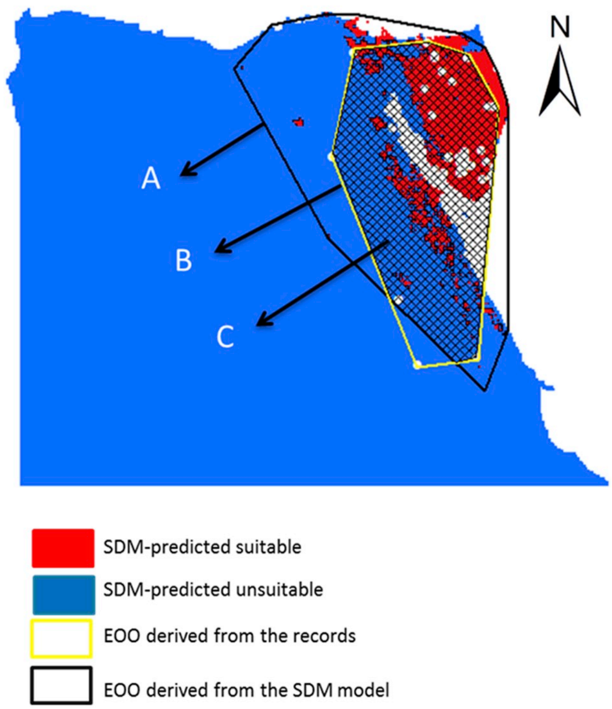

Fig. 1. Binarized map for Chiliadenus montanus showing the calculation of the Jaccard similarity index (in this case equal to 0.61) = C/(A + B–C), where A is the EOO derived from the SDM model, B is the EOO derived from the records, and C is the area of overlap between A and B.

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, nor their close relatives: they could be several or many years or many decades. Thus we scaled all estimates of declines to the standard ten-year period (IUCN, 2016) as well as a fifty-year period. The first probably underestimates the threat level, whereas the second probably overestimates it. The predicted change in suitable habitat was calculated as the difference in EOO/AOO between the current and each future map, expressed as a percentage. The percentages were then used to classify each species according to the IUCN criteria, and then the regional adjustment applied (Table S3): LC = loss < 30%, VU = loss > 30%, EN = loss > 50%, CR = loss > 80%, EX = 100% loss (IUCN, 2016). 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 Introduction). Again it was enough if either metric (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, 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* and *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, 2012). We did this by downloading all the global records from

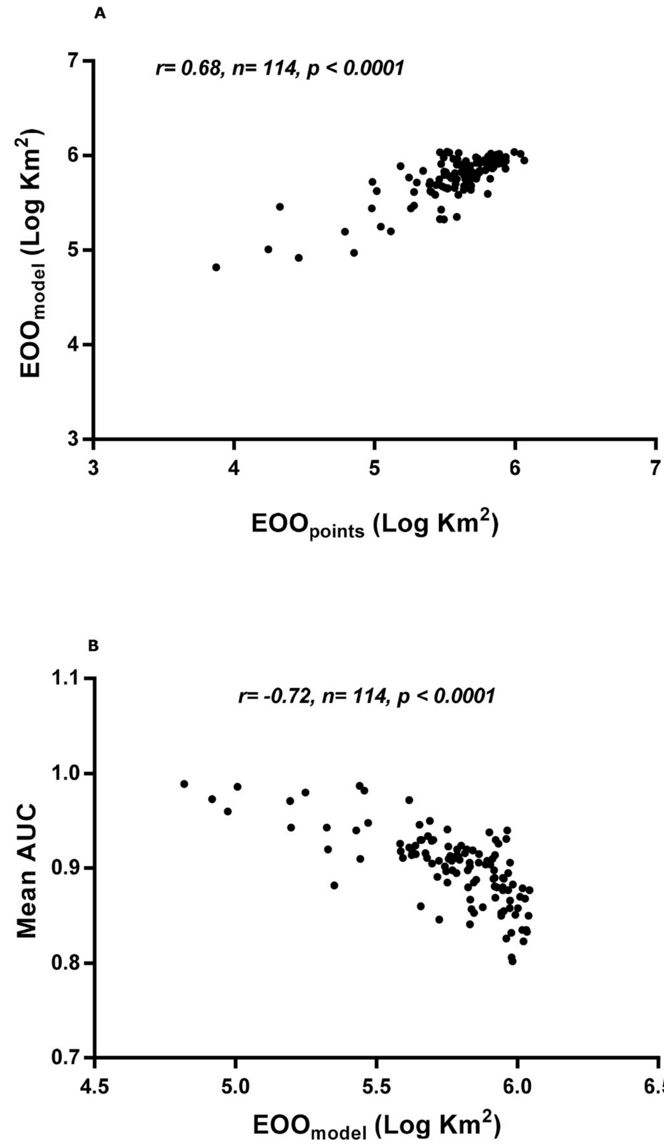

Fig. 2. Scatterplots showing the relationships between the Extent of Occupancy (EOO) measurements for the records (EOOrecords), the species distribution models (EOOmodel) and the model quality (area under the curve, AUC) of the SDMs: a) EOOrecorda and EOOmodel; and b) EOOmodel and AUC. These indicate how good the SDMs are in relation to the more traditional IUCN methods of calculating the EOO. The correlations are Pearson correlations that assume linearity.

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 (Bachman et al., 2011).

3. Results

3.1. Model performance

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 Kaky and Gilbert, 2016). There was a significant positive

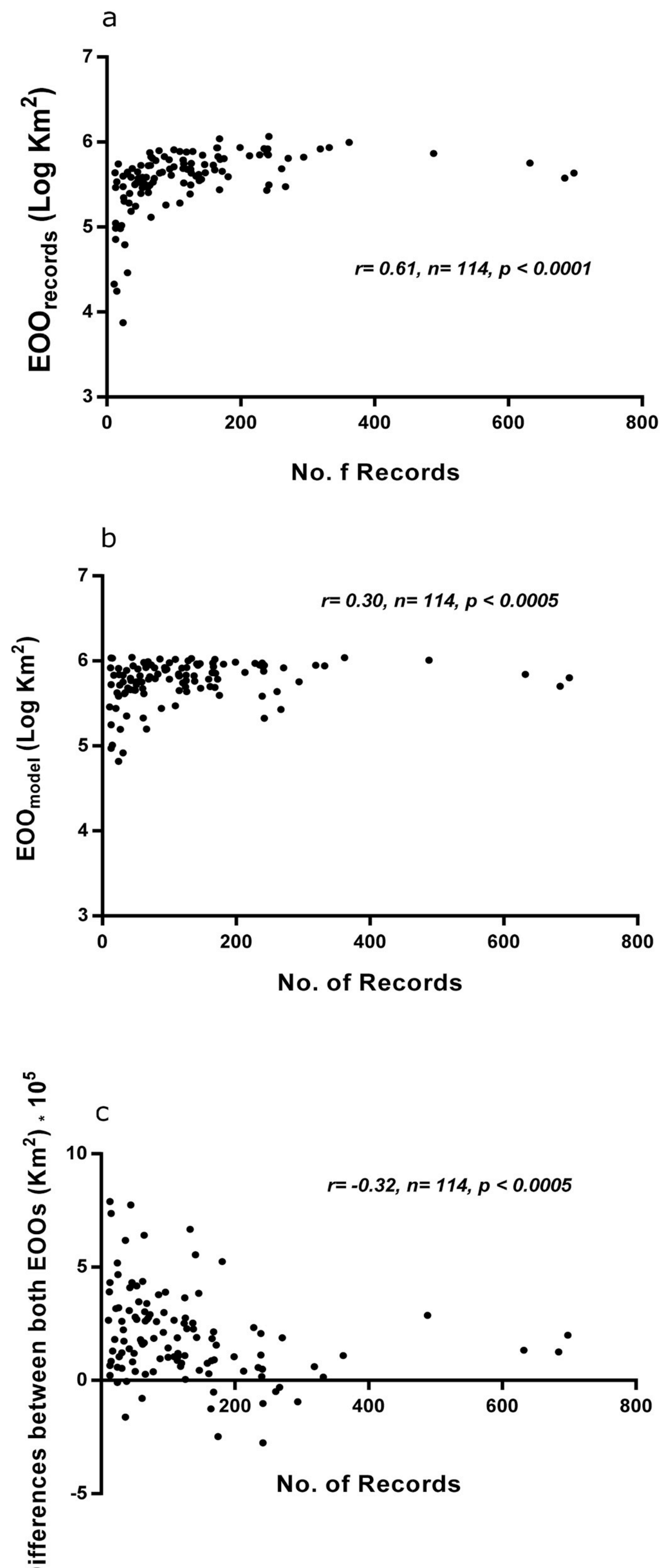

Fig. 3. Scatterplots exploring variables affecting the validity of measuring the Extent of Occupancy from species distribution models (EOOmodel). The relationships between: a) the number of records and EOOrecords; b) the number of records and EOOmodel; c) the number of records and the differences between EOOrecords and EOOmodel. All correlations are Pearson correlations that assume linearity.

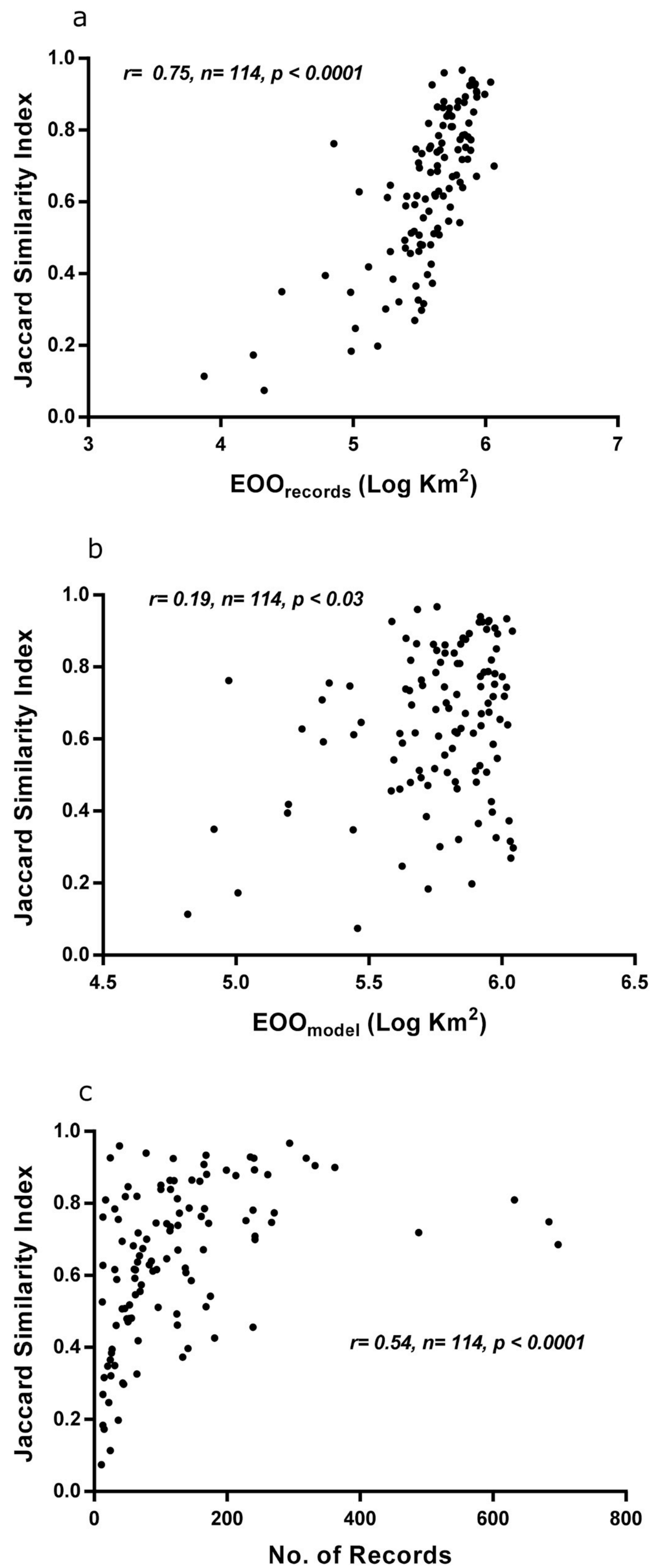

Fig. 4. Scatterplots with Spearman rank correlations showing: a) the relationship between EOOmodel and Jaccard Similarity Index; b) the relationship between EOOrecords and Jaccard Similarity Index; c) the number of the records and Jaccard Similarity Index.

Table 1
Number of plant species categorized into each of the preliminary National IUCN categories based on $EOO_{records}$, and on $AOO_{records}$ under three different assumptions about the minimum distance between 'locations'. These are 'preliminary' because of uncertainty in the sub-criterion 'continuing decline'.

Category	EOO	AOO > 20 km^2	AOO > 50 km^2	AOO > 100 km^2
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

correlation between EOO_{model} and $EOO_{records}$ (Fig. 2a), and a significant negative correlation between EOO_{model} and AUC values (Fig. 2b). The number of records was significantly positively related to both $EOO_{records}$ and EOO_{model} (Fig. 3a and b), and negatively to the differences between $EOO_{records}$ and EOO_{model} (Fig. 3c). The Jaccard Similarity Index was significantly positively related to the $EOO_{records}$ and the number of records (Fig. 4a and b), but the relationship was not significant for EOO_{model} (Fig. 4b).

3.2. Species classifications under current conditions

For the present-day data, most of the species were classified preliminarily using $EOO_{records}$ and $AOO_{records}$ as LC (Table 1 & S4). 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' (Table 1, S4 & S8). All species were classified as LC when using modelled current distributions (Table 2 & S5). The comparison between our Egyptian data and the GBIF global data (see Table S9) suggests that Egyptian records represent a reasonable proportion of the global data, and hence that it is worth assessing them regionally. Rather than accepting these proportions as accurate, we believe they highlight the inadequacies of the GBIF dataset.

3.3. Species classifications with future climate change

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 2 and 3 & S5).

When declines were based on declines over 50 years, not surprisingly there was more change. Assuming unlimited dispersal, no species were predicted to become extinct at any future time (Tables 2 and S6). There were four species evaluated as CR under the A2 scenario, three of them by 2020 (*Agathophora alopecuroides, Cymbopogon schoenanthus,* and *Deverra tortuosa*) and one by 2080 (*Andrachne aspera*) because it was predicted to lose more than 80% of its suitable habitat. Under the B2a scenario, seven species were evaluated as CR, four of them by 2020 (*Agathophora alopecuroides, Avena barbata, Deverra tortuosa,* and *Lavandula pubescens*) and three by 2080 (*Agathophora alopecuroides, Asclepias sinaica,* and *Teucrium polium*). Under the A2a scenario, twelve species were evaluated as EN, two by 2050 and ten by 2080 because they were predicted to lose more than 50% of their suitable habitat. Under the B2 scenario, eleven species were evaluated as EN (Table 2 and S6). Under the A2a scenario, 21 species were classified as VU, five of them by 2020, eight by 2050 and a further eight by 2080 (Table 2 and S6). Under the B2a scenario there were 21 species classified as VU, nine by 2020, five by 2050, and a further seven by 2080 (Table 2 and S6). For the A2a scenario there were 34 species evaluated as NT, seven by 2020, 15 by 2050, and 12 by 2080. Under the B2a scenario there were 28 species evaluated as NT, three by 2020, 13 by 2050, and a further 12 by 2080 (Table 2 and S6). 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 50 years rather than 10, again no species was predicted to become Extinct under either scenario. Under the A2a scenario, six species were classified as CR, three species by 2020 (*Acacia pachyceras, Agathophora alopecuroides* and *Nitraria retusa*) and another three by 2080 (*Agathophora alopecuroides, Andrachne aspera* and *Lavandula pubescens*) (Table 3 and S6), but only by 2080 were they predicted to lose more than 80% of their suitable habitat. By 2020, 37 species were classified as EN, 23 by 2020, three by 2050, and 11 by 2080 (Table 3 and S6). There were 34 species classified as VU, 21 by 2020, five by 2050 and a further eight by 2080 (Table 3 and S6). 47 species were classified as NT, 28 by 2020, ten by 2050, and a further nine by 2080. The majority was consistently classified as LC (Table 3 and S6). Under the B2a scenario there were seven species classified as CR, six by 2020 (*Agathophora alopecuroides, Avena barbata, Fagonia glutinosa, Lavandula pubescens, Nitraria retusa, Urginea maritima)*, and one by 2080 (*Agathophora alopecuroides*) (Table 3, S6). There were 37 species evaluated as EN, 30 by 2020, four by 2050, and three by 2080.33 species were classified as VU, 22 by 2020, four by 2050, and seven more by 2080 (see Table 3 and S6). There were 54 species classified as NT, 29 by 2020, 15 more by 2050, and a further ten by 2080: again the majority was consistently classified as LC under all circumstances (Table 3 and S6).

4. Discussion

Overall our results suggest that reasonable estimates can be made of the risk of extinction even when data are sparse, by using IUCN Red List categories coupled with the results of species distribution models projected into the future under different climate-change scenarios. We were able to make this conclusion because SDM methodology is 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

Table 2
Number of plant species assessed in each IUCN category assuming unlimited dispersal.

Category	Assessments based on 50 years							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	3	0	1	4	0	3	0	0	0	0	0	0	0
Endangered	0	0	2	10	1	4	6	0	0	0	0	0	0	0
Vulnerable	0	5	8	8	9	5	7	0	0	0	0	0	0	0
Near Threat	0	7	15	12	3	13	12	0	0	1	1	1	0	3
Least Concern	114	99	89	83	97	92	86	114	114	113	113	113	114	111

Table 3
Number of plant species assessed in each IUCN category assuming no dispersal.

Category	Assessments based on 50 years							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	3	0	3	6	0	1	0	0	0	0	0	0	0
Endangered	0	23	3	11	30	4	3	0	0	0	0	0	0	0
Vulnerable	0	21	5	8	22	4	7	0	0	0	0	0	0	0
Near Threat	0	28	10	9	29	15	10	0	1	0	3	2	0	1
Least Concern	114	39	96	83	27	91	93	114	113	114	111	112	114	113

approaches can now be applied for Red-Listing globally and regionally to classify the risk of extinction.

This is important for developing countries with few available data, 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 of the models increases in species occupying a small geographical range and restricted environmental tolerance (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.

Limitations to the use of SDMs are well known; for example, when the available data are inadequate for the modelling process to be effective (Kadmon et al., 2003; Wisz et al., 2008), or when the predictions involve extrapolation outside the limits of the existing predictors (Elith and Leathwick, 2009; Saupe et al., 2012). A number of recent studies have raised questions about the validity of predicting solely using environmental variables: there are other elements that play significant roles in shaping species distributions, for example, human activities (Newbold et al., 2015), dispersal limitation and biotic interactions (Pearson and Dawson, 2003). 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). Of course, SDMs will be more robust when there is a good quality data with low bias, and incorporate the role of human disturbance and species interactions. However, such ‘ideal’ approaches are usually not available, especially in data-sparse countries such as Egypt.

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 and continuing decline were the only two available criteria. 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 Table S7). The Red List claims that a cell size of 4 km^2 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 Table S7 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 proven 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 SDMs 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 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 virtually nothing is known 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 therefore 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., 2015). 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 hence their risk of extinction could be lower because 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 (Brummitt et al., 2015), although this comparison may be biased by the way plants have been selected to be assessed.

In general, most scientists realize that the effects of global climate change are increasing, and may soon match human disturbance as the main factor affecting species distributions in the future. A recent study confirms that climate and human activities together dominate in shaping plant distribution (Fois et al., 2017; Abdelaal et al., 2019): conversion and degradation of habitats are known to cause significant declines in biodiversity (Newbold et al., 2015). Globally, extinction risks are growing and population sizes are declining (Tittensor et al., 2014; Pimm et al., 2014), and we appreciate that conservation planning will be incomplete without taking into account human activities (Faleiro et al., 2013). Our SDMs lack these and other biotic influences, 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.

At about 15% of the total land, PAs in Egypt potentially represent a good level of conservation (El-Gabbas et al., 2016) when compared with the global average of about 12% (Chape et al., 2005). Egyptian PAs appear to 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), 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, because species can track the effect of climate change by find new suitable habitat (Thuiller et al., 2005). Under the no-dispersal assumption, as Thuiller (2004) found, the B2 scenario was slightly more harmful than A2, perhaps because the pattern of projected CO_2 and NO_2 emissions under the A2 scenario is 'safer for species diversity' than the B2 scenario (Thuiller, 2004), although it is considered to be the more negative scenario for global equilibrium (Nakicenovic et al., 2000). On the other hand, the average number of species predicted to become threatened between 2020 and 2050 in both scenarios decreases, perhaps because the predicted levels of CO_2 and NO_2 emissions are lower under the A2 than the B2 scenario (Thuiller, 2004). This result needs more investigation, because based on the IPCC reports, predicted gas emissions increase gradually in both scenarios. In view of the increased risk of extinction, conservation in Egypt needs to be prioritized quickly and given more resources to avoid this outcome.

From this case study, we conclude that SDMs are helpful tools for estimating the risk of extinction using IUCN Red-List criteria, because of their ability to estimate 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 the same species in neighbouring countries, so as to create 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, 2012): however, the data are completely lacking.

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Appendix A. Supplementary data

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