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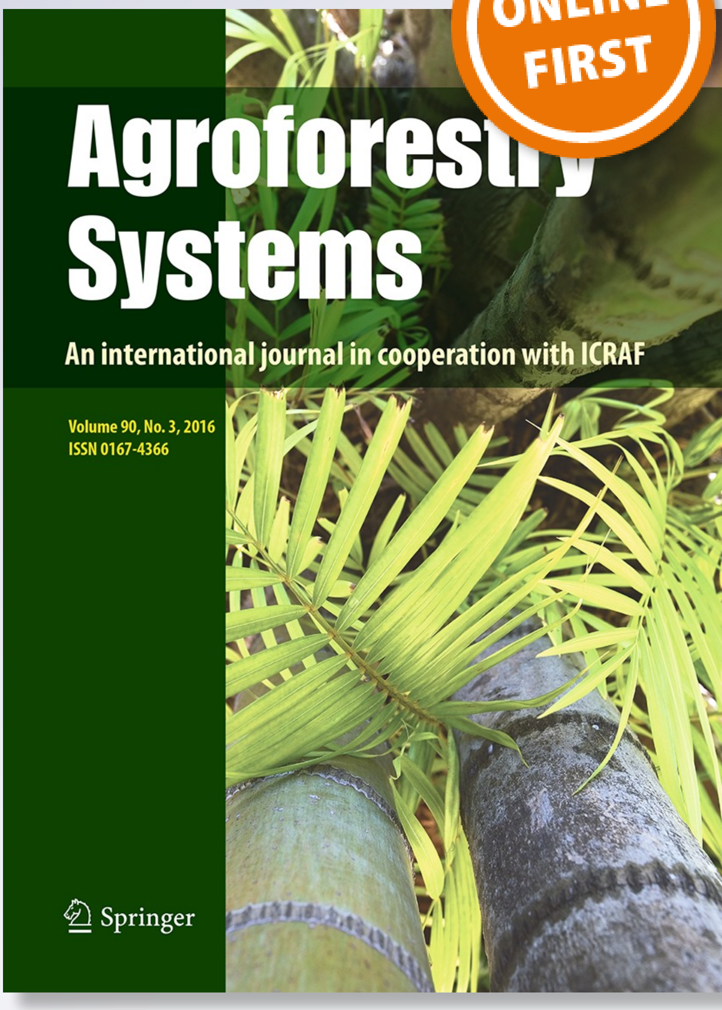

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Abstract Sustainable conservation of tropical resources required understanding of their distribution for effective assessment and definition of conservation priorities. In tropical areas, wild palms are highly valued keystone resources with growing demand for both subsistence uses and commercial trade. Here we focused on eight such species (*Borassus aethiopum* Mart., *Eremospatha macrocarpa* (G.Mann & H.Wendl.) H.Wendl., *Hyphaene thebaica* Mart., *Laccosperma opacum* (G.Mann & H.Wendl.) Drude, *Phoenix reclinata* Jacq., *Raphia hookeri* G.Mann & H.Wendl., *Raphia sudanica* A. Chev., and *Raphia vinifera* P.Beauv.). This study tested (i) how those palms distributions may be affected under future climate scenarios, and (ii) if species are effectively conserved currently and under future forecasts for their native distributional areas. Finally, we defined spatial priorities for the species' conservation. Available bioclimatic and soil data layers were used for the modelling with maximum entropy approaches, and resulting maps were overlaid on the existing protected areas network. Results showed that much of the distribution of the species will remain largely stable, albeit with some expansion and retraction in some species; relationships with protected areas networks suggest that protected portions of species distributions will also remain stable. The areas identified as highest conservation priority differ between models even though the highest-priority areas holding most palm species are located along the coast (from Guinea to Nigeria). Further development of these analyses could aid in forming a more complete picture of the distributions and populations of the species, which in turn could aid in developing effective conservation strategies for this botanically important family.

Keywords Biodiversity · Ecological niche · GIS · Representative concentration pathways · Zonation

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Introduction

Tropical areas not only harbour most of global biodiversity (Gentry 1988), but they also frequently hold burgeoning human populations. As a result, increasing demand for food, fuel, and land for agriculture exerts high pressure on limited resources (Scoones 1995). All of these factors are under the additional pressure of climate modification over recent decades and into the future. Palms raise non-timber forest product potential,

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as they represent a very important botanical family throughout the tropics and subtropics (Joyal and Deshaies 1996; Henderson et al. 1997). They rank among the most commonly mentioned plant families in the ethnobotanical literature (Macía 2004; Sosnowska and Balslev 2009) and constitute keystone resources for subsistence of local people (Brokamp et al. 2011). These conditions set incentives for destructive levels of palm extraction from natural forest stands: although little or no quantitative information exists about the exploitation of African palms, evidence indicates that global demand for palm products is outstripping sustainable supply (Byg and Balslev 2001).

Palm distributions in the tropics are particularly poorly documented. Distributional studies to date have focused primarily on the role of the environment, with climate often being assumed to be the main range-limiting factor (Blach-Overgaard et al. 2010; Pearson and Dawson 2003). Because tropical regions also experience little intra-annual climatic variability, particularly in terms of temperature, species there may have evolved narrow climatic tolerances. Still, sustainable management strategies of these economically important species require detailed understanding of distributions of the species and their distributional limitations and occurrence patterns in the absence of limitations (Collen et al. 2008), which also may serve as a proxy for their availability as resources. A recent continent-scope assessment of factors affecting African palm species distributions identified climate as the only strong environmental factor controlling their distributions (Blach-Overgaard et al. 2010). This strong response to climate suggests that African palms will be sensitive to future climate changes (Blach-Overgaard et al. 2010).

In West Africa, some palm species are of great socioeconomic importance to local people (Kouassi et al. 2008; Gyan and Shackleton 2005; Barot and Gignoux 2003), but distributional assessments are still lacking. In addition, different palms have been found on soils ranging from hydromorphic to highly sandy (Akoègninou et al. 2006; Burkill 1997); some species are dependent on a local water table (Dransfield 1988; Tuley 1995). Bjorholm et al. (2008) also revealed that climate and soil constitute important controls on regional-scale palm species' distributions in tropical areas; so soil data should be incorporated in studies assessing palm distributions in West Africa.

Protected areas were established in Africa mostly in response to declining large animal numbers (Balmford et al. 1992). Only recently have they been considered areas for the protection of biodiversity generally, of nature, or natural resources (Marshall et al. 2012). Creating and managing protected areas is still critical to ensure the persistence of species. As conservation continues to develop a 'biodiversity for livelihoods' mandate, information on the ways, in which the protected areas network will respond to future climates especially for palms, is crucial. It seems then necessary to incorporate species' range shifts in spatial conservation plans to ensure their effectiveness in the future (Hannah 2010).

From developing modelling tools and procedures (Elith et al. 2010; Guisan et al. 2007) to empirical studies (Papes and Gaubert 2007), use of niche models is expanding because of their capacity to quantify multiple correlates of species distributions and use these to project future conditions (Fitzpatrick and Hargrove 2009). Ecological niche modelling (ENM) has emerged as a powerful tool for understanding species' present-day distributions and anticipating future shifts in response to environmental changes. ENM has been implemented successfully in prediction and subsequent field verification of additional localities of known species (Syfert et al. 2013; Owens et al. 2012; Peterson et al., 2011) although ideal methodologies are still being explored (Fitzpatrick and Hargrove 2009; Peterson et al. 2011; Zurell et al. 2009). Maximum entropy approaches have recently been introduced to the field and have yielded excellent results in comparative tests (Elith et al. 2010; Pearson et al. 2007). It is a general-purpose algorithm that uses presence-only data to model ecological niches and project potential distributions (Phillips et al. 2006) within a region. These scenarios give insights into how the future might unfold in key areas: socioeconomic, technological, and environmental conditions; emissions of greenhouse gases and aerosols; and climate (Moss et al. 2010). When applied in climate change research, scenarios should help to evaluate uncertainty about human contributions to climate change, responses of the Earth system to human activities, impacts of a range of future climates, and implications of different approaches to mitigation and adaptation (Moss et al. 2010).

This study aimed to illuminate the distributions of eight native, medium to wide-ranging, and wild and commercially important palm species' distributions across West Africa by testing several ideas. Based on previous findings that closely related species share similar ecological conditions (Marshall et al. 2012) and that palms are poor dispersers (Cunningham and Milton 1987), we expected the species distributions' to remain largely stable. Also given the wide distribution of protected areas in West Africa (Locke and Dearden 2005), and the fact that they are assumed to conserve tropical species (Vellak et al. 2009) sustainably, we expect palm species to be conserved effectively currently and under future forecasts in their native distributional area. Assessing the veracity of these two ideas quantitatively is a major goal in this paper.

Materials and methods

Species occurrence records

We examined eight wild palm species based on occurrence data from across their geographical distributions (Fig. 1). The species were *B. aethiopum* (L.) Mart, *Eremospatha macrocarpa* (G. Mann & H. Wendl.) H. Wendl., *Laccosperma opacum* (G. Mann & H. Wendl.) Drude, *Hyphaene thebaica* (L.) Mart, *Phoenix reclinata* Jacq., *Raphia hookeri* G.Mann & H. Wendl., *R. sudanica* A. Chev., and *R. vinifera* P. Beauv. Among these species, only *B. aethiopum* and *H. thebaica* are dioecious. About 65 % of the localities came from recent fieldwork by the authors, while 35 % were based on data associated with herbarium records (Table 1). Data were quality controlled by identifying and removing duplicate records with ENM tools (www.ENMTools.com; Warren et al. 2010); we also removed herbarium from records collected before 1950, reducing effects of temporal bias and matching occurrence data to the climate datasets.

Environmental data

Environmental layers in this study comprised data on climate and soils; the former is assumed to be the main

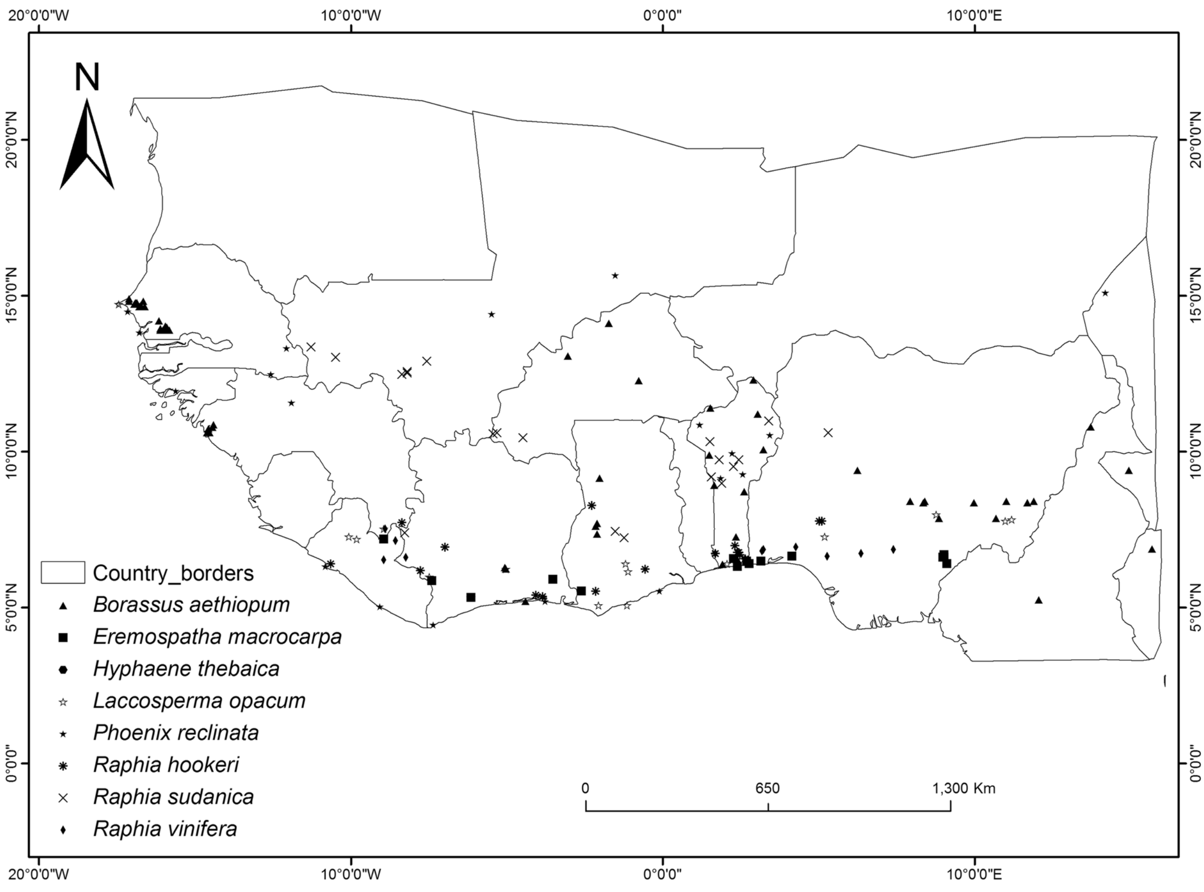


Fig. 1 Geographic distribution of eight palm species occurrence across West Africa included in this study

Table 1 Records used in this study and their sources

Species	Number of records			Total
	Fieldwork	Literature	GBIF	
Borassus aethiopum	92	16	20	128
Eremospatha macrocarpa	40	15	10	65
Laccosperma opacum	34	14	4	52
Hyphaene thebaica	72	25	15	112
Phoenix reclinata	55	20	10	85
Raphia hookeri	63	8	6	77
Raphia sudanica	45	6	4	55
Raphia vinifera	25	3	5	33

GBIF global biodiversity information facility

factor shaping distributions of species over broad extents (Pearson and Dawson 2003; Parviainen et al. 2008). As such, we examined the 19 'bioclimatic' variables at a resolution of 2.5′ (Hijmans et al. 2005). Owing to common collinearity and non-independence of climate dimensions (Zuur et al. 2010), we examined correlation patterns among variables to select those not closely correlated. Hence, we included only a subset of variables with Pearson correlation coefficients below 0.80 (Elith et al. 2010). In addition, expert knowledge of the ecological affiliation of each species was taken into account in selecting variables. Because palm distributions also relate to soils (Blach-Overgaard et al. 2010; Hawthorne 1990), we added detailed soil layers to analyses in the form of the Harmonized World Soil Database version 1.2 (FAO/IIASA/ISRIC/ISSCAS/JRC 2012) which has been used by Sanchez et al. (2010); and Beck (2013).

To assess potential impacts of climate changes on palm distributions, we transferred present-day model rule sets to two future climate models namely HadGEM2-ES and CNRM-CM5, recently used for West Africa (Panitz et al. 2013; Good et al. 2013). These climate models with relatively drastic views of future conditions are based on the representative concentration pathway (RCP) 8.5 for the 2050 time horizon. RCPs are the third generation of scenarios and are preferred to Special Report on Emissions Scenarios (SRES) because they allow more flexibility (and reduced costs) in modelling processes (van Vuuren et al. 2011); RCPs imply collaboration between impacts, adaptation, and vulnerability research, and climate and integrated assessment modelling (van Vuuren and Carter 2014). These new scenarios have been developed to explore different combinations of demographic, socioeconomic, land use, and technology scenario backgrounds (Moss et al. 2010). RCP 8.5 has already been used for studying African ecosystems (Breil and Panitz 2013; Panitz et al. 2013; Wu et al. 2013; Marinho et al. 2013) and represents an updated version of the SRES A2 scenario.

Modelling the distribution of the species

The parts of the environment that have been accessible to the species via dispersal over relevant periods of time symbolized by **M** (Barve et al. 2011; Saupe et al. 2012) was first defined for each species within the study region. **M** depends on opportunities for and constraints on movements of the species; factors not often included in modelling efforts, although exceptions exist (Kot et al. 1996; Engler and Guisan 2009; Cabral and Schurr 2010).

The maximum entropy approach (Maxent, ver. 3.3.3 k; Phillips et al. 2006) was used for modelling species ecological niche. This approach is based on probability density estimation (where the presence data are assumed to be drawn from some probability distribution over the study region). Maxent models were developed using 10,000 background points, a maximum of 1000 iterations, a convergence threshold of 0.00001, and a random 75 % of the data points set aside for intrinsic testing (Fielding and Bell 1997; Guisan and Zimmermann 2000). We corrected for geographic sampling bias using background data as proposed by Philips et al. (2009) and recommended by Syfert et al. (2013), as using background data gave a substantial improvement in model performance (Philips et al. 2009). For that purpose, we generated background data (sometimes referred to as "pseudo-absences") which has a similar geographical sampling bias to that of the presence data.

Maps were thresholded to binary to avoid effects of overfitting (Peterson et al. 2007). To this end, we sought the highest threshold that included 95 % of the input data used in model calibration. That approach was a reasonable way to prioritize correct prediction of presences over correct prediction of absences and to take into account the noisy nature of biodiversity data (Peterson et al. 2011). The present-day map of each species was combined with the two future climate forecasts to generate a map showing agreement as regards the species distributional area and stability.

To determine the potential of protected areas across West Africa distributional area of each palm species, the combined map (present-day and future model distribution) was overlaid on the protected area network, and relevant areas estimated in ArcGIS 10.1. Finally, a spatial conservation analysis helped to identify priority areas for the conservation of the palms. We used spatial prioritization algorithm Zonation version 4.0.0b26. Zonation ranks areas according to their priority for conservation and is designed for the use with multiple species (Nur et al. 2011). The ranking is achieved by removing grid cells sequentially from the study area that have low predicted probabilities of occurrence and thus the lowest conservation value.

Model evaluation

The area under the receiver operating characteristic (ROC) curve, known as the AUC, is widely used to assess the predictive accuracy of distributional models. However, some authors have begun to criticize the indiscriminate use of AUC as the standard measurement of accuracy in distribution models (Austin and Van Niel 2011; Lobo et al. 2008). As such, new indices have been proposed and have proven effective in evaluating model performance. Among these new approaches is the partial ROC approach (Peterson et al. 2008). This novel approach provides a firmer foundation for evaluation of predictions from ecological niche models.

First, model performance was assessed by dividing the occurrence data available for each species randomly into calibration (75 %) and evaluation (25 %) subsets; a good model is expected to predict correctly the occurrence of the palm trees at the evaluation sites (Phillips et al. 2006). In light of criticisms on the AUC metric (Peterson et al. 2008; Lobo et al. 2008), we used a recently proposed modification named Partial ROC (Peterson et al. 2008). ROC analysis is a method designed to evaluate the specificity (absence of commission error) and sensitivity (absence of omission error) of a diagnostic test (Fielding and Bell 1997). We calculated partial AUCs using a program based on the trapezoid method (Barve 2008). Partial AUC values are presented as a ratio between the AUC (with modified x-axis, from traditional applications) and the null expectation of AUC (which unlike traditional ROC approaches is not equal to 0.5 and is variable; Peterson et al. 2008). Bootstrapping manipulations to permit evaluation of statistical significance of AUCs (as compared with null expectations) were achieved by resampling 50 % of the test points with replacement 1000 times from the overall pool of testing data.

Moreover, model success was also evaluated visually, examining how well-mapped probability values matched presence records. A good model should identify regions of high probability that cover most presence records, and areas of low probability should contain few or no presence points (Sanchez et al. 2010; Saupe et al. 2012). Available literature on each palm species was used to determine if high-probability areas models corresponded with areas known to hold the species, even though precise locations were not always available.

Results

Results from the correlation analysis and additional expert knowledge of the ecological affiliations of the species from fieldwork identified six bioclimatic variables and soil as contributing to the environmental variation across the study region (Table 2): annual mean temperature, minimum temperature of the wettest month, mean temperature of wettest quarter, precipitation of driest month, precipitation of wettest quarter, and precipitation of driest quarter. Globally the palms are differently affected by the bioclimatic variables. Soils data were relevant to the presence of *Eremospatha macrocarpa*, *Raphia hookeri*, *R. sudanica*, and *R. vinifera*, whereas *Hyphaene thebaica* occurrence showed little relation to soils (Table 2).

Model evaluations indicated that all eight models were robust and yielded predictions statistically significantly better than random. The frequency histogram

Table 2 Variables contribution in each palm species model

Species	Annual mean temperature	Minimum temperature of Wettest Month	Mean temperature of wettest Quarter	Precipitation of driest month	Precipitation of Wettest Quarter	Precipitation of driest Quarter	Soil
Borassus aethiopum	3.0	10.7	24.3	4.6	46.3	1.7	9.4
Eremospatha macrocarpa	5.0	1.3	0.6	10.0	46.5	5.9	30.7
Hyphaene thebaica	20.5	20.0	18.4	12.5	12.8	11.8	4.0
Laccosperma opacum	5.9	4.8	8.0	8.7	36.2	16.3	20.1
Phoenix reclinata	7.8	6.6	11.9	12.0	20.7	22.8	18.2
Raphia hookeri	15.3	12.5	3.3	11.9	14.0	20.0	23.0
Raphia sudanica	10.8	5.1	2.8	6.9	29.9	14.9	29.6
Raphia vinifera	5.0	13.7	10.4	15.7	12.8	17.5	24.9

developed from the distribution of null values (Fig. 2) among 1000 replicates clearly showed that AUC ratios were well above 1.0 for all species (1.0 and 1.9 being, respectively, minimum and maximum values). As such, all models showed excellent performance.

Model results showed that distributions of the palm species will remain largely stable (darker blues; Fig. 2), although some species are expected to experience some retraction of present-day distributional areas. For *B. aethiopum* in particular, we noted some tendency toward retraction along the northern fringe of the range in the Sahel, particularly in northern Nigeria (broad light-blue area); future range expansion will likely be limited to small areas in Senegal, Guinea Bissau, Guinea, and Sierra Leone and in southern Ghana and Côte d'Ivoire and along the Nigeria-Cameroon border. For *E. macrocarpa*, some retraction is anticipated in Liberia and Côte d'Ivoire and some expansion particularly from Côte d'Ivoire to Nigeria. For *H. thebaica*, models anticipated more expansion than retraction particularly in Mauritania, Mali, and Nigeria. Retraction of distributional areas is anticipated for *L. opacum* from Togo to Nigeria, although the species range is overall anticipated to be relatively stable. For *P. reclinata*, models anticipated more expansion (northern Benin and Nigeria) than retraction (Guinea Bissau, Senegal, and Guinea). Among the *Raphia* species, *R. sudanica* is expected to experience expansion of its distributional area from Guinea Bissau to Benin; though *R. hookeri* and *R. vinifera* share the same general present distributional predicted areas, *R. hookeri* is expected to expand, whereas *R. vinifera* is expect to retract. Some palm species encounter conversion of low suitability present-day areas into future distribution, among which *Hyphaene thebaica* encounters the highest conversion. For medium-suitability areas, an increase is noticed in conversion of present-day distribution into future distribution except for *Raphia sudanica*, *R. vinifera* (for the two future models), and especially *H. thebaica* (for one future model). As for highly suitable areas, only *B. aethiopum* encounters reduction of the present-day suitable areas into future distribution (Table 3).

Assessment of relationships between palm species distributions and the protected areas network across West Africa revealed some diversity, although protection levels will remain generally stable (Fig. 3). *B. aethiopum* showed some tendency toward retraction in the protected areas of Benin, Nigeria, and Côte d'Ivoire and some indications for expansion in Senegal, Ghana, and northern Nigeria. *E. macrocarpa* showed a tendency toward expansion (south Côte d'Ivoire to Nigeria); *L. opacum* showed similar tendencies. For *H. thebaica*, models indicated minor retraction in Senegal and Burkina Faso and some expansion in Nigeria. For *P. reclinata*, some retraction is expected in Senegal, northern Benin, and Guinea Bissau, and some expansion is anticipated along both between Guinea-Côte d'Ivoire and Nigeria-Benin borders. With little retraction, *R. hookeri* and *R. vinifera* are expected to expand in Côte d'Ivoire and Ghana, while *R. sudanica* will experience more expansion in northern Benin, Burkina Faso, Côte d'Ivoire, and Guinea Bissau.

The areas identified as highest conservation priority (Fig. 4) differed slightly between present-day conditions and the two futures. The highest prioritization

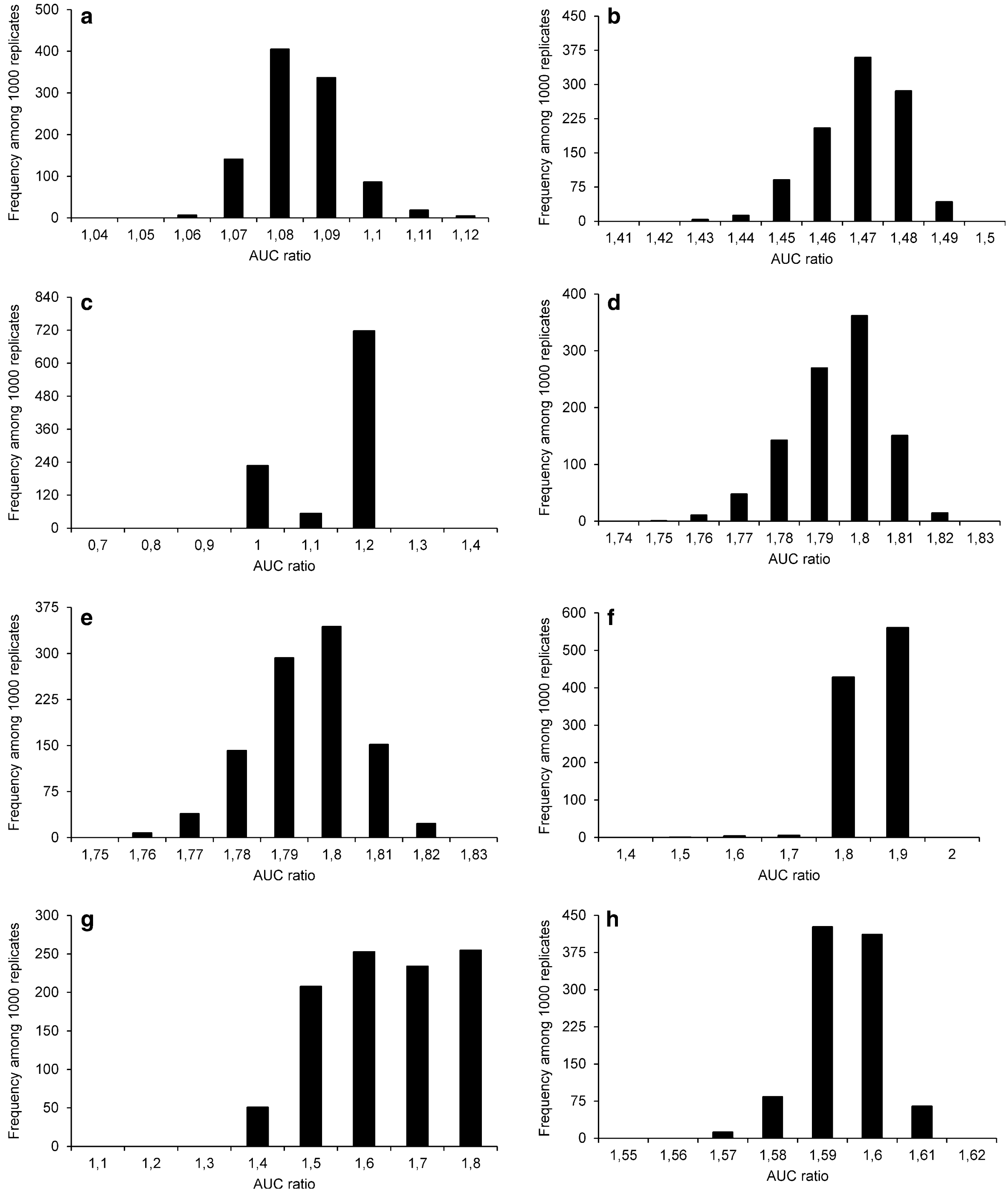


Fig. 2 Maps showing variation of AUC ratios for 1000 replicates using the Partial ROC procedure for **a** *Borassus aethiopum*, **b** *Eremospatha macrocarpa*, **c** *Hyphaene thebaica*, **d** *Laccosperma opacum*, **e** *Phoenix reclinata*, **f** *Raphia hookeri*, **g** *Raphia sudanica*, and **h** *Raphia vinifera*

Table 3 Dynamic of suitable areas for palms accounting for the present and the two future models

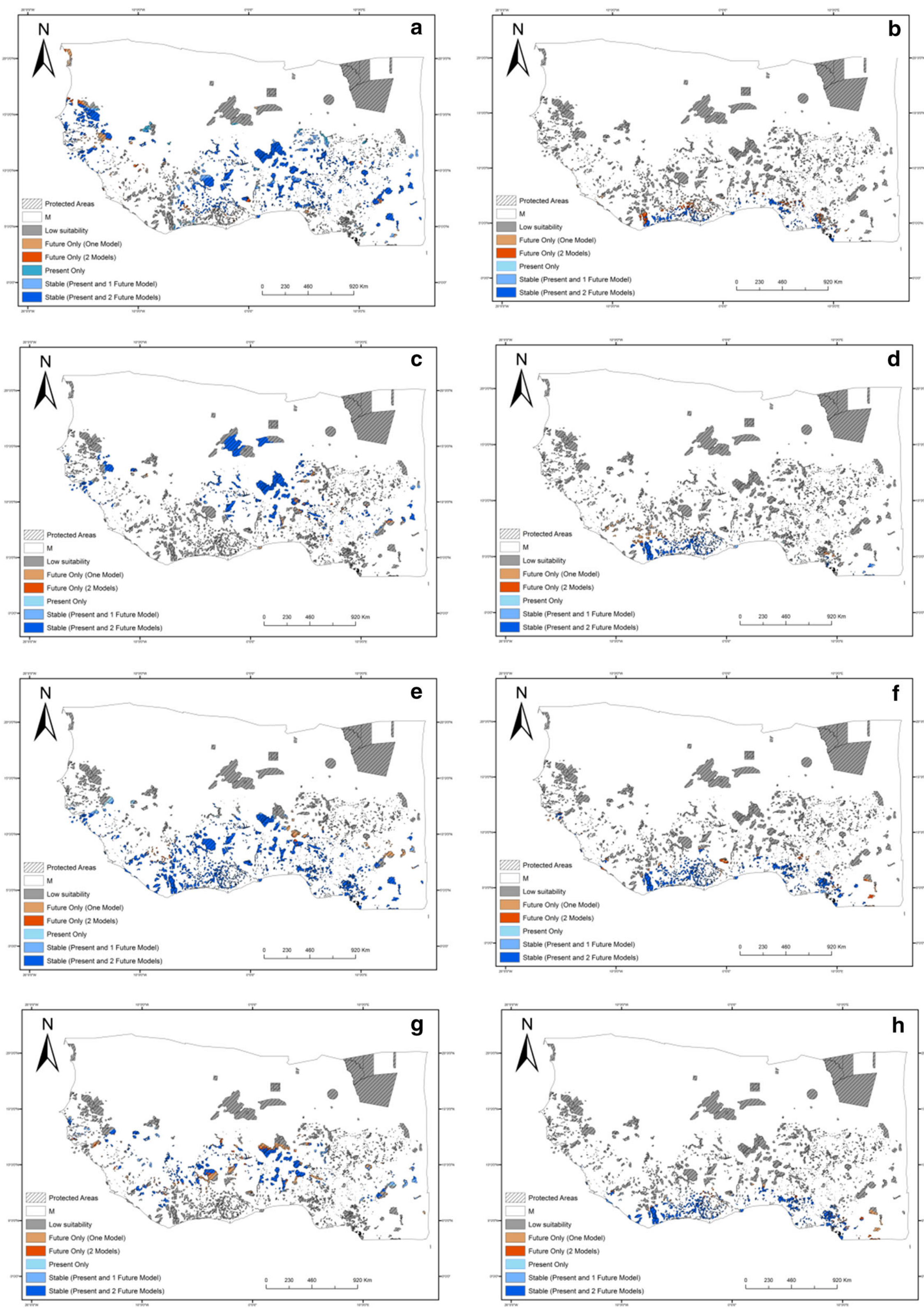
Species	Model	Low suitability		Medium suitability		High suitability	
		Area (km^2)	Trends (%)	Area (km^2)	Trends (%)	Area (km^2)	Trends (%)
Borassus aethiopum	Present	2940703.4		727182.36		968886.35	
	CNRM-CM5	2821985.8	−4.0	1307814.1	79.8	506972.19	−47.7
	HadGEM2-ES	2669928.3	−9.2	1281154.9	76.2	685688.85	−29.2
Eremospatha macrocarpa	Present	3637512.6		609254.55		389599.33	
	CNRM-CM5	3573671.5	−1.8	629851.9	3.4	433248.63	11.2
	HadGEM2-ES	3550448.8	−2.4	625561.68	2.7	460654.84	6.3
Hyphaene thebaica	Present	854074.82		2900639.9		866497.26	
	CNRM-CM5	467549.08	−45.3	3050029.4	5.2	1119193.6	29.2
	HadGEM2-ES	463856.5	−45.7	2866446.2	−1.2	1307109.7	50.8
Laccosperma opacum	Present	3794799.5		352502.77		489469.78	
	CNRM-CM5	3448849.5	−9.1	383810.54	8.9	504112.04	3.0
	HadGEM2-ES	3739325.4	−1.5	374743.63	6.3	522703.01	6.7
Phoenix reclinata	Present	3142685.4		1289180.4		204906.24	
	CNRM-CM5	2616119.1	−16.8	1746142.7	35.4	274510.33	34.0
	HadGEM2-ES	2572597.8	−18.1	1666997.6	29.3	297155.25	45.02
Raphia hookeri	Present	3701545.8		729658.31		205418.51	
	CNRM-CM5	3640693	−1.6	759796.61	4.1	236282.51	15.0
	HadGEM2-ES	3664129.1	−1.0	733436.27	0.5	239206.69	16.4
Raphia sudanica	Present	3027041.5		1210334.2		399396.41	
	CNRM-CM5	3112675.2	2.8	1066067.4	−11.9	458008.14	14.7
	HadGEM2-ES	2933958.5	−3.1	1129204.1	−6.7	573395.96	25.9
Raphia vinifera	Present	3099612.4		1147773.8		309385.89	
	CNRM-CM5	2847748.5	−8.1	862932.75	−24.8	266090.83	26.92
	HadGEM2-ES	2708881.8	−12.6	934372.45	−18.6	293517.79	5.13

Positive percentage indicate gain and negative percentage indicate loss. Low suitability stands for probability <0.4; medium suitability stands for probability between 0.4 and 0.7; high suitability stands for probability is >0.7

areas holding most palm species (top 2 and 2–5 % of the study area) are located along the coast (from Guinea to Nigeria) and in some areas along the Sudanian zone. This area was also consistently retained in the most important 5–10 % of the study area. Some parts of this area are covered by existing protected areas network. These regions would still hold wild palms in the future. Performance curves measuring the effectiveness of proposed networks clearly showed a high correlation between the lost of study area and the reduction of the average proportion of suitable areas for the species (Fig. 5) for the present-day. This situation also stands for the two future models (CNRM-CM5 and HADGEM2-ES). Correlatively, high costs are needed to set good conservation planning (hosting the highest diversity within the group) and increase it. Differences in uncertainty and suitable areas modelling do not increase between present and the two future models.

Discussion

This study estimated present-day distributions and developed future forecasts for eight palm species, and assessed the effectiveness of West African protected areas in covering the species distributional area. Overall, model performed well in predicting suitable conditions for each species. For the palms, the distribution of AUC ratios was well above 1.0. So the models were judged as statistically significantly better than random. The mapped probability values matched


a
b
c
d
e
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g
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Protected Areas
M
Low suitability
Future Only (One Model)
Future Only (2 Models)
Present Only
Stable (Present and 1 Future Model)
Stable (Present and 2 Future Models)
0 230 460 920 Km

◀**Fig. 3** *Maps* showing distribution and conservation of palms within protected areas across West Africa **a** *B. aethiopum*, **b** *Eremospatha macrocarpa*, **c** *Hyphaene thebaica*, **d** *Laccosperma opacum*, **e** *Phoenix reclinata,* **f** *Raphia hookeri*, **g** *Raphia sudanica*, and **h** *Raphia vinifera*; Hatches areas are protected areas; *grey* indicates low suitability areas, *orange* indicates areas suitable in one future model, *red* two future models, *light blue* indicates areas suitable at present, *medium blue* present and one future model, *dark blue* present, and the two future models. (Color figure online)

presence records and expert judgment of the known occurrence areas for each species, further corroborating model results for each species. Model predictions did extend to some degree beyond known ranges, likely the result of key environmental variables not being included in model calibration.

Ecological niche modelling has often been considered a powerful tool for estimating distributional potential of species (Syfert et al. 2013), particularly in the face of climate change. Previous criticism of the Special Report on Emissions Scenarios led to development of a new set of scenarios called representative concentration pathways (van Vuuren and Carter 2014). These new scenarios are based both on greenhouse gas emission and human development factors (developments in technology, changes in energy generation and land use, global and regional economic circumstances, and population growth). As such, they include most current threats to species and provide excellent basis for development of detailed future forecasts.

Globally, palm distributions are governed by combination of effects of climate (temperature and precipitation) and substrates (soils). This idea is consistent with Blach-Overgaard et al. (2010), suggesting that African palms are limited by combination of climatic dimensions and other environmental conditions. Other studies have shown that palm species' distributions are sensitive to environmental variation at multiple spatial scales (Salm et al. 2007; Walther et al. 2007; Bjorholm et al. 2008). We found both precipitation and temperature variables contributing to the models, indicating a balanced influence of these variables on the species' distributions. This balanced influence of environmental factors is consistent with the idea that both water availability and temperature are important factors in controlling

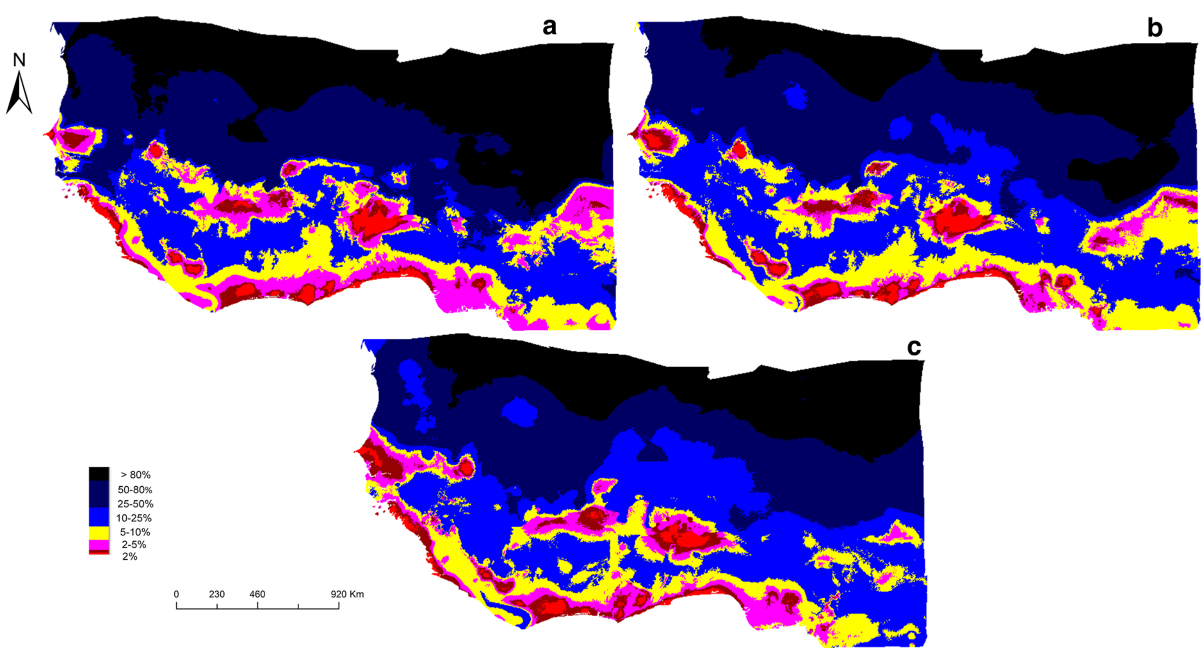

Fig. 4 *Maps* showing potential prioritization areas for conserving palm richness across West Africa: **a** present-day distribution, **b** future distribution for CNRM-CM5, **c** future distribution for HADGEM-ES. Areas were identified using Zonation, and the colours reflect the priority for conservation: *red* the best 2 % of the study area; *dark red* the best 2–5 %; *magenta* the best 5–10 %; *yellow* the best 10–25 %; *light blue* the best 25–50 %; *dark blue* the best 50–80 %; *black* the best 80–100 % (or the least valuable 20 %). (Color figure online)

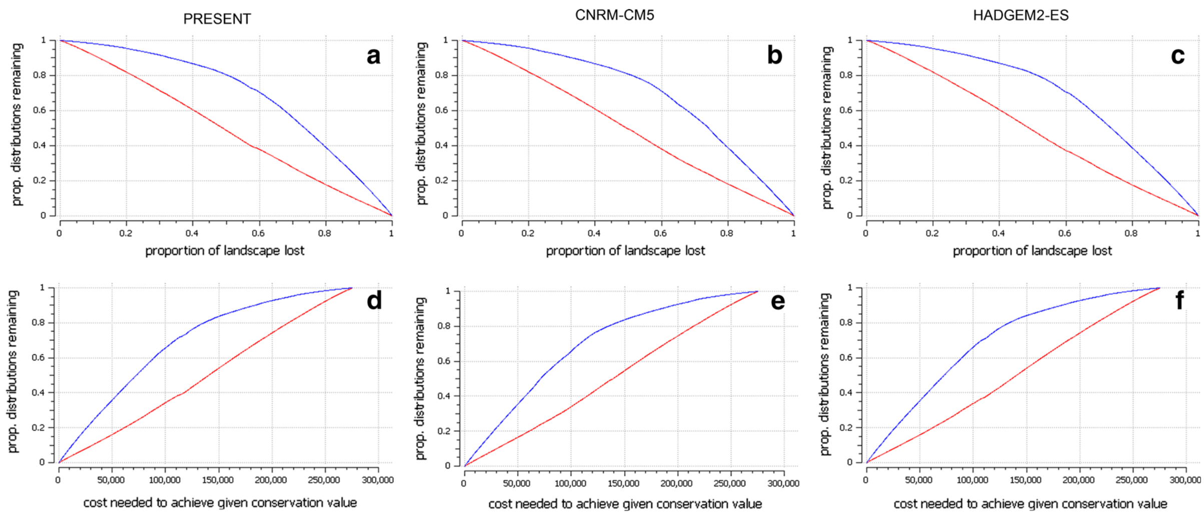

Fig. 5 Performance curves measuring effectiveness of setting conservation priorities for palm species. **a–c** Graphs showing the proportion of the West Africa lost and corresponding average proportions of suitable areas remaining for wild palms (frequency of projections). **d–f** Graphs showing the costs of considering uncertainty in conservation planning and corresponding average proportion of suitable areas remaining. The *red line* indicates the scenario considering costs of uncertainty; the *blue line* shows for the scenario considering environmental change; results are shown for the present (PRES), future CNRM-CM5 (CNR), and future HADGEM2-ES (HAD) of suitable areas for palm species. (Color figure online)

species' occurrence patterns in subtropical and tropical zones (Purseglove 1972). Although palm species were affected by soils to different degree, the importance of this factor in controlling African palm distributions has been demonstrated (Blach-Overgaard et al. 2010; Tuley 1995).

Our findings were that wild palm suitable areas will remain largely stable in future decades thus supporting the first hypothesis. Indeed, palms are generally known to be poor dispersers (Dransfield 1988): for most species seeds fall under the parent tree and germinate if not dispersed by primates. This limited dispersal is the case particularly for *B. aethiopum* and *Hyphaene thebaica* (personal observation); for other species like *Raphia* sp or rattan palms, found in marshy areas, water flow can help with dispersal. Other studies have shown that mammals or birds may contribute to seeds dispersal although substantial variability exists among species (Zona and Henderson 1989). Local people living in distributional areas of the species also contribute to the palm dispersal by discarding seeds after consuming the fruits (personal observation). These diverse dispersal mechanisms may permit rapid and efficient expansion of palm distributions beyond current distributional areas when suitable conditions exist.

Assessment of the relationship of palm species distribution to protected areas showed good potential of current protected areas to conserve populations of each species. In addition, our future projections revealed stability in protected areas-species distribution relationships, even though expansions and reductions may occur in some cases. These findings support the hypothesis that protected areas effectively conserve wild palms current and in the future. However, for most of sub-Saharan Africa, the future course climate change is still not fully understood, which could lead to further threats; sub-Saharan Africa has been cited as one of the most vulnerable area to the climate change (Boko et al. 2007). The protected areas are already threatened by human population expansion, illicit exploitation of resources, and fragmentation of the habitat as mentioned elsewhere (Houehanou et al. 2013; Clerici et al. 2007; Bruner et al. 2001), such that spatial footprints of protected areas are only part of the story.

Most wild palm distributions are expected to remain largely stable in the face of future changing climate, even under the most drastic scenarios, and the protected areas network will continue to host much of the range of each of the species. However, human pressure on habitats and species continues, sometimes causing unforeseeable modifications to landscapes that can lead to disappearance of species and conversion of current protected areas to agroforestry systems. Hence, given inherent uncertainties in suitable areas, model projections, and climate forecasts (Garcia et al. 2014; Hunter et al. 2010), environmental education is needed to sensitize local people about conserving resources and reducing pressure on protected areas. Proper incentives should be provided to allow the local people to benefit from other income-generating activities, thus leading to rule enforcement, facilitating conservation of protected areas.

We believe that our results offer a scientific support to a planning and decision-support tool for conservation of socioeconomically important palms. Our modelling exercise indeed indicated that highest conservation priorities fall within already existing protection areas. This result leads to a probable good conservation of the palm richness within the protected area network. Nevertheless, in most African countries, governance of social–ecological systems is weak, leading to the occurrence of weak interactions between actors who use natural resources and actors in charge of the management of these resources and of activities related to use of the resources. These weak relations, added to rapid changes in African landscapes, lead to insufficient management of the resources (Faysse et al. 2014), increasing threats to these resources. Many theories of natural resources management also assume that the ''building blocks'' of good governance are within reach; these theories provide limited guidance about where to start in order to improve governance of the social–ecological systems when these building blocks are not within reach, at least not in short term. Even social learning could help to solve the problem, a concerted action should be suggested (Faysse et al. 2014) which could in turn lead to more effective action wherein multiple actors collectively learn about and develop an understanding of each others' interests to guarantee a sustainable future of their common resources. However, implementing social learning in the African context of weak governance cannot be taken for granted, as poverty levels are high with a raging demography and increasing human needs. Thus, co-management could be suggested, laws should be enforced, staff increased, and necessary funds provided for actions as community-based conservation are more effective in human modified-landscapes (Norris et al. 2010).

Biophysical models such as those explored herein can provide key insights into human–environment interactions, particularly the influence of demographics and socioeconomic features on suitable areas for species. However, integration of human demographics and probabilities of conversion of natural areas to human modified landscape is a central consideration and may alter some way the outputs of the biophysical models. The suitable areas are often described in terms of population dynamics: the area is the set of environmental conditions in which the population is stable or growing without immigration (Garcia et al. 2012).We recommend integrating the information presented here with similar data for other very useful species, and other stakeholder interests, to contribute effectively to biodiversity conservation in tropical areas. Further development of these models should include adaptation of suitable areas modelling to human-managed landscapes, taking into account human population dynamics, changes in agricultural practices, and household attributes.

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