

## Assessing climate change impacts for vertebrate fauna across the West African protected area network using regionally appropriate climate projections

D. J. Baker<sup>1</sup>\*, A. J. Hartley<sup>2</sup>, N. D. Burgess<sup>3,4</sup>, S. H. M. Butchart<sup>5</sup>, J. A. Carr<sup>6</sup>, R. J. Smith<sup>7</sup>, E. Belle<sup>3</sup> and S. G.Willis<sup>1</sup>

<sup>1</sup>School of Biological & Biomedical Sciences, Durham University, Mountjoy Site, Durham DH1 3LE, UK, <sup>2</sup>Met Office Hadley Centre, FitzRoy Road, Exeter, Devon EX1 3PB, UK, <sup>3</sup>UNEP-WCMC, 219 Huntington Road, Cambridge, UK, <sup>4</sup>Center for Macroecology, Evolution and Climate, Natural History Museum, University of Copenhagen, Copenhagen, Denmark, <sup>5</sup>BirdLife International, Wellbrook Court, Girton, Cambridge CB3 0NA, UK, <sup>6</sup>IUCN Global Species Programme, 219c Huntingdon Road, Cambridge, UK, <sup>7</sup>Durrell Institute of Conservation and Ecology, School of Anthropology and Conservation, University of Kent, Canterbury, Kent CT2 7NR, UK

\*Correspondence: David J. Baker, School of Biological & Biomedical Sciences, Durham University, Mountjoy Site, Durham DH1 3LE, UK. E-mail: d.j.baker@durham.ac.uk

## ABSTRACT

**Aim** We conduct the first assessment of likely future climate change impacts for biodiversity across the West African protected area (PA) network using climate projections that capture important climate regimes (e.g. West African Monsoon) and mesoscale processes that are often poorly simulated in general circulation models (GCMs).

Location West Africa.

**Methods** We use correlative species distribution models to relate species (amphibians, birds, mammals) distributions to modelled contemporary climates, and projected future distributions across the PA network. Climate data were simulated using a physically based regional climate model to dynamically downscale GCMs. GCMs were selected because they accurately reproduce important regional climate regimes and generate a range of regional climate change responses. We quantify uncertainty arising from projected climate change, modelling methodology and spatial dependency, and assess the spatial and temporal patterns of climate change impacts for biodiversity across the PA network.

**Results** Substantial species turnover across the network is projected for all three taxonomic groups by 2100 (amphibians = 42.5% (median); birds = 35.2%; mammals = 37.9%), although uncertainty is high, particularly for amphibians and mammals, and, importantly, increases across the century. However, consistent patterns of impacts across taxa emerge by early to midcentury, suggesting high impacts across the Lower Guinea forest.

**Main conclusions** Reducing (e.g. using appropriate climate projections) and quantifying uncertainty in climate change impact assessments helps clarify likely impacts. Consistent patterns of high biodiversity impacts emerge in the early and mid-century projections, while end-of-century projections are too uncertain for reliable assessments. We recommend that climate change adaptation should focus on earlier projections, where we have most confidence in species responses, rather than on end-of-century projections that are frequently used. In addition, our work suggests climate impact should consider a broad range of species, as we simulate divergent responses across taxonomic groups.

#### **Keywords**

Amphibians, birds, climate adaptation, mammals, regional climate model, species distribution models.

**Diversity and Distributions** 

## INTRODUCTION

Protected area (PA) networks are a core component of the global effort to protect biodiversity from multiple and increasing anthropogenic threats. Although much variation exists in the quality of protection provided (Coad *et al.*, 2013), PA status can significantly reduce the impacts of these threats (Butchart *et al.*, 2012). However, climate change is driving shifts in species' ranges (Chen *et al.*, 2011; Van Der Wal *et al.*, 2013) and this redistribution of species against a background of static PA networks has the potential to decrease their effectiveness as a conservation measure. Assessing potential climate change impacts on biodiversity across these networks is necessary for identifying impact hotspots/ coldspots and adaptation opportunities (Hannah *et al.*, 2007; Araujo *et al.*, 2011).

Correlative species distribution models (SDMs) have been the dominant methodology for assessing climate change impacts to biodiversity (Guisan et al., 2013) and have been applied to many different climatic regions (e.g. montane, desert). The two dominant sources of uncertainty in SDM projections have consistently been shown to derive from choice of modelling methodology and general circulation models (GCMs; Garcia et al., 2012; Bagchi et al., 2012), that is the low-resolution physically based models used to simulate global climates. Uncertainty due to choice of GCM is unusually incorporated into biodiversity impact assessments by using multiple GCMs, giving biodiversity responses across a range of climate trajectories (e.g. Garcia et al., 2012). However, GCMs are designed to model large-scale climatic fields and are often poor at capturing key regional climate features that are most likely to affect biodiversity (Cook & Vizy, 2006; Dosio et al., 2015). Consequently, climate change impact assessments across many regions are unlikely to yield useful indices of potential impacts because they poorly represent regional climates. The regional appropriateness of climate projections is seldom discussed in the ecological literature, but should be the starting point for any assessment of potential future impacts of climate change on biodiversity as this will help reduce uncertainty (Christensen et al., 2013; Flato et al., 2013).

The West African region contains high levels of biodiversity and endemism (e.g. West Guinea forests) across multiple taxonomic groups (Myers *et al.*, 2000; Kier *et al.*, 2009) and is likely to be impacted severely by climatic changes (Diffenbaugh & Giorgi, 2012). Assessing the potential resilience of the region's PA network to climate change is a priority, especially given the high irreplaceability and biodiversity value of many of the region's PAs (Rodrigues *et al.*, 2004). However, like many biodiversity hotspots, the region's climate is dominated by complex regional weather patterns, for example the West African Monsoon (WAM). Most GCMs have been shown to be poor at capturing the WAM, and in a few models, this feature is entirely omitted (Cook & Vizy, 2006). Thus, without careful selection of climate data, a key feature of a globally important biodiversity hotspot is likely to be poorly captured by the climate projections, and this alone should invalidate any assessment of future climate change impacts.

Here, for the first time, we assess potential climate change impacts for biodiversity across the West African PA network using an ensemble of climate projections that provide good simulations of the region's historic climate and incorporate the influence of mesoscale features (e.g. complex topography, coastal features) on climate dynamics. Climate projections were produced by downscaling regionally appropriate GCMs (i.e. those that capture regionally important climate regimes) to ecologically relevant spatial scales using a physically based regional climate model (RCM). GCMs were selected from a perturbed physics ensemble (PPE), in which model parameters relating to the atmosphere are perturbed producing a range of climate projections, and an ensemble selected that can accurately represent historic climates and which encompass a range of future outcomes (McSweeney et al., 2012). RCM projections have been shown with 'high confidence' to add value to GCM projections in regions with complex topography and important mesoscale phenomenon (Di Luca et al., 2012; Flato et al. 2013), providing better representations of precipitation cycles across western and southern Africa (Dosio et al., 2015).

We modelled the relationship between contemporary species distributions and climate using correlative SDMs and accounted for species' specific dispersal capabilities in projected range shifts. From this, we assessed the spatial and temporal patterns of projected climate change impacts for West African species for three vertebrate groups [amphibians (n = 146), birds (n = 768) and mammals (n = 382)] across the West African PA network. We quantified uncertainty in these projections pertaining to different initial choices and data sources in SDM creation (climate data, modelling methodology and spatial dependency) and assessed the spatial and temporal patterns of climate change impacts, and uncertainty in impacts, for biodiversity across the PA network.

## METHODS

## **Regional climate models**

Climate projections were derived for the Africa CORDEX domain: longitude range = -24.64, 60.28; latitude range = -45.76, 42.24 (Giorgi et al., 2009). A perturbed physics ensemble (PPE), in which uncertain model parameters are systematically perturbed to produce a range of climates, was produced using the HADCM3 GCM for the SRES A1B emissions scenario. Simulations from the individual ensemble members were compared to observed temperature and precipitation data from across Africa and against climate regimes (e.g. spatio-temporal distributions of precipitation maxima) from individual climatic regions (e.g. West Sahel and Western Tropical Africa) following McSweeney et al. (2012). Models that were unable to capture important climate features across these three regions were discarded and, from the remaining models, a five-member ensemble was selected that represented the breadth of future temperature and precipitation projections (Buontempo *et al.*, 2015). Each of the five ensemble members was downscaled to a c. 50 km spatial resolution for the period 1949–2100, using the Met Office Hadley Centre's physically based PRECIS (Jones *et al.*, 2004) regional climate modelling (RCM) system. To set the RCM within a global climate context, the RCM is driven at the boundaries by time-dependent large-scale fields (e.g. wind, temperature, water vapour, surface pressure and sea surface temperature) provided by the five-member PPE ensemble.

Four bioclimatic variables were calculated for each time period from the monthly RCM data, for each of the five ensemble members: mean temperature of the warmest month, mean temperature of the coldest month, precipitation seasonality (coefficient of variation of mean monthly precipitation) and an aridity index (mean precipitation/ potential evapotranspiration). Such bioclimatic variables have been shown previously to be good predictors of species distributions across taxonomic groups in tropical and subtropical systems (Araújo et al., 2006; Barbet-Massin & Jetz, 2014). For the baseline (1971-2000) and three future periods ('2040' = 2011–2040; '2070' = 2041–2070; '2100' = 2071 - 2100), the variables were calculated as means over these periods. Because the baseline data are derived from the RCM, there are five different baseline dataset, each validated against observed climate data. This has an advantage over statistically interpolated observed data in regions where ground climate observations are sparse (Sylla *et al.*, 2013), as the dynamic projections are able to capture greater spatial heterogeneity across the region and uncertainty in contemporary climate records.

## Species distribution modelling

Species distribution data for the breeding ranges were derived from refined species distribution maps of all extant bird (from BirdLife International & NatureServe, 2013), mammal and amphibian (both from IUCN, 2014) species found breeding in the West African region (see Fig. 1 for extent) and were intersected with a  $0.44^{\circ}$  grid (ca. 50 km  $\times$  50 km at the equator). A species was considered to occur in a cell if the distribution polygon overlapped  $\geq 10\%$  of the cell, which is a liberal threshold that helps maximize the representation of species with restricted ranges. All areas beyond the range extent are incredibly unlikely to contain false absences and, therefore, for modelling we consider all cells beyond the range to be true absences. There is some potential for commission error when using refined distribution maps. However, the availability of reliable unbiased point data here is limited and refined species distribution maps, when used at conservative spatial resolutions, are likely to be representative of species climate tolerances. Species were only included in the analysis if  $\geq 75\%$  of their breeding range occurred within the full RCM extent (Table 1), thus, omitting species for which we were unable to model a large proportion of the species-climate relationship. All species breeding within West Africa with a total range

Figure 1 Location of protected areas that have a 'dissimilar' altitudinal profile, as a surrogate for climate, from the cell (s) in which they are embedded. A mean difference > 100 m between the altitudinal profile of the PA and the cell (s) in which it is embedded is considered to represent a difference that could affect the biodiversity found in the PA.



Table 1 Summary statistics showing the initial number of species from each taxonomic group that breed within the West African region (species pool), the number of species excluded by each criterion and the total number of species included in the analysis. The results for the exclusion criteria are nested from left to right

Taxa	Regional species pool	Number of species exclu	uded by criteria (sec	Number of species	Median AUC	
		< 75% RCM overlap	< 5 presences	Single block	included	(min, max)
Amphibians	206	40 (19.4%)	14 (6.8%)	6 (2.9%)	146 (70.9%)	0.98 (0.89, 1.00)
Birds	830	60 (7.2%)	1 (0.1%)	1 (0.1%)	768 (92.5%)	0.97 (0.71, 1.00)
Mammals	407	17 (4.2%)	7 (1.7%)	1 (0.3%)	382 (93.8%)	0.97 (0.76, 1.00)

extent occupying fewer than five cells were also omitted from the analysis due to difficulties in modelling such sparse data (see Table S1 & Fig. S1 in Supporting Information).

We used an approach to species distribution modelling that quantified the uncertainty in projected distributions caused by selecting different climate projections and modelling approaches, and due to potential spatial dependency in species' distributions.

For modelling, we divided the dataset into spatially disaggregated blocks, rather than random k-fold partitioning, which allowed us to capture uncertainty due to spatial dependency in our projections. For each of the five RCM climate projections, the dataset was divided into five blocks (Fig. S2), such that the mean and variance of each bioclimatic variable was approximately equal across the blocks (see Bagchi et al., 2013 for details); thus, each block has the potential to capture the species-climate relationship. Importantly, the spatial autocorrelation within each block is higher than between blocks; thus, where spatial autocorrelation is high, models trained on n-1 blocks (the jackknifing approach adopted here), where n is the total number of blocks, performed poorly when tested on the withheld block. The variation in predicted probability of occurrence across the withheld blocks can be used to assess the effect of spatial autocorrelation on projected distributions.

We modelled the relationship between a species' baseline distribution (representing the period 1971-2000) and the four contemporaneous bioclimate variables using all combinations of four modelling methods [generalized linear models (GLMs), generalized additive models (GAMs), generalized boosted models (GBMs) and random forests (RFs)] and five RCM climate projections (20 combinations in total). We conditioned each of these model combinations using the five n-1 blocks of cells. Thus, for each species, 100 models were fit to a subset of the baseline distribution data, that is each combination of block (5), RCM climate projection (5) and modelling methodology (4). For all four modelling approaches, the median area under the receiver operating characteristic plot (AUC) from across the five blocks was used to assess final model accuracy. The model cross-validation protocol follows Bagchi et al. (2013). Ultimately, species distributions models were developed for 1296 species across all taxa (Table 1).

Species' specific dispersal potential was incorporated into projections of future range shifts by adjusting projected climate suitability values by a colonization probability (Barbet-Massin *et al.*, 2012). This latter value was derived by assuming that a species' natal dispersal probability, as a function of distance, is described by a gamma distribution [shape = (mean distance/standard deviation)<sup>2</sup>; scale = mean distance/shape], and that independent natal dispersal events across a time period (e.g. 30 years) can be described by the sum of *x* gamma distributions, where *x* equals the number of generations expected within the period (length of period [years]/minimum age first breeding [years]). The colonization probability distribution over the focal time period was rescaled such that at distances at or below the distance at which the probability of dispersal is maximized, the colonization probability equals 1. Climate suitability was adjusted by colonization potential (climate suitability x colonization potential), which is a function of distance. The suitability of unoccupied cells located below the distance at which the probability of dispersal is maximized remains unaltered (i.e. climate suitability × 1), but the suitability of cells located beyond this distance is reduced proportional to distance (see Barbet-Massin *et al.* (2012) for further details).

Species-specific estimates of mean natal dispersal distance and age of first breeding were available for all birds (from BirdLife International; Table S2). For non-volant mammals, we obtained species' specific body mass and age-of-firstbreeding data from two data sources (Ernest, 2003; Jones et al., 2009), with missing values inferred as the mean of values from closest relatives, and used allometric equations to estimate median dispersal distances from these data (Sutherland et al., 2000; Table S3). For Chiroptera, there are no similar allometric equations; however, categorical mean natal dispersal estimates are available from IUCN (Carr et al., 2014). We used the mid-point of these categorical estimates as the mean natal dispersal for these species. No similar data are available for amphibians, but a literature search suggested that mean annual dispersal distances of 0.2 km yr<sup>-1</sup>, with infrequent longer distance dispersal events, are representative (e.g. Araújo et al., 2006; Smith & Green, 2006). We therefore set mean natal amphibian dispersal to 0.2 km and assumed annual dispersal events. Comprehensive estimates for the standard deviation of natal dispersal were unavailable for any of the taxonomic groups, so we used a value [mean  $\times$  1.5] to approximately match the typical standard deviations of natal dispersal estimated for European birds based on recapture data (Paradis et al., 2002).

The median (95% quantiles) dispersal-adjusted climate suitability was obtained for each cells in the study region, derived from the 100 estimates of suitability (climate ensemble [5]  $\times$  SDM [4]  $\times$  block [5]), thus accounting for uncertainty in climate projections, modelling methodology and spatial dependency.

## **Protected area impacts**

PA polygons were obtained from the World Database on Protected Areas (WDPA: IUCN & UNEP-WCMC, 2013) and gridded on to a  $0.44^{\circ}$  grid, calculating the percentage overlap of each PA with each grid cell. For this analysis, we only include PAs that had known boundaries (Visconti *et al.*, 2013), and thus excluding 195 PAs currently only mapped as a point locations. All PAs with spatial boundaries were included regardless of their IUCN category because a very large proportion of PAs across the region currently still lack this information in the WDPA, but are likely to have considerable biodiversity value compared to areas not designated. However, following standard practice for handling WDPA data (e.g. Venter *et al.*, 2014; Butchart *et al.*, 2015), Biosphere Reserves (n = 16) were excluded because they may include large areas that are not considered PAs (Dudley, 2008; Coetzer *et al.*, 2013). Across the region, a total of 1926 PA polygons were selected for final analysis.

For PA-specific assessments, we took a conservative approach by assuming the PA had the suitability of the cell(s) in which it is embedded. Such an approach is likely to perform well where a PA is representative of the average climate in a cell, but may provide poor representation of a PA's climate where the site is positioned in a location atypical of the grid cell (e.g. a mountain top). We assessed where this is likely to occur by comparing the altitudinal profiles of each PA with the profile of the cell(s) in which it is embedded using 90 m<sup>2</sup> elevation data (Jarvis et al., 2008). For each PA, we calculated the mean difference in altitude between a sample of 200 altitudinal units taken randomly from within the PA and a sample of 800 from the cell(s) as a whole. Where a PA occurred across multiple cells, samples were taken from across the cells weighted by the proportion of the PA overlapping each cell. Figure 1 shows the PAs where the mean difference between the altitudes for the two samples was > 100 m (c. equal to a 1 °C difference based on lapse rate; Danielson et al., 2003), which might suggest a biologically meaningful outlier.

For each PA, a weighted mean of suitability for each species was calculated, with weights equal to the percentage of a PA's extent that overlaps a cell. Species turnover for each PA j ( $T_j[t]$ ) between the  $t_i$  = baseline (1971–2000) and  $t_2$  = future [2040; 2070; 2100] time periods was calculated using the Bray–Curtis index (a continuous analogue to commonly used turnover metrics, e.g. Hole *et al.*, 2009), a measure of dissimilarity between two communities, using the weighted suitability, as:

$$T_{j}[t] = \frac{\sum_{k=1}^{s} |P_{jk}[t_{2}] - P_{jk}[t_{1}]|}{\sum_{k=1}^{s} P_{jk}[t_{1}] + \sum_{k=1}^{s} P_{jk}[t_{2}]}$$

where  $P_{jk}$  = weighted suitability of species k (s = total number of species) in PA j. Species turnover was calculated separately for each of the 100 projections, and the 95% quantiles from across these values were used to assess uncertainty. Species turnover is measured relative to the current community composition, providing the likely range of impacts at a site/area-specific level, and needs to be judged with consideration of patterns of regional biodiversity.

The contribution of each component of uncertainty to projected impacts was assessed by partitioning the variance in turnover estimates across the PA network between each of the potential sources of uncertainty (including all two-way interactions) using ANOVA. The percentage of the total sum of squares attributable to each component was calculated by dividing the sum of squares for each variable or interaction by the total sum of squares (i.e. Diniz-Filho *et al.*, 2009). Species turnover values were logit-transformed prior to analysis to conform to the assumption of normally distributed residuals.

To identify sites that are consistently projected to experience the highest or lowest impacts from climate change across taxonomic groups, using species turnover as a metric of impact, we determined the proportion of times each PA was ranked in the upper and lower quartile across the 100 jackknife projections of species turnover. Those PAs in which  $\geq$  95% of the turnover estimates fell within the upper or lower quartiles were termed 'high impact' or 'low impact', respectively.

For each species, the change in climate suitability across the PA network was measured as the summed suitability across all PAs for the future period divided by the suitability for the baseline period. Where this value was > 1, a species was projected to gain suitability across the PA network, and where this value was < 1, a species was projected to lose suitability. For each species, this projected change in suitability was calculated for each of the 100 projections and the 95% quantiles used to assess confidence in the projections. Where 95% CI of these projections do not span unity (i.e. there is a consensus on projected change), we term changes as 'extremely likely'. Additionally, we assessed separately species of conservation concern (IUCN, 2014), which might particularly susceptible to the impacts of climate change and are important for setting conservation priorities.

## RESULTS

Models for all species within each taxon showed good model discrimination throughout (Table 1). For 11% of PAs (219), the mean elevation difference between the PA and the 50 km cells in which it is embedded was > 100 m, suggesting that the PA's climate could be dissimilar from the mean climate of these cells (Fig. 1). The results for these PAs should be treated with some additional caution.

#### Species turnover across the PA network

For all three taxonomic groups, species turnover is projected to increase across the next century, with the median turnover across the region's PA network projected to exceed 35% for all three taxonomic groups by 2100 (Fig. 2). Amphibians are projected to experience the highest levels of turnover across the network, with a median (95% quantiles) projected turnover of 42.5% (30.1, 68.6) by 2100. Bird and mammal species turnover is projected to be slightly lower than amphibians, with bird turnover projected to increase from a median of 16.3% (14.1, 22.4) by 2040 to 35.2% (25.5, 46.0) by 2100 and mammals to increase from 18.4% (16.1, 24.2) to 37.9% (26.2, 55.7) over the same period.

However, uncertainty in projected turnover also increases through the century for all three taxonomic groups, with projections for amphibians and mammals least certain (Figs. 3a,b). Uncertainty is lowest for all three groups up to the 2040. During this period, the variation in turnover



Figure 3 Projected species turnover (Bray-Curtis index), as a measure of change in community composition reflecting both gain and loss of species, for the West African protected area network between the baseline (1971-2000) and future time periods for amphibians, birds and mammals. (a) The spatial pattern of species turnover across the region's PA network for two focal future time periods (2040 and 2100). The focal plot shows the Guinea forest region, where many of the highest impacts are projected to occur for all three taxonomic groups. Colours reflect the category encompassing the median projected turnover. Colour intensity reflects uncertainty in turnover projections; the intensity indicates the range of all turnover values encompassed by 95% of the projected estimates of turnover for each PA. (b) The number of PAs falling within each uncertainty category for each time period and taxonomic group. Note: the region shown in (a) is cropped to allow clearer visualization of the results and, consequently, not all PAs are shown.

among models for the majority of PAs for birds and mammals is < 20 percentage points (for example: 21-40% turnover at a single site). Uncertainty for amphibians is higher across the majority of PAs, even in this earlier time period. By 2100, estimates of uncertainty in species turnover for amphibians exceed 40 percentage points at 70% of sites (Fig. 3b). Similarly, uncertainty in species turnover for birds and mammals increases by this period, such that turnover

>40

estimates for the majority of PAs exceed 20 and 30 percentage points, respectively.

The major sources of variation in species turnover across the PA network were consistent for all three taxonomic groups in all time periods, the majority of variation being accounted for by modelling methodology and climate projections (Fig. 4; results shown for 2100 only). The interaction between climate projection and modelling methodology also accounted for on average c. 10% of variability in turnover estimates. By contrast, spatial autocorrelation and the



Figure 4 The proportion of the total sum of squares attributed to each component of uncertainty (CLIM = climate data; SDM = modelling methodology; SA = spatial autocorrelation; and RESID = residual variation) for a protected area calculated by dividing the sum of squares for each factor by the total sum of squares. Results for amphibians (a), birds (b) and mammals (c) are shown for the 2100 time period only.

remaining interactions contributed little to the overall uncertainty for the majority of PAs.

#### Species' climate suitability across the PA network

Based on the median change in suitability (i.e. calculated across jackknife projections), the majority of species in each taxonomic group are projected to have decreasing suitability across the PA network by at least 2070 [Fig. 5: amphibians = 63% of spp. (92 spp.); birds = 55% (419); mammals = 63% (239)]. Uncertainty in these projections means that for many of these species, there is no overall consensus in the directional trend (increase vs. decrease). By 2100, there is only directional consensus in changing suitability (i.e. 'extremely likely') for fewer than 37% of species in each taxonomic group, and the greater proportion of these species are 'extremely likely' to experience decreasing suitability across the network [amphibians (increase vs. decrease) = 7% (10) vs. 20% (29); birds = 12% (88) vs. 19% (149); mammals = 9% (36) vs. 20% (75)]. For birds, there is a change in the proportion of species expected to be favourably/ adversely impacted by climate change over the century. Many birds are projected to experience increased suitability up to 2040, but between 2070 and 2100, most birds are projected to be adversely affected (Fig. 5).



Figure 5 Number of species within each taxonomic group, and in each time period, projected to experience increasing or decreasing climate suitability across the West African PA network. Light shading shows the number of species with increasing or decreasing suitability across the network based on the median estimate of suitability (calculated across 100 jackknife estimates of suitability) in each time period, and dark shading indicates species where 95% of the projected estimates of change in climate suitability for a species showed directional consensus (increasing or decreasing).

## D. J. Baker et al.

Among the species included here, 39 amphibian, 44 bird and 51 mammal species are of conservation concern. Among these species, amphibians are projected to be most impacted by climate change with > 75% of amphibians projected as 'extremely likely' to experience a decline in climate suitability across the PA network in all time periods (Table 2). For birds and mammals of conservation concern, the uncertainty is higher, with > 70% and > 49% of species, respectively, showing no consensus in the direction of their projected change in climate suitability across the network in all time periods. No species of conservation concern were projected to be 'extremely likely' to experience increasing suitability.

# Identifying robust 'high-' and 'low'-impact PAs and assessing congruence between taxonomic groups

Although uncertainty is high, some PAs are consistently  $(\geq 95\%$  of turnover estimates) ranked in the upper or low quartiles (Fig. 6) and there is some taxonomic congruence between these sites (Table 3). By 2070, the majority of PAs that are consistently projected to experience the highest climate change impacts are located in the Upper Guinea forests and are primarily located in Ivory Coast. These high-impact sites also extend west of the Ivory Coast for birds (Table 3). By 2070, 32 PAs are consistently projected to be 'highimpact' sites for two or more taxonomic groups, indicating some potentially important congruence in impacts, although this declines over time. The number of PAs projected to be 'high-impact' sites for a single taxonomic group fell from 96 to 39 between 2040 and 2100. There are few PAs consistently projected to be 'low-impact' sites. Those that do occur are found across the eastern portion of the region, for example Nigeria and Benin. Importantly, the spatial pattern of these sites changes across time, suggesting different priorities at different time periods.

## DISCUSSION

This study provides the first assessment of climate change impacts to species from a range of taxonomic groups across the biodiversity-rich West African PA network. To our knowledge, this is the first tropical biodiversity impact study that uses climate models validated against regional climate observations and dynamically downscaled to an ecologically relevant spatial scale. Our results suggest that climate change has the potential to severely impact regional fauna and to reduce the effectiveness of the PA network to conserve the region's biodiversity. This assessment should serve to raise awareness of the potential threat the climate change poses to this region and aid in the targeting of in situ research and monitoring and the identification of appropriate adaptation measures with the aim of strengthening the existing PA network (Schwartz, 2012; Guisan et al., 2013). Using a regionally appropriate, dynamically downscaled ensemble of climate projections, which captures both large-scale (e.g. West African Monsoon) and local climate regimes, we have attempted to reduce the uncertainty associated with projections across climatically complex regions. Our projections of climate change impacts account for as much uncertainty as is currently feasible (i.e. climate projections, modelling methodologies and spatial autocorrelation of species' ranges), meaning that we can explicitly acknowledge the uncertainty associated with such assessments.

Our results indicate that there is considerable spatial heterogeneity in projected impacts, both within and between taxonomic groups, with the average severity of projected impacts and their uncertainty increasing towards the end of century. The high uncertainty associated with the end-of-century projections across much of the region brings into question their value in climate change impact assessment (see also Chapman *et al.*, 2014), but the uncertainty associated with

Table 2 Change in species' specific climate suitability across the PA network between the baseline period (1971–2000) and each of thethree focal future time periods for species of conservation concern

	Period	IUCN Status				Change in climate suitability between the baseline and future time periods		
Taxonomic group		CR	EN	VU	NT	Increase	Decrease	No consensus
Amphibians	2040	1	13	13	12	0%	87.2% (34)	12.8% (5)
	2070					0%	87.2% (34)	12.8% (5)
	2100					0%	74.4% (29)	25.6% (10)
Birds	2040	0	3	20	21	0%	29.6% (13)	70.4% (31)
	2070					0%	25% (11)	75% (33)
	2100					0%	27.3% (12)	72.7% (32)
Mammals	2040	5	12	17	17	0%	51% (26)	49% (25)
	2070					0%	43.1% (22)	56.9% (29)
	2100					0%	49% (25)	51% (26)

Reported are the percentages (number) of species classified as 'extremely likely' to experience increasing or decreasing climate suitability across the network in each time period (95% quantiles show directional consensus). Those species showing no directional consensus in the change in suitability are reported as 'no consensus'. The numbers of species in each IUCN threat category are reported: CR = critically endangered; EN = endangered; VU = vulnerable; and NT = near threatened.



Figure 6 West African PAs that are quantified as being 'high-impact' and 'low-impact' sites under projection of future climate change, determined by whether the projected turnover for the PA was consistently ( $\geq$  95% of jackknifed projections) ranked in the upper ('high impact') or lower ('low impact') quartile of turnover estimates across the network in each of the three focal time periods and for each taxonomic group. Note: the region shown in cropped to allow clearer visualization of the results and, consequently, not all PAs are shown.

**Table 3** The number of protected areas (PA) consistently ( $\geq$  95% of jackknifed projections) ranked in the highest or lowest quartile for species turnover across estimates of uncertainty in each time period

	Numl highes group taxon	ber of PAs st impacts for 1–3 omic grou	Num lowe grou taxoi	Number of PAs in lowest impacts group for 1–3 taxonomic groups		
Time period	3	2	1	3	2	1
2040	5	8	96	0	18	65
2070	11	21	70	0	23	65
2100	0	6	39	0	15	87

The confluence in projected climate change impacts across taxonomic groups is indicated by the number of PAs that were classified as either 'high-impact' or 'low-impact' sites for two or three taxonomic groups in each time period.

early- and mid-century projections is lower and distinct patterns emerge despite the uncertainty. Such spatio-temporal variation in confidence in climate change impacts adds an additional layer of complexity to dilemmas over when to undertake monitoring or research versus conservation action (McDonald-Madden *et al.*, 2010).

By 2070, the eastern region of the Upper Guinea forest contains the greater proportion of PAs that are consistently

projected to experience the highest impacts across the network for all three taxonomic groups. The PAs of southern Nigeria are also consistently projected to experience some of the highest impacts for mammals by 2040, which is concordant with the projections of mammal species loss over a similar period (Visconti *et al.*, 2011). Hole *et al.* (2009) projected severe impacts of climate change for birds in northern Senegal using different species distributions, climate data and modelling approaches. Our results suggest greater caution must be taken in assuming severe impacts in this region due to the substantial uncertainty in projections.

The congruence in projections of high impacts across taxonomic groups by mid-century suggests a potential opportunity for conservation management that could benefit a broad suite of species. However, there are also differences in the spatial and temporal patterns of impacts across the three taxonomic groups that could have important implications for prioritizing conservation efforts based on taxonomically biased assessments. Currently, much better data exist globally on the distributions of birds and mammals compared to other terrestrial taxa (Darwall *et al.*, 2011; Feeley & Silman, 2011). As a result, most climate impact assessments on biodiversity in the tropics tend to focus on these groups and, as a result, potentially overlook key sites for other taxonomic groups. Thus, it is important to note key differences in both the spatial and temporal patterns of impacts across taxonomic groups, which are relevant to conservation monitoring, planning and prioritization (Myers *et al.*, 2000).

The mismatch between the spatial resolution of climate data and the spatial scales relevant to the persistence of many of the studied species (Wiens & Bachelet, 2010) will inevitably introduce additional uncertainty into the projections (e.g. Gillingham et al., 2012). For example, fine-scale spatial variability in climatic conditions could provide refugia for species despite the surrounding landscape experiencing conditions that are broadly incompatible with a species' persistence (Scheffers et al., 2014). The climatic conditions predicted for single grid cells are representative of the mean climate expected in a cell, but cannot capture the finer-scale climatic variability. PAs with climate conditions that are particularly distinct from those in the surrounding landscape could facilitate the persistence of species at fine spatial scales, and this could be particularly relevant in areas of high relief, where PAs are often located (Joppa & Pfaff, 2009). For the current analyses, this possibility is of less concern as West Africa is almost uniformly of low relief. Nonetheless, we have highlighted PAs where extra caution should be used when interpreting the results.

Current understanding of natal dispersal is poor for most species and, therefore, approximations based on surrogate species data (including allometric equations) and simple 'buffer' approaches are often used where data limitations prevent more complex dispersal simulations (Bateman et al., 2013). Dispersal assumptions can substantially alter projections of climate change impacts (Early & Sax, 2011) and, therefore, consideration of dispersal potential, even if crude, can be important for assessing extinction risks. The dispersal estimates used in this study are potentially at the upper end of realized dispersal potential because, for example, they include no consideration of landscape permeability (Schloss et al., 2012) and barriers to dispersal (e.g. physical, climatic). The velocity of climate change is likely to differ between landscapes, for example savanna vs. montane, creating strong spatial heterogeneity in the rates of range shift required to keep pace with shifting climate spaces (Loarie et al., 2009; Schloss et al., 2012). Furthermore, vegetation and human responses to climate change will affect land use patterns over time, creating greater imperative for range shifts, but also potentially altering landscape permeability (Mahmood et al., 2014). However, where climate change impact assessments are made across multiple taxonomic groups and large geographic regions, adopting even a simple approach to incorporate dispersal is often better than assuming either no dispersal or unlimited dispersal scenarios.

A frequent problem for multitaxa analyses conducted across broad spatial scales and at relatively coarse resolutions is the inevitable omission of species with small range extents that are difficult to model due to a paucity of data. Many of these species are classified among those of greatest conservation concern. Their omission from assessments could therefore bias adaptation strategies towards more widespread taxa (Platts *et al.*, 2014). The primary limitation here is the spatial resolution of the gridded climate data, which becomes increasingly uncertain at finer resolutions (Isotta *et al.*, 2014). Fine-scale climate data enables more species with small ranges to be modelled (Ochoa-Ochoa *et al.*, 2012), but the results must be viewed with caution due to the likely high uncertainty in the underlying climate data. Species with a range too restricted to be included in such modelling processes could be separately considered using, for example, expert elicitation of threats and tolerances, and the two approaches combined to provide a holistic overview of threats for all taxa.

Large-scale impact assessments serve to highlight potential spatial and temporal heterogeneity in climate change impacts and should be used to guide the targeting of monitoring, further research and identification of conservation action and adaptation interventions (Guisan et al., 2013). In regions with high spatial and temporal resolution data on the distribution and abundance of species, broad-scale analyses have been used with some confidence to set conservation targets and even establish new PAs (Carroll et al., 2010; Struebig et al., 2015). However, such data are lacking for the majority of biodiversity-rich areas and, consequently, here the principle objective is to guide the targeting of in situ research and monitoring and to identify sites at which appropriate adaptation actions need to be most urgently implemented (Hole et al., 2011). Monitoring is crucial for determining whether projected impacts eventuate and for assessing the efficacy of adaptation responses. Our study facilitates the identification of those locations and taxa for which climate change impacts may be experienced earliest, and therefore helps to set monitoring priorities in the region. Further research is required to establish the potential for habitat or climate barriers to prevent species from tracking shifting climate or for species' persistence to be maintained by the availability of suitable microclimates. An understanding of uncertainty in projected impacts helps determine the practical value of research, where high uncertainty suggests a focus on basic data, monitoring and iterative decision-making in response to changing circumstances (Polasky et al., 2011).

In conclusion, climate change across West Africa is projected to have a large impact on species distributions and reduce the effectiveness of the PA network to protect the region's fauna. However, we also show that there is high uncertainty in projected impacts and that this uncertainty tends to increase through time and can vary considerably between taxonomic groups. As a result of this, we make two recommendations: (1) adaptation planning should primarily consider early-, and possibly mid-, century impact projections in order to have most confidence in species responses (Chapman et al., 2014) and (2) future studies of climate change impacts should incorporate a broad suite of species and use multiple approaches to balance biases present in different approaches (e.g. correlative, trait-based, expert opinion). These recommendations should help to reduce unforeseen consequences arising from adaptive management based on the current norm of using long-term projections with high uncertainty and a taxonomic bias due to a restricted sample of species.

## ACKNOWLEDGEMENTS

We would like to thank the many individuals involved in collating species (distribution, conservation status and traits) and protected areas data, which made this research possible. The Global Environment Facility (GEF) funded DJB and SGW to undertake this work as part of the PARCC West Africa project.

## REFERENCES

- Araújo, M.B., Thuiller, W. & Pearson, R.G. (2006) Climate warming and the decline of amphibians and reptiles in Europe. *Journal of Biogeography*, **33**, 1712–1728.
- Araújo, M.B., Alagador, D., Cabeza, M., Nogués-Bravo, D. & Thuiller, W. (2011) Climate change threatens European conservation areas. *Ecology Letters*, 14, 484–492.
- Bagchi, R., Crosby, M., Huntley, B., Hole, D.G., Butchart, S.H.M., Collingham, Y., Kalra, M., Rajkumar, J., Rahmani, A., Pandey, M., Gurung, H., Trai, L.T., Van Quang, N. & Willis, S.G. (2013) Evaluating the effectiveness of conservation site networks under climate change: accounting for uncertainty. *Global Change Biology*, **19**, 1236–1248.
- Barbet-Massin, M. & Jetz, W. (2014) A 40-year, continentwide, multispecies assessment of relevant climate predictors for species distribution modelling. *Diversity and Distributions*, 20, 1285–1295.
- Barbet-Massin, M., Thuiller, W. & Jiguet, F. (2012) The fate of European breeding birds under climate, land-use and dispersal scenarios. *Global Change Biology*, **18**, 881–890.
- Bateman, B.L., Murphy, H.T., Reside, A.E., Mokany, K. & Van Der Wal, J. (2013) Appropriateness of full-, partialand no-dispersal scenarios in climate change impact modelling. *Diversity and Distributions*, **19**, 1224–1234.
- BirdLife International & NatureServe (2013) *Bird Species Distribution Maps of the World.* Version 3.0. BirdLife International and NatureServe, Cambridge, UK and Arlington, USA.
- Buontempo, C., Mathison, C., Jones, R., Williams, K., Wang, C. & McSweeney, C. (2015) An ensemble climate projection for Africa. *Climate Dynamics*, 44, 2097–2118.
- Butchart, S.H.M., Scharlemann, J.P.W., Evans, M.I. *et al.* (2012) Protecting important sites for biodiversity contributes to meeting global conservation targets. *PLoS One*, 7, e32529.
- Butchart, S.H.M., Clarke, M., Smith, R.J. *et al.* (2015) Shortfalls and solutions for meeting national and global conservation area targets. *Conservation Letters*, in press.
- Carr, J.A., Hughes, A.F. & Foden, W.B. (2014) A climate change vulnerability assessment of West African species. UNEP-WCMC technical report.

Carroll, C., Dunk, J.R. & Moilanen, A. (2010) Optimizing resiliency of reserve networks to climate change: multispecies conservation planning in the Pacific Northwest, USA. *Global Change Biology*, **16**, 891–904.

- Chapman, S., Mustin, K., Renwick, A.R., Segan, D.B., Hole, D.G., Pearson, R.G. & Watson, J.E.M. (2014) Publishing trends on climate change vulnerability in the conservation literature reveal a predominant focus on direct impacts and long time-scales. *Diversity and Distributions*, **20**, 1221–1228.
- Chen, I.-C., Hill, J.K., Ohlemüller, R., Roy, D.B. & Thomas, C.D. (2011) Rapid range shifts of species associated with high levels of climate warming. *Science*, **333**, 1024–1026.
- Christensen, J.H., Krishna Kumar, K., Aldrian, E., An, S.-I., Cavalcanti, I.F.A., deCastro, M., Dong, W., Goswami, P., Hall, A., Kanyanga, J.K., Kitoh, A., Kossin, J., Lau, N.-C., Renwick, J., Stephenson, D.B., Xie, S.-P. & Zhou, T. (2013) Climate phenomena and their relevance for future regional climate change. In: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. T.F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley). Cambridge University Press, Cambridge, UK and New York, NY, USA.
- Coad, L., Leverington, F., Burgess, N.D., Cuadros, I.C., Geldmann, J., Marthews, T., Mee, J., Nolte, C., Stoll-Kleeman, S., Vansteelant, N., Zamora, C., Zimsky, M. & Hockings, M. (2013) Progress towards the CBD protected area management effectiveness targets. *Parks*, 19(1), 14–24.
- Coetzer, K.L., Witkowski, E.T.F. & Erasmus, B.F.N. (2013) Reviewing Biosphere Reserves globally: effective conservation action or bureaucratic label? *Biological Reviews.*, **89**, 82–104.
- Cook, K.H. & Vizy, E.K. (2006) Coupled model simulations of the West African monsoon system: twentieth- and twenty-first-century simulations. *Journal of Climate*, **19**, 3681–3703.
- Danielson, E.W., Levin, J. & Abrams, E. (2003) *Meteorology*. McGraw-Hill, Boston.
- Darwall, W.R.T., Holland, R.A., Smith, K.G., Allen, D., Brooks, E.G.E., Katarya, V., Pollock, C.M., Shi, Y., Clausnitzer, V., Cumberlidge, N., Cuttelod, A., Dijkstra, K.-D.B., Diop, M.D., García, N., Seddon, M.B., Skelton, P.H., Snoeks, J., Tweddle, D. & Vié, J.-C. (2011) Implications of bias in conservation research and investment for freshwater species. *Conservation Letters*, **4**, 474–482.
- Di Luca, A., de Elía, R. & Laprise, R. (2012) Potential for added value in precipitation simulated by high-resolution nested Regional Climate Models and observations. *Climate Dynamics*, **38**, 1229–1247.
- Diffenbaugh, N.S. & Giorgi, F. (2012) Climate change hotspots in the CMIP5 global climate model ensemble. *Climatic Change*, **114**, 813–822.

Diniz-Filho, J.A.F., Mauricio Bini, L., Fernando Rangel, T., Loyola, R.D., Hof, C., Nogués-Bravo, D. & Araújo, M.B. (2009) Partitioning and mapping uncertainties in ensembles of forecasts of species turnover under climate change. *Ecography*, **32**, 897–906.

Dosio, A., Panitz, H.-J., Schubert-Frisius, M. & Lüthi, D. (2015) Dynamical downscaling of CMIP5 global circulation models over CORDEX-Africa with COSMO-CLM: evaluation over the present climate and analysis of the added value. *Climate Dynamics*, **44**, 2637–2661.

Dudley, N. (ed.) (2008) *Guidelines for Applying Protected Area Management Categories.* IUCN, Gland, Switzerland.

- Early, R. & Sax, D.F. (2011) Analysis of climate paths reveals potential limitations on species range shifts. *Ecology Letters*, 14, 1125–1133.
- Ernest, S. (2003) Life history characteristics of placental nonvolant mammals. *Ecology*, **84**, 3402.
- Feeley, K.J. & Silman, M.R. (2011) The data void in modeling current and future distributions of tropical species. *Global Change Biology*, **17**, 626–630.
- Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S.C., Collins, W., Cox, P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C. & Rummukainen, M. (2013). Evaluation of Climate Models. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (ed. by T.F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley), pp. 741–882. Cambridge University Press, Cambridge, UK and New York, NY, USA.
- Garcia, R.A., Burgess, N.D., Cabeza, M., Rahbek, C. & Araújo, M.B. (2012) Exploring consensus in 21st century projections of climatically suitable areas for African vertebrates. *Global Change Biology*, **18**, 1253–1269.
- Gillingham, P.K., Palmer, S.C.F., Huntley, B., Kunin, W.E., Chipperfield, J.D. & Thomas, C.D. (2012) The relative importance of climate and habitat in determining the distributions of species at different spatial scales: a case study with ground beetles in Great Britain. *Ecography*, **35**, 831– 838.
- Giorgi, F., Jones, C. & Asrar, G. (2009) Addressing climate information needs at the regional level: the CORDEX framework. *World Meteorological Organization (WMO) Bulletin*, **58**, 175.
- Guisan, A., Tingley, R., Baumgartner, J.B. et al. (2013) Predicting species distributions for conservation decisions. *Ecology Letters*, **16**, 1424–1435.
- Hannah, L., Midgley, G., Andelman, S., Araújo, M., Hughes, G., Martinez-Meyer, E., Pearson, R. & Williams, P. (2007)
  Protected area needs in a changing climate. *Frontiers in Ecology and the Environment*, 5, 131–138.
- Hole, D.G., Willis, S.G., Pain, D.J., Fishpool, L.D., Butchart, S.H.M., Collingham, Y.C., Rahbek, C. & Huntley, B. (2009) Projected impacts of climate change on a conti-

nent-wide protected area network. *Ecology Letters*, **12**, 420–431.

- Hole, D.G., Huntley, B., Arinaitwe, J., Butchart, S.H.M., Collingham, Y.C., Fishpool, L.D.C., Pain, D.J. & Willis, S.G. (2011) Toward a management framework for networks of protected areas in the face of climate change. *Conservation Biology*, 25, 305–315.
- Isotta, F.A., Frei, C., Weilguni, V., Perčec Tadić, M., Lassègues, P., Rudolf, B., Pavan, V., Cacciamani, C., Antolini, G., Ratto, S.M., Munari, M., Micheletti, S., Bonati, V., Lussana, C., Ronchi, C., Panettieri, E., Marigo, G. & Vertačnik, G. (2014) The climate of daily precipitation in the Alps: development and analysis of a high-resolution grid dataset from pan-Alpine rain-gauge data. *International Journal of Climatology*, **34**, 1657–1675.
- IUCN (2014) The IUCN red list of threatened species. Version 2014.2.
- IUCN & UNEP-WCMC (2013) The World Database on Protected Areas (WDPA) [December Release]. UNEP-WCMC, Cambridge, UK.
- Jarvis, A., Reuter, H., Nelson, A. & Guevara, E. (2008) Holefilled seamless SRTM data V4, International Centre for Tropical Agriculture (CIAT). Available from http:// srtm.csi.cgiar.org.
- Jones, R.G., Noguer, M., Hassell, D.C., Hudson, D., Wilson, S.S., Jenkins, G.J. & Mitchell, J.F.B. (2004) Generating high resolution climate change scenarios using PRECIS. pp. 40, Met Office Hadley Centre, Exeter, UK.
- Jones, K.E., Bielby, J., Cardillo, M. *et al.* (2009) PanTHERIA: a species-level database of life history, ecology, and geography of extant and recently extinct mammals. *Ecology*, **90**, 2648.
- Joppa, L.N. & Pfaff, A. (2009) High and far: biases in the location of protected areas. *PLoS One*, **4**, e8273.
- Kier, G., Kreft, H., Lee, T.M., Jetz, W., Ibisch, P.L., Nowicki, C., Mutke, J. & Barthlott, W. (2009) A global assessment of endemism and species richness across island and mainland regions. *Proceedings of the National Academy of Sciences*, **106**, 9322–9327.
- Loarie, S.R., Duffy, P.B., Hamilton, H., Asner, G.P., Field, C.B. & Ackerly, D.D. (2009) The velocity of climate change. *Nature*, **462**, 1052–1055.
- Mahmood, R., Pielke, R.A., Hubbard, K.G., Niyogi, D., Dirmeyer, P.A., McAlpine, C., Carleton, A.M., Hale, R., Gameda, S., Beltrán-Przekurat, A., Baker, B., McNider, R., Legates, D.R., Shepherd, M., Du, J., Blanken, P.D., Frauenfeld, O.W., Nair, U.S. & Fall, S. (2014) Land cover changes and their biogeophysical effects on climate. *International Journal of Climatology*, **34**, 929–953.
- McDonald-Madden, E., Baxter, P.W., Fuller, R.A., Martin, T.G., Game, E.T., Montambault, J. & Possingham, H.P. (2010) Monitoring does not always count. *Trends in Ecology & Evolution*, 25, 547–550.
- McSweeney, C.F., Jones, R.G. & Booth, B.B.B. (2012) Selecting Ensemble Members to Provide Regional Climate Change Information. *Journal of Climate*, **25**, 7100–7121.

- Myers, N., Mittermeier, R.A., Mittermeier, C.G., da Fonseca, G.A.B. & Kent, J. (2000) Biodiversity hotspots for conservation priorities. *Nature*, **403**, 853–858.
- Ochoa-Ochoa, L.M., Rodríguez, P., Mora, F., Flores-Villela, O. & Whittaker, R.J. (2012) Climate change and amphibian diversity patterns in Mexico. *Biological Conservation*, **150**, 94–102.
- Paradis, E., Baillie, S.R. & Sutherland, W.J. (2002) Modeling large-scale dispersal distances. *Ecological Modelling*, **151**, 279–292.
- Platts, P.J., Garcia, R.A., Hof, C., Foden, W., Hansen, L.A., Rahbek, C. & Burgess, N.D. (2014) Conservation implications of omitting narrow-ranging taxa from species distribution models, now and in the future. *Diversity and Distributions*, 20, 1307–1320.
- Polasky, S., Carpenter, S.R., Folke, C. & Keeler, B. (2011) Decision-making under great uncertainty: environmental management in an era of global change. *Trends in Ecology* & *Evolution*, **26**, 398–404.
- Rodrigues, A.S.L., Akçakaya, H.R., Andelman, S.J. *et al.* (2004) Global gap analysis: priority regions for expanding the global protected-area network. *BioScience*, **54**, 1092–1100.
- Scheffers, B.R., Edwards, D.P., Diesmos, A., Williams, S.E. & Evans, T.A. (2014) Microhabitats reduce animal's exposure to climate extremes. *Global Change Biology*, **20**, 495–503.
- Schloss, C.A., Nuñez, T.A. & Lawler, J.J. (2012) Dispersal will limit ability of mammals to track climate change in the Western Hemisphere. *Proceedings of the National Academy of Sciences of the United States of America*, **109**, 8606–8611.
- Schwartz, M.W. (2012) Using niche models with climate projections to inform conservation management decisions. *Biological Conservation*, **155**, 149–156.
- Smith, M.A. & Green, D.M. (2006) Sex, isolation and fidelity: unbiased long-distance dispersal in a terrestrial amphibian. *Ecography*, **29**, 649–658.
- Struebig, M., Wilting, A., Gaveau, D., Meijaard, E. & Smith, R.J., The Borneo Mammal Distribution Consortium, Fischer, M., Metcalfe, K. & Kramer-Schadt, S. (2015) Targeted conservation to safeguard a biodiversity hotspot from climate and land-cover change. *Current Biology*, 25, 372–378.
- Sutherland, G., Harestad, A., Price, K. & Letzman, K. (2000) Scaling of natal dispersal distances in terrestrial birds and mammals. *Conservation Ecology*, **4**, 16.
- Sylla, M.B., Giorgi, F., Coppola, E. & Mariotti, L. (2013) Uncertainties in daily rainfall over Africa: assessment of gridded observation products and evaluation of a regional climate model simulation. *International Journal of Climatology*, **33**, 1805–1817.
- Van Der Wal, J., Murphy, H.T., Kutt, A.S., Perkins, G.C., Bateman, B.L., Perry, J.J. & Reside, A.E. (2013) Focus on poleward shifts in species' distribution underestimates the

fingerprint of climate change. Nature Climate Change, 3, 239–243.

- Venter, O., Fuller, R.A., Segan, D.B., Carwardine, J., Brooks, T., Butchart, S.H.M., Di Marco, M., Iwamura, T., Joseph, L., O'Grady, D., Possingham, H.P., Rondinini, C., Smith, R.J., Venter, M. & Watson, J.E.M. (2014) Targeting global protected area expansion for imperiled biodiversity. *PLoS Biology*, **12**, e1001891.
- Visconti, P., Pressey, R.L., Giorgini, D., Maiorano, L., Bakkenes, M., Boitani, L., Alkemade, R., Falcucci, A., Chiozza, F. & Rondinini, C. (2011) Future hotspots of terrestrial mammal loss. *Philosophical Transactions of the Royal Society B*, **366**, 2693–2702.
- Visconti, P., Di Marco, M., ÁLvarez-Romero, J.G., Januchowski-Hartley, S.R., Pressey, R.L., Weeks, R. & Rondinini, C. (2013) Effects of errors and gaps in spatial data sets on assessment of conservation progress. *Conservation Biology*, 27, 1000–1010.
- Wiens, J.A. & Bachelet, D. (2010) Matching the multiple scales of conservation with the multiple scales of climate change. *Conservation Biology*, **24**, 51–62.

## SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

 Table S1 West African species excluded from the analysis and the primary exclusion criteria.

Figure S1 Species richness maps of the baseline distribution for omitted species.

Figure S2 Spatially disaggregated blocks.

Table S2 Estimates of dispersal for bird species.

Table S3 Estimates of dispersal for mammal species.

## BIOSKETCH

**David J. Baker** is interested in studying the impacts of environmental change on biodiversity and in trying to understand and quantity uncertainty in order to deliver better guidance for management.

Author contributions: All authors were involved in discussing the original idea. A.J.H. produced the climate projections, and D.J.B. performed the analysis and, with S.G.W., wrote the manuscript. J.A.C. and S.H.M.B. provided species distribution and trait data. All authors provided comments on the manuscript.

Editor: Rafael Loyola