



# Priority conservation areas and a global population estimate for the critically endangered Philippine Eagle

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## Keywords

area of habitat; conservation planning; gap analysis; population size; range metrics; species distribution models; protected area coverage; IUCN Red List.

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## Abstract

Many range-restricted taxa are experiencing population declines, yet we lack fundamental information regarding their distribution and population size. Establishing baseline estimates for both of these key biological parameters is however critical for directing conservation planning for at-risk range-restricted species. The International Union for the Conservation of Nature (IUCN) Red List uses three range metrics that define species distributions and inform extinction risk assessments: extent of occurrence (EOO), area of occupancy (AOO) and area of habitat (AOH). However, calculating all three metrics using standard IUCN approaches relies on a geographically representative sample of locations, which for rare species is often spatially biased. Here, we apply model-based interpolation using Species Distribution Models (SDMs), correlating occurrences with remote-sensing covariates, to calculate IUCN range metrics, protected area coverage and a global population estimate for the Critically Endangered Philippine Eagle (*Pithecophaga jefferyi*). Our final range wide continuous SDM had high predictive accuracy (continuous Boyce Index = 0.934) and when converted to a binary model estimated an AOH as 28 624 km<sup>2</sup>, a maximum EOO as 617 957 km<sup>2</sup>, and a minimum EOO as 275 459 km<sup>2</sup>, with an AOO as 53 867 km<sup>2</sup>. Based on inferred habitat from the AOH metric, we estimate a global population of 392 breeding pairs (range: 318–447 pairs), or 784 mature individuals, across the Philippine Eagle global range. Protected areas covered 32% of AOH, 13% less than the target representation, with the continuous model identifying key habitat as priority conservation areas. We demonstrate that even when occurrences are geographically biased, robust habitat models can quantify baseline IUCN range metrics, protected area coverage and a population size estimate. In the absence of adequate location data for many rare and threatened taxa, our method is a promising spatial modelling tool with widespread applications, particularly for island endemics facing high extinction risk.

## Introduction

Species that are rare due to either a restricted geographic range, habitat specificity or small population size are at greater risk of extinction because their populations may not be as resilient to perturbations in the environment (Rabinowitz, Cairns, & Dillon, 1986; Gaston, 1994; Jeliaskov *et al.*, 2022). Therefore, quantifying the two key biological parameters of range extent and population size is fundamental for directing conservation action for threatened rare taxa (Jones *et al.*, 1995; Marcer *et al.*, 2013; Syfert *et al.*, 2014). Habitat loss and fragmentation are the two primary threats to biodiversity globally (Díaz *et al.*, 2019), particularly for tropical biodiversity hotspots (Brooks *et al.*, 2002). Determining baseline range metrics and population estimates for

threatened species with restricted ranges and low abundance can thus inform conservation priorities. This is achieved by quantifying the effects of habitat loss and fragmentation on range extent and population size for these at-risk taxa (IUCN, 2001).

The International Union for the Conservation of Nature (IUCN) Red List uses two primary spatial range metrics that seek to define species distributions and inform extinction risk assessments (IUCN, 2019): extent of occurrence (EOO) and area of occupancy (AOO). EOO represents the upper bound of a species distribution, measuring the overall geographic extent of localities and degree of risk spread. Conversely, AOO represents the lower bound of a species distribution. By quantifying where the species occurs, AOO is thus linked to population size (Gaston & Fuller, 2009). Recently, the

IUCN developed a new deductive range metric, area of habitat (AOH, Brooks *et al.*, 2019), defined as the extent of habitat factors, such as landcover and elevation, for a species within its range. Estimating AOH is important because it can be used in supporting conservation risk assessments by quantifying habitat loss and protected area coverage (Brooks *et al.*, 2019; Sutton *et al.*, 2022).

Protected areas are a fundamental tool for conservation (Rodrigues & Cazalis, 2020) and have been successful in reducing habitat loss and fragmentation for many taxa (Brooks, Wright, & Sheil, 2009; Geldmann *et al.*, 2013), including apex predators, such as the Asiatic lion (*Panthera leo persica*; Venkataraman, 2009). However, despite wide coverage in the global protected area network, gaps in protected area coverage still exist with new areas being continually added (Rodrigues *et al.*, 2004a, 2004b). Additionally, not all protected areas are located in places deemed effective for conservation, but often designated by socio-economic factors related to competing human activities (Pringle, 2017; Morán-Ordóñez, 2020). Key Biodiversity Areas (KBAs; BirdLife International, 2020) are key sites of international significance for biodiversity which contain: (1) populations of globally threatened species, (2) populations and communities of range or biome restricted species or (3) substantial congregations of bird species. KBAs also protect areas important for biodiversity and aim to overlap with the entire global protected area network (Donald *et al.*, 2019). Identifying key sites within the existing KBA network as new protected areas is usually accomplished using a gap analysis (Scott *et al.*, 1993). This analysis simultaneously calculates protected area coverage within predicted AOH, thus defining priority sites for protection or conservation action.

Various spatial workflows have been proposed and implemented for calculating AOH, which overlay and clip elevational and landcover preferences within the range of species presence points (Brooks *et al.*, 2019). Deductive methods using clipped environmental layers with expert-drawn maps (Harris & Pimm, 2008), or inductive modelling methods using inverse distance weighted interpolation (Palacio *et al.*, 2021), and logistic regression (Dahal *et al.*, 2021; Lumbierres *et al.*, 2021), have been successful in estimating AOH. However, these techniques rely on a spatially homogeneous sample of presence points. For many rare species in remote areas that are difficult to survey, presence data are either insufficient, or may be heavily biased towards a well-sampled region but lacking elsewhere (Syfert *et al.*, 2014; Dahal *et al.*, 2021). Because of the rarity of these species, occurrence data are limited and thus calculating range metrics based solely on point data is likely to result in unreliable estimates (Pena *et al.*, 2014). To overcome this issue of sampling bias in calculating AOH a new approach for measuring AOH is required for those rare species with high extinction risk that inhabit remote regions lacking adequate presence data.

The Philippine Eagle (*Pithecophaga jefferyi*) is a large tropical forest raptor and one of the most threatened raptors globally, currently classified as 'Critically Endangered' on the IUCN Red List (BirdLife International, 2018). The

Philippine Eagle is endemic to four islands in the Philippine archipelago (Mindanao, Leyte, Samar and Luzon; Figure S1), and is sparsely distributed across lowland and montane dipterocarp forests (Salvador & Ibanez, 2006). The population has declined drastically over the past 50 years, mainly due to habitat loss through deforestation (Kennedy, 1977; Bueser *et al.*, 2003; Panopio *et al.*, 2021) and persecution (Salvador & Ibanez, 2006; Ibañez *et al.*, 2016). Thus, the Philippine Eagle fulfils all three components of rarity, and along with its large body size, slow breeding cycle (one young every 2–3 years), and forest dependency would be associated with a higher risk of extinction (Kittelberger *et al.*, 2021). Despite this elevated extinction risk, fundamental aspects of the species' biology such as distribution and population size are still uncertain (Collar, 1997; Collar, Mallari, & Tabaranza, 1999; BirdLife International, 2018) and need updating using a robust methodology.

Most Philippine Eagle research has been conducted on the island of Mindanao (Miranda *et al.*, 2000; Bueser *et al.*, 2003), and thus occurrence data are biased towards this island. Bueser *et al.* (2003) estimated between 82 and 233 breeding pairs for Mindanao, and extrapolating this figure across all range islands suggests a global total of between 340 (BirdLife International, 2018) and 500 pairs (Salvador & Ibanez, 2006). However, pair densities on the other range islands, especially Luzon, are unknown and thus this population size figure should be treated with caution (Miranda, Salvador, & Bueser, 2008). Because of these research disparities, there are no current range-wide estimates for the species' global range extent and population size, despite it being a raptor of high priority for research and conservation (Buechley *et al.*, 2019). Indeed, the IUCN Red List suggests that further research into distribution, population size and ecological requirements is urgently required to inform conservation actions (BirdLife International, 2018).

Here, we use Species Distribution Models (SDMs) calibrated with remote sensing covariates and presence-background data for the Philippine Eagle on the island of Mindanao, and then predict into the other less-well sampled islands using inductive model-based interpolation (Rodríguez *et al.*, 2007; Franklin, 2009). SDMs are **predictive spatial models that infer species-habitat associations by correlating species presence points with habitat covariates that represent the focal species optimal conditions and resources** (Guisan, Thuiller, & Zimmermann, 2017; Matthiopoulos, Fieberg, & Aarts, 2020). Indeed, SDMs can inform IUCN species range metrics and predict habitat in areas that may lack occurrence data for inclusion in Red List assessments (Marcer *et al.*, 2013; Pena *et al.*, 2014; Syfert *et al.*, 2014; Breiner *et al.*, 2017). Using interpolated model predictions, range metrics such as AOH, EOO and AOO can then be calculated based on inferred or predicted habitat following IUCN Red List guidelines (IUCN, 2019). First, we present an updated approach to estimating species range metrics and population size based on predicted habitat for the Philippine Eagle, and second, we demonstrate how our methodology can be incorporated into protected area conservation planning for rare species facing extinction.

## Materials and methods

### Species locations

We compiled Philippine Eagle point localities from the Global Raptor Impact Network (GRIN, McClure *et al.*, 2021), a data information system for population monitoring of all raptor species. For the Philippine Eagle, GRIN includes presence-only data consisting of nest locations ( $n = 48$ ) from unstructured surveys (i.e. with no true absence data) conducted on Mindanao by the Philippine Eagle Foundation since 1978 to the present (Miranda *et al.*, 2000; Ibañez *et al.*, 2016), along with community science data from the Global Biodiversity Information Facility ( $n = 27$ ; GBIF, 2021). We discarded eBird (Sullivan *et al.*, 2009) occurrences from the GBIF dataset because we deemed the locations were too unrepresentative for this particular analysis.

Duplicate locations and those with no geo-referenced coordinates were removed and then combined into a single database. Only locations recorded from year 1980 onwards were included to match the temporal timeframe of the habitat covariates, while retaining sufficient sample size for robust modelling (van Proosdij *et al.*, 2016). A total of 75 geo-referenced records were compiled across the Philippine Eagle range after data cleaning all of which are from Mindanao. Additionally, we included GPS tracking data from six nesting adult Philippine Eagles from the island of Mindanao sourced from the Philippine Eagle Foundation and pooled this with the nest and community science data to better represent habitat use of a rare species with limited occurrences (Fletcher Jr *et al.*, 2019; see Appendix S1).

For the Mindanao model, we used the nest and community science localities from the island of Mindanao, combined with the filtered GPS tracking fixes. We then manually applied a spatial filter between each point, resulting in a single occurrence in each 1-km raster grid cell, resulting in a filtered subset of 373 occurrence records for the Mindanao calibration models. We used spatial filtering because it is the most-effective method to account for sampling bias (Kramer-Schadt *et al.*, 2013; Boria *et al.*, 2014; Fourcade *et al.*, 2014) and to ensure we retained the nest locations and GPS fixes as priority data points because of their geolocation accuracy and direct relevance to optimal conditions and resources for Philippine Eagle occurrence. To evaluate the final continuous range-wide model, we used all nest and community science localities recorded from 1980 onwards and applied a 1-km spatial filter between each location, regardless of the origin of the point locality.

### Habitat covariates

We defined the species' accessible area (Barve *et al.*, 2011) as consisting of the mainland area of all known range islands: Mindanao, Leyte, Samar and Luzon (BirdLife International, 2018; Figure S1). We extracted the polygons from the World Wildlife Fund (WWF) terrestrial ecoregions shapefile (Olson *et al.*, 2001), which correspond to either lowland

or montane moist tropical forest. We masked the tropical pine forest ecoregion in the north of Luzon because Philippine eagles are habitat specialists of tropical moist dipterocarp forests (Kennedy, 1977; Bueser *et al.*, 2003; Salvador & Ibanez, 2006), and thus unlikely to occur in this ecoregion. Raster covariate layers were cropped to a delimited polygon consisting of the mainland area of all the known range islands. We selected covariates *a priori* based both on environmental factors related empirically to resources and conditions influencing Philippine Eagle distribution (Bueser *et al.*, 2003; Ibañez *et al.*, 2003; Salvador & Ibanez, 2006).

We predicted occurrence using six continuous covariates at a spatial resolution of 30 arc-seconds (~1-km; Figure S2) derived from multiple satellite remote sensing products. These consisted of three surface reflectance bands, which represent proxies of vegetation biomass, sourced from the Moderate Resolution Imaging Spectroradiometer (MODIS, <https://modis.gsfc.nasa.gov/>): Band 1 Red (i.e. plant biomass); Band 2 Near Infrared (i.e. leaf and canopy biomass); B7 Short Wave Infrared (i.e. senescent biomass), combined with Evergreen Forest landcover downloaded from the Earth-Env repository (<https://www.earthenv.org>) and a Leaf Area Index biophysical measure downloaded from the Dynamic Habitat Indices repository (<https://silvis.forest.wisc.edu/data/dhis/>). Additionally, we included Human Footprint Index as a measure of human land use sourced from the Socioeconomic Data and Applications Center (SEDAC; <https://sedac.ciesin.columbia.edu>). Full details on covariates and processing are provided in the Appendix S1.

### Species distribution models

All Philippine Eagle occurrences and nest locations deposited in GRIN are from the island of Mindanao, with no occurrences across the Eastern Visayas and Luzon. Due to this geographical sampling bias, which would likely bias any model predictions (Syfert *et al.*, 2014), we developed a model workflow (Figure S3) to first predict habitat suitability for Mindanao (Figure S3, box 3a). Next, we projected each Mindanao model into the islands of the Eastern Visayas and Luzon (Figure S3, boxes 3b,c), before finally merging each island model into a single range-wide prediction (Figure S3, box 3c). We parametrised the SDMs using a fine pixel grid (~1-km), equivalent to fitting an inhomogeneous Poisson process (IPP) with loglinear intensity (Baddeley *et al.*, 2010). We did this because the IPP framework is the most-effective method to model presence-only data (Warton & Shepherd, 2010), common to many raptor monitoring programmes which solely seek to identify occupied areas (Geary, Haworth, & Fielding, 2018).

We fitted SDMs using penalised logistic regression, via maximum penalised likelihood estimation (Hefley & Hooten, 2015) in the R package maxnet (Phillips *et al.*, 2017). Penalised logistic regression imposes a regularisation penalty on the model coefficients, shrinking towards zero the coefficients of covariates that contribute the least to the model, reducing model complexity (Gastón & García-Viñas, 2011). We limited model complexity because this is necessary when

the primary goal is to use SDMs for predictive transferability in space (Helmstetter *et al.*, 2021). The maxnet package fits the SDM as a form of infinitely weighted logistic regression (presence weights = 1, background weights = 100), based on the maximum entropy algorithm, MAXENT (Phillips *et al.*, 2017). MAXENT is designed for presence-background SDMs and is mathematically equivalent to estimating the parameters for an IPP (Renner & Warton, 2013; Renner *et al.*, 2015). We used a tuned penalised logistic regression algorithm because this approach outperforms other SDM algorithms (Valavi *et al.*, 2021), including ensemble averaged methods (Hao *et al.*, 2020). Full details on the model parameter settings are outlined in the Appendix S1.

We evaluated calibration accuracy for the Mindanao model using a random sample of 3730 background points at a recommended 1:10 ratio to the presence data (Helmstetter *et al.*, 2021). For the range-wide model, we used a random sample of 10 000 background points as pseudo-absences recommended to sufficiently sample the background calibration environment (Barbet-Massin *et al.*, 2012; Guevara *et al.*, 2018). We used Continuous Boyce index (CBI; Hirzel *et al.*, 2006) as a threshold-independent metric of how predictions differ from a random distribution of observed presences (Boyce *et al.*, 2002). CBI is consistent with a Spearman correlation ( $r_s$ ) and ranges from  $-1$  to  $+1$ . Positive values indicate predictions consistent with observed presences, values close to zero suggest no difference with a random model, and negative values indicate areas with frequent presences having low environmental suitability. We calculated mean CBI using five-fold cross-validation on 20% test data with a moving window for threshold independence and 101 defined bins in the R package *enmSdm* (Smith, 2019).

For the Mindanao model, we further tested the optimal predictions against random expectations using partial Receiver Operating Characteristic ratios (pROC), which estimate model performance by giving precedence to omission errors over commission errors (Peterson, Papeş, & Soberón, 2008). Partial ROC ratios range from 0 to 2 with 1 indicating a random model. Function parameters were set with a 10% omission error rate, and 1000 bootstrap replicates on 50% test data to determine significant ( $\alpha = 0.05$ ) pROC values  $>1.0$  in the R package *ENMGadgets* (Barve & Barve, 2013). Lastly, the final range-wide continuous prediction was tested using CBI and then converted into a binary threshold prediction based on expert validation from J.C.I., which we term *model* AOH (Figure S3, box 5), to be distinct from the standard IUCN AOH methodology (Brooks *et al.*, 2019).

We validated our models in conjunction with expert judgement because this approach gives most benefit to conservation risk assessments (Marcer *et al.*, 2013; Syfert *et al.*, 2014). Following modelling protocols established by Velásquez-Tibatá *et al.* (2019), we assessed a range of four binary thresholds for biological realism (median, 75% upper quantile, maximising the sum of sensitivity and specificity (maxTSS) and Cohen's Kappa), using expert critical feedback to assess the predictive ability of our models (Figure S3, boxes 4b,c). Both maxTSS and upper quantile binary models

were evaluated as plausible range extents but we chose maxTSS because this threshold is recommended for spatial conservation applications (Liu, White, & Newell, 2013). We followed a participatory modelling process methodology to ensure a robust expert validation of our models, concurring with current knowledge of species biology and its application to conservation planning (Ferraz *et al.*, 2020).

## Range sizes

To calculate *model* AOH in suitable pixels, we reclassified the continuous prediction to a binary threshold prediction (Figure S3, boxes 4a,b), using all pixel values equal to or greater than the maxTSS threshold from the continuous model. We calculated two further IUCN range metrics from our *model* AOH binary prediction. First, Area of Occupancy (AOO) was calculated as the number of raster pixels predicted to be occupied, scaled to a  $2 \times 2$  km grid (4-km<sup>2</sup> cells) following IUCN guidelines (IUCN, 2018) in the R package *redlistr* (Lee *et al.*, 2019). Second, we converted the *model* AOH raster to a polygon using an 8-neighbour patch rule and applied a smoothing function using the Chaikin algorithm (Chaikin, 1974) in the R package *smoothr* (Strimas-Mackey, 2021). From this, we calculated Extent of Occurrence (EOO), fitting a minimum convex polygon (MCP) around the furthest boundaries of the smoothed *model* AOH polygon following IUCN guidelines (IUCN, 2018). We calculated both a maximum EOO, including all the area with the MCP, and a minimum EOO, masking the areas that could never be occupied within the MCP, in our case over the ocean (Marcer *et al.*, 2013). All range metric calculations were performed using a Transverse cylindrical equal area projection following IUCN guidelines (IUCN, 2018).

## Population size estimation

We calculated the number of Philippine Eagle pairs our *model* AOH could support as directly proportional to the available habitat within a given home range required by a breeding pair of Philippine Eagles (Kennedy, 1977; Krupa, 1989). Based on the premise that central-place foragers, such as the Philippine Eagle, require a semi-fixed area of habitat to survive and reproduce, we calculated the habitat area required for each pair on home range estimates from six breeding adult Philippine Eagles fitted with satellite telemetry tags (Table S1). We calculated home range sizes using three different estimators to provide a range of habitat area estimates for calculating population size because of variation in outputs between different home range estimation methods (Signer & Fieberg, 2021; see Appendix S1).

Using the habitat area from the three estimates, we then calculated the median, and a range of minimum to maximum population sizes of potential breeding pairs that our *model* AOH prediction could support using the formulation of Kennedy (1977),

$$\hat{T}(N/n) t$$



where  $T_{\text{hat}}$  = total population size;  $N$  = area of habitat;  $n$  = home range estimate and  $t$  = sample total multiplied by 2. We used the IUCN Red List definitions for population size as the total number of mature individuals across the species range (IUCN, 2019), then divided that figure by 2 to give the number of potential breeding pairs.

## Protected area gap analysis

We assessed the level of protected area coverage within the Key Biodiversity Area (KBA) network using the World Database of Protected Area (WDPA) terrestrial shapefile for the Philippines (as of June 2021; UNEP-WCMC & IUCN, 2021). We quantified how much protected area representation is needed for the Philippine Eagle dependent on the *model* AOH to calculate a protected area 'representation target' following the formulation of Rodrigues *et al.* (2004a),

$$\text{Target} = \max(0.1, \min(1, -0.375 \times \log_{10}(\text{range size}) + 2.126))$$

where 'Target' is equal to the percentage of protected target representation required for the species 'range size', as used in subsequent applications of the formula (Butchart *et al.*, 2015; Di Marco *et al.*, 2017). We calculated the difference between the current level of KBA coverage compared to the target level representation for terrestrial WDPA coverage using the *model* AOH intersected with the KBA polygons (as of September 2020; BirdLife International, 2020), establishing those KBAs covering areas of habitat suitability  $\geq$  maxTSS threshold. The KBA network polygons were then overlaid with the continuous maps for each island identifying gaps in habitat suitability  $\geq$  maxTSS threshold which were not covered by the terrestrial WDPA polygons. We used the continuous models to identify priority conservation areas because continuous predictions give more precision for identifying spatial conservation planning hotspots than binary outcomes (Guillera-Aroita *et al.*, 2015). We used the R program (v3.5.1; R Core Team, 2018) for model development and geospatial analysis using the raster (Hijmans, 2017), rgdal (Bivand, Keitt, & Rowlingson, 2019), rgeos (Bivand & Rundel, 2019) and sp (Bivand, Pebesma, & Gomez-Rubio, 2013) packages.

## Results

### Species distribution models

For the Mindanao models, only one candidate model had an  $\Delta\text{AIC}_c \leq 2$ . The best-fit SDM for the island of Mindanao ( $\Delta\text{AIC}_c = 0.0$ ) had a beta coefficient penalty of  $\beta = 1$  with linear and quadratic terms as model parameters, with high-calibration accuracy (mean CBI = 0.934), and was robust against random expectations (pROC = 1.534, SD  $\pm$  0.079, range: 1.248–1.771). The optimal model shrinkage penalty was able to retain 10 non-zero beta coefficients, only setting to zero the quadratic terms for Band 1 Red and Evergreen Forest (Table 1), meaning most covariate terms were highly informative to model prediction (Figures S4–S6).

**Table 1** Parameter estimates from the penalised linear and quadratic beta coefficients derived from the response functions for each habitat covariate from the optimal Species Distribution Model for the Philippine Eagle on Mindanao island

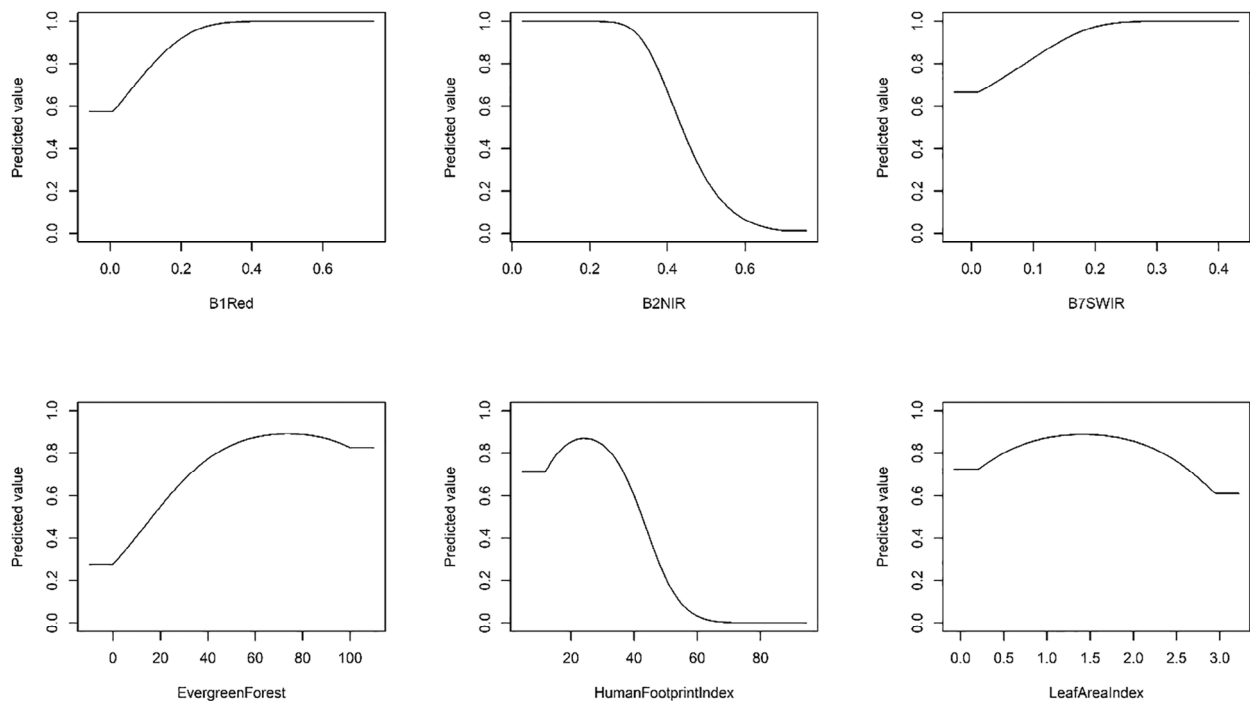
Covariate	Linear	Quadratic
B1 Red	5.636	0.000
B2 Near Infrared	−6.500	−7.455
B7 Short Wave Infrared	4.018	11.213
Evergreen Forest	0.052	0.000
Human Footprint Index	0.157	−0.003
Leaf Area Index	1.027	−0.362

From the penalised beta coefficients (Table 1), Philippine Eagles on Mindanao were most positively associated with Band 1 Red surface reflectance values  $>0.4$  (i.e. dense, healthy green plant biomass), followed by lower Band 7 Short Wave Infrared surface reflectance values between 0.2 and 0.4 (i.e. senescent or old-growth biomass) and most negatively associated with Band 2 Near Infrared surface reflectance values  $>0.3$  (i.e. leaf and canopy biomass; Fig. 1). Philippine Eagles had a unimodal response to Leaf Area Index values of 1.5 (i.e. multiple layered canopy cover), and a positive linear response to Evergreen Forest cover between 70–80% (Fig. 1). Philippine Eagles had a positive relationship up to Human Footprint Index values of 20 (i.e. areas of low human impact) decreasing sharply to areas with high-impact human infrastructure.

On Mindanao, the largest continuous areas of Philippine Eagle habitat were confined to mountainous regions with high forest cover across the eastern and central mountain ranges of Kitanglad, Pantaron, Diwata and the Bukidnon plateau (Fig. 2). Patchy areas of habitat were identified throughout western Mindanao, largely confined to areas of steep, forested terrain, and extending further south into the Tiruray Highlands and Mount Latian complex. Little habitat was predicted across the now largely deforested lowland plains. The range-wide continuous model had high predictive performance (CBI = 0.955) and was able to capture key areas of habitat when projected to the islands of Luzon and the Eastern Visayas (Fig. 3). For the Eastern Visayas, highest habitat suitability was predicted in a small area of north-eastern Samar. Only small patches of high-suitability habitat were predicted for Leyte. In Luzon, the largest continuous area of Philippine Eagle habitat was predicted in the northern Sierra Madres mountain range in the east of the island, with smaller patches further south. Further high-suitability areas were predicted in the north of Luzon in the northern Cordillera mountain range and a smaller area of habitat was predicted for the Zambales mountain range in the far west of Luzon (Fig. 3).

### Range metrics and population size

The reclassified binary model (maxTSS threshold = 0.560) calculated a *model* AOH = 28 624 km<sup>2</sup> (Fig. 4). From the *model* AOH, maximum EOO was 617 957 km<sup>2</sup> and minimum EOO 275 459 km<sup>2</sup> (Fig. 4), with an



**Figure 1** Penalised logistic regression response functions for each habitat covariate from the optimal Species Distribution Model for the Philippine Eagle on Mindanao island. The curves show the contribution to model prediction (y-axis) as a function of each continuous habitat covariate (x-axis). Maximum values in each response curve define the highest predicted relative suitability. The response curves reflect the partial dependence on predicted suitability for each covariate and the dependencies produced by interactions between the selected covariate and all other covariates. Absolute reflectance values on the x-axes of the top row panels are expressed as the ratio of reflected over incoming radiation, meaning reflectance can be measured between the values of zero and one. Reflectance values of 3–4 indicate healthy vegetation.

AOO = 53 867 km<sup>2</sup>. The median territorial habitat area based on the home range estimates from the six adults was 73 km<sup>2</sup> using the KDE estimator (Table 2; Figure S7), with a minimum and maximum range of 64 and 90 km<sup>2</sup> of territorial habitat area using the median home range estimates from the r-LoCoH and 99% MCP estimators, respectively (Table 2; Figure S8). Using our formulation based on habitat area from home range estimates, we calculated the *model* AOH could potentially support 392 breeding pairs (range: 318–447), or 784 mature individuals, across the entire Philippine Eagle range based on the *model* AOH area of 28 624 km<sup>2</sup> (Fig. 4). The area of habitat in Mindanao (17 040 km<sup>2</sup>) could potentially support 233 breeding pairs (range: 190–266; Figure S9), in Luzon (AOH = 9348 km<sup>2</sup>) 128 pairs (range: 104–146; Figure S10) and in the Eastern Visayas (AOH = 2236 km<sup>2</sup>) 31 pairs (range: 25–35; Figure S11).

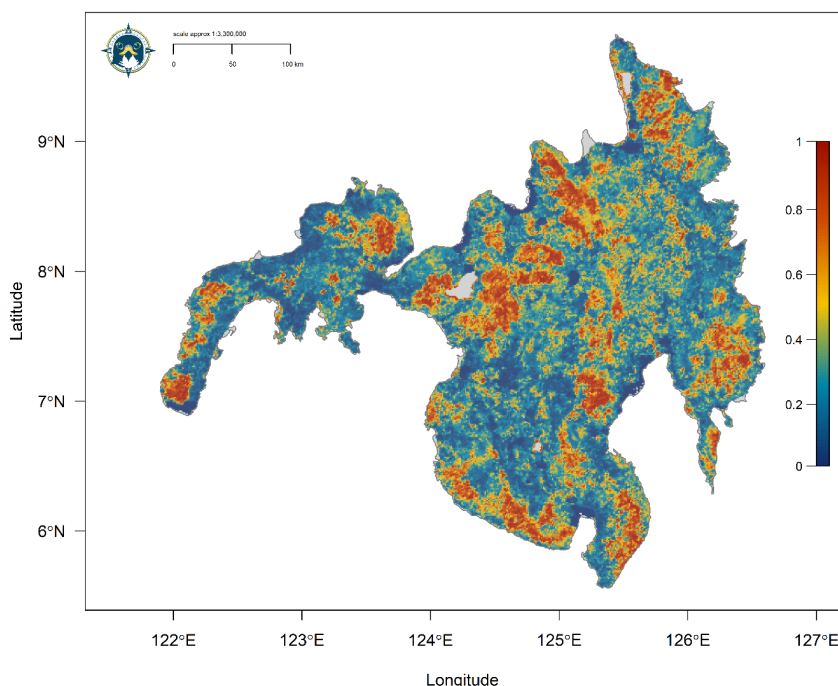
### Priority conservation areas

Across the Philippine Eagle range, the current WDPA network covered 32.4% (9274 km<sup>2</sup>) of the *model* AOH (Figure S12), 12.6% less than the target protected area representation of 45%. The KBA network covered 67% (19 180 km<sup>2</sup>) of the *model* AOH (Figure S13), double the

coverage within the WDPA network. We identified priority areas of Philippine Eagle habitat that are currently classified as KBAs but without protected area coverage in the WDPA network on all range islands.

On Mindanao, priority KBAs for upgrading to protected areas include (Fig. 5): (1) Mount Hilong-hilong and (2) Mount Kampalili-Putting Bato in the Eastern Mindanao Biodiversity Corridor. In southern-central Mindanao, priorities are extending the protected area for Mount Apo Natural Park (3) into the northern part of the KBA, along with protected status for the Mount Latian complex and Mount Busa-Kiamba KBAs (4). Protected areas could also be extended in the Mount Piagayungan and Butig Mountains and Munai/Tambo KBAs (5) in east-central Mindanao. In northern-central Mindanao, priority KBAs for protection include the Mount Kaluayan – Mount Kinabalian Complex along with the adjacent Mount Balatukan, and the Mount Tago Range KBAs (6). Additionally, we recommend new KBAs and/or protected areas be established in: (A) Sibuco-Sirawai region of western Mindanao (Fig. 5; dashed blue circle A); (B) the Daguma Range-Palimbang region of southern Mindanao (dashed blue circle B) and (C) Mount Sinaka in central Mindanao (dashed blue circle C).

In the Eastern Visayas, most habitat within the KBA network on Samar was contained within the Samar Island



**Figure 2** Continuous species distribution model for the Philippine Eagle on the island of Mindanao using a penalised logistic regression model algorithm. Map denotes habitat suitability prediction with red areas (values closer to 1) having highest habitat suitability, orange/yellow moderate suitability and blue/green low suitability (values closer to zero).

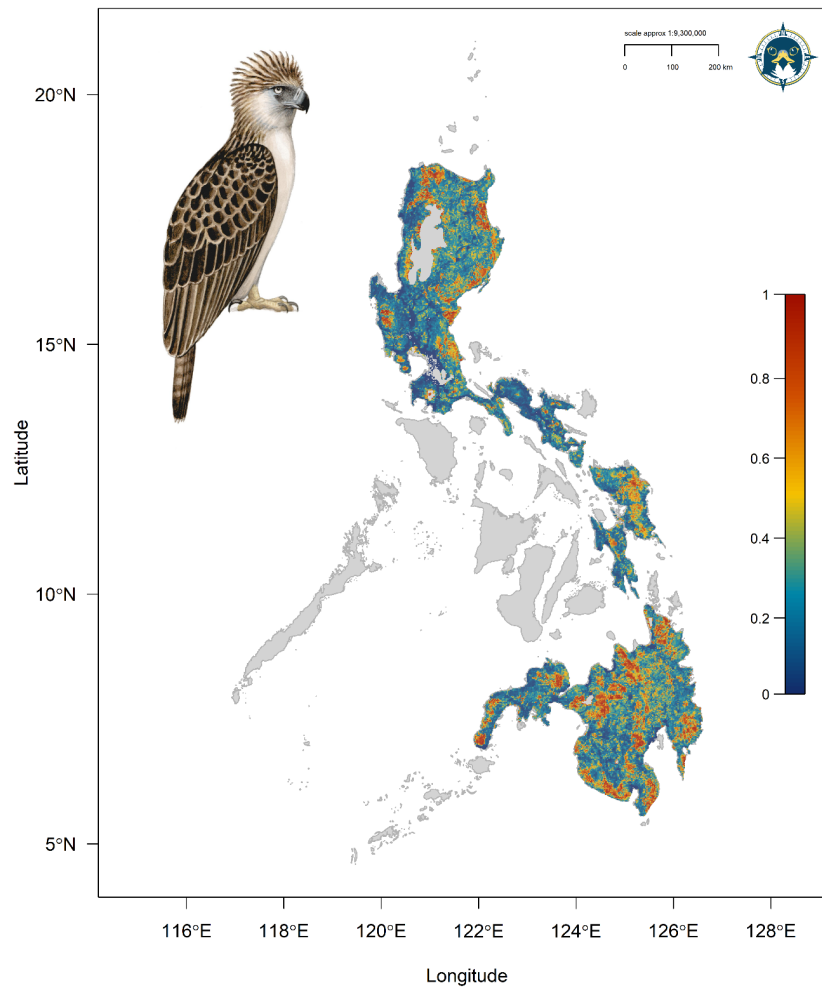
Natural Park (IUCN Cat. II; Fig. 6). The north-east of the island had highest habitat suitability and should be prioritised for further protection extending across north-east Samar beyond the national park. This would include high-suitability habitat which has no coverage within either the KBA or protected area networks. The priority KBA for protection in Leyte was Anonang-Lobi Range, which contains the largest areas of habitat (Fig. 6). Furthermore, the pockets of high-suitability habitat within the Mount Nacolod KBA in the east of Leyte must be prioritised for habitat protection and as potential reintroduction sites (Fig. 6). For Luzon, priority KBAs for proposed new protected areas include (Fig. 7): (1) the Apayao Lowland Forest in northern Luzon, along with extending this KBA and the Balbalasang-Balbalan KBA west to cover further high-suitability habitat. Connecting high-suitability habitat along the Sierra Madre Range by protecting the North Central Sierra Madre Mountains KBA (2) and Mount Dingalan and Aurora Memorial National Park KBAs (3) in eastern Luzon. Lastly, (4) the Zambales Mountains could also be upgraded for protection if surveys identify a population here, otherwise the KBA should be prioritised for potential reintroductions.

## Discussion

Range-restricted tropical raptors are particularly threatened by human-induced land use activities (Cruz, Santulli-Sanzo, & Ceballos, 2021), with many experiencing severe population declines and in need of immediate research and conservation (McClure *et al.*, 2018; Buechley *et al.*, 2019).

Correlating occurrence data from multiple sources with remote-sensing environmental data, we provide a first estimate of Area of Habitat for the Philippine Eagle, update the species' IUCN range metrics and provide a baseline global population estimate. By establishing baselines for these important biological parameters, we then applied our model outputs for directing long-term monitoring and priority conservation planning for this Critically Endangered raptor. Despite issues of geographic sampling bias in our occurrence dataset, we were able to overcome any analytical setbacks by implementing a robust and straightforward modelling framework. We view our methodology as a widely applicable tool for quantifying species-habitat associations for many taxa of conservation concern.

Our *model* AOH map updates previous estimates of potential habitat for the Philippine Eagle, further refining the habitat map from Krupa (1989). Our *model* AOH estimate of 28 624 km<sup>2</sup> confirms the Philippine Eagle as a range-restricted and endemic species, which are not always mutually exclusive (Gaston, 1994). We were able to use our binary model prediction to calculate a first estimate for AOO (53 867 km<sup>2</sup>) and an updated EOO bounded from the *model* AOH polygon (see Fig. 4). Our maximum EOO (617 957 km<sup>2</sup>) was 11% larger than the current IUCN estimate (551 000 km<sup>2</sup>; BirdLife International, 2018). However, when considering the area of EOO not covering the unoccupiable area of the ocean, our minimum EOO (275 459 km<sup>2</sup>) was 50% less. We posit that using a minimum EOO is more relevant for species that range across island archipelagos because including areas that cannot be occupied within the



**Figure 3** Range-wide species distribution model for the Philippine Eagle using a penalised logistic regression model algorithm. Map denotes continuous prediction with red areas (values closer to 1) having highest habitat suitability, orange/yellow moderate suitability and blue/green low suitability. Illustration by Bryce W. Robinson.

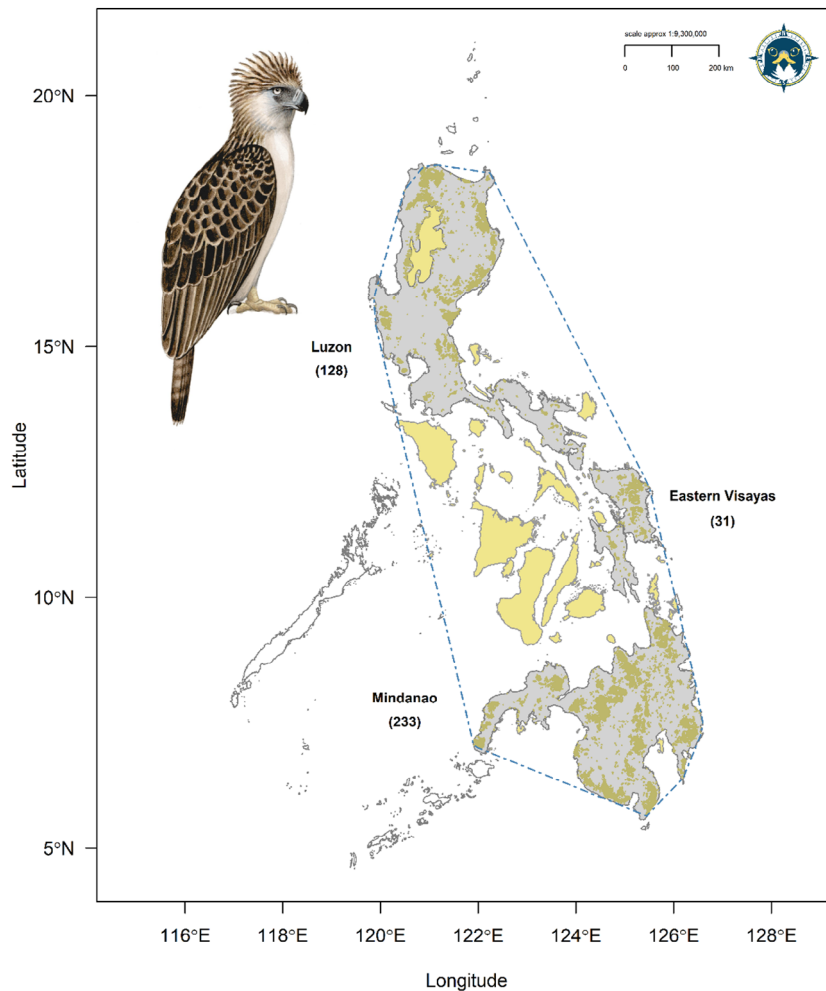
entire area of the MCP in the EOO range metric calculation is potentially misleading. We recognise the need to have a consistent global methodology for species range metrics but not at the cost of inflating risk spread in the EOO range metric for threatened island ranging species. Thus, we recommend that both a minimum and maximum EOO be reported in future IUCN range assessments where relevant.

Area of Habitat maps are useful in many conservation applications such as protected area assessments, targeting surveys and monitoring habitat loss (Brooks *et al.*, 2019). Here, we also applied our *model* AOH to calculating a key biological parameter used in IUCN conservation risk assessments, that of a global population estimate (IUCN, 2019). However, we stress that our global estimate of 392 pairs (784 mature individuals) is the *potential* breeding population size based on inferred habitat from SDM outputs which may not always link to population parameters (Lee-Yaw *et al.*, 2021). Our global population size of 392 pairs was higher than a current extrapolated estimate of 340 pairs

(BirdLife International, 2018) and from an earlier estimate of 88–221 pairs (Krupa, 1989). However, the key difference here is that we used an empirical estimate of habitat area needed for each pair based on home range estimates. Assuming our baseline population estimate is accurate, we urge more investment and research, such as ground-truthing surveys, into conserving these remaining populations and their forest habitat.

Our median population estimate for Mindanao ( $n = 233$  pairs) was at the upper limit of the current population range estimate for the island (82–233 pairs; Bueser *et al.*, 2003), but greater than other previous population estimates (Kennedy, 1977; Krupa, 1989). Bueser *et al.* (2003) calculated population size using a different method based on habitat within a circular plot around known nest sites from nearest neighbour distances and total forest habitat. That our population size estimate for Mindanao was at the upper limit of the range given by Bueser *et al.* (2003), gives credence to our method that uses home range estimates with our area of





**Figure 4** Range metrics for the Philippine Eagle showing the reclassified binary *model* area of habitat (AOH) area (brown) and extent of occurrence (EOO, hashed blue polygon). Grey island polygons represent the species accessible area. Yellow polygons define the national boundary of the Philippines not within the species accessible area. Values in parentheses refer to the median number of Philippine Eagle breeding pairs that the area of habitat on each island could support. Illustration by Bryce W. Robinson.

**Table 2** Home range estimates for six breeding adult Philippine Eagles using three home range estimators

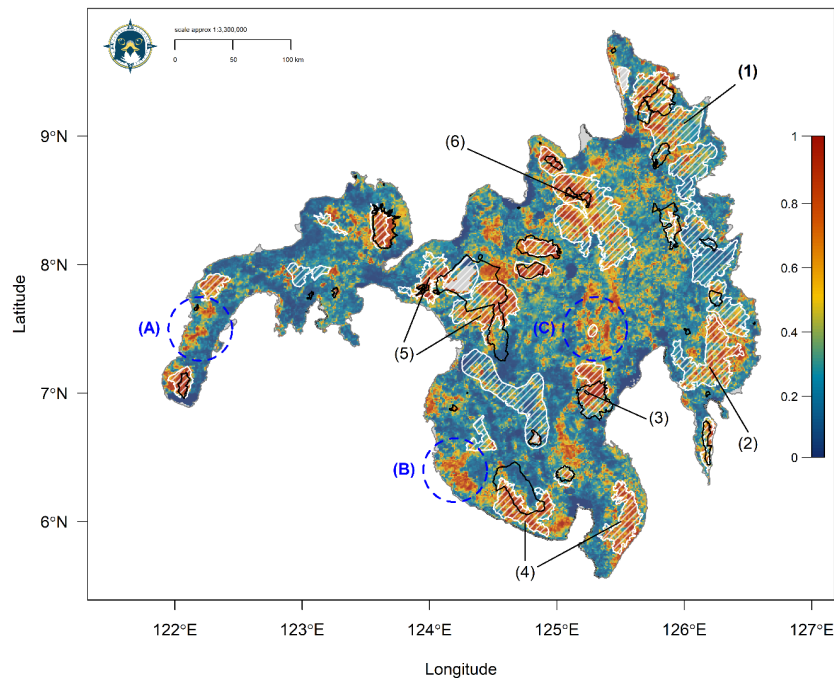
Adult ID	r-LoCoH	95% KDE	99% MCP
001F	61	70	88
002F	85	75	105
003F	37	43	36
004M	66	107	91
005M	53	41	57
006F	120	147	173
Median	64	73	90

All values are km<sup>2</sup>. r-LoCoH, radius local convex hull; KDE, Kernel density estimate, MCP, minimum convex polygon.

habitat size. The median population estimate for Luzon ( $n = 128$  pairs) was nearly half that for Mindanao but higher than from a previous estimate of 33–83 pairs, that used assumed territory sizes of 60–100 km<sup>2</sup> with the then area of

remaining forest habitat in the Philippines (Krupa, 1989). Exploratory ground-truthing surveys are thus required across Luzon to establish the accuracy of our baseline population estimate.

Historically, Philippine Eagles were recorded throughout Luzon (Kennedy, 1977) but with most records largely restricted to the Sierra Madre range (Poulsen, 1995; Panopio *et al.*, 2021), albeit at assumed low densities (Krupa, 1989). Indeed, surveys in the north of Luzon discovered the first nest in the northern Cordillera range (Abaño, Salvador, & Ibañez, 2016), and our model predicted extensive Philippine Eagle habitat across both the Sierra Madre and Cordillera ranges. Our estimate of 31 pairs (range: 25–35 pairs) for the Eastern Visayan islands of Leyte and Samar was greater than earlier estimates (Kennedy, 1977; Krupa, 1989). Previous pair estimates for Samar ranged between 8 and 19 pairs (Krupa, 1989), with numbers on Leyte estimated to be between 8 and 10 pairs (Kennedy, 1977), or as low as 1–4



**Figure 5** Gap Analysis for Philippine Eagle habitat on the island of Mindanao showing spatial coverage of the World Database on Protected Areas (WDPA) network (black polygons) compared to the Key Biodiversity Area (KBA) network coverage (white hashed polygons) within the continuous model prediction. Map denotes habitat suitability prediction with red areas (values closer to 1) having highest habitat suitability, yellow moderate suitability and blue low suitability (values closer to zero). Numbered arrows indicate priority KBAs for protection: (1) Mount Hilong-hilong, (2) Mount Kampalili-Putting Bato, (3) Mount Apo, (4) Mount Latian & Mount Busa-Kiamba, (5) Mount Piagayungan & Butig Mountains and Munai/Tambo, (6) Mount Kaluayan-Mount Kinabalian Complex, Mount Balatukan and Mount Tago Range. Hashed blue circles indicate areas of high-suitability habitat recommended as new KBAs and/or protected areas: (A) Sibuco-Sirawai, (B) Daguma Range-Palimbang and (C) Mount Sinaka.

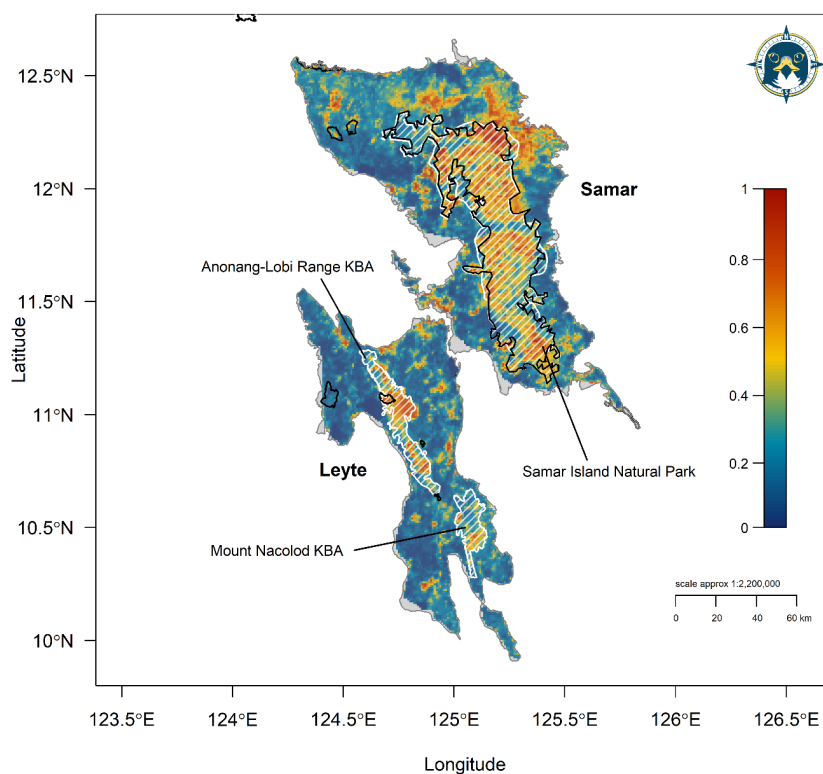
pairs (Krupa, 1989). Like Luzon, we urge more surveys on Leyte and Samar to ground-truth our estimates because even though this is the smallest sub-population it is still viable for maintaining genetic diversity and building on reintroduction efforts.

The Philippines is one of the most biodiverse countries globally (Myers *et al.*, 2000), with an established community-based protected area system (Senga, 2001; Posa *et al.*, 2008). Our gap analysis was able to identify 15 current KBAs on all range islands (both with and without any form of protection), as priority sites for new or extended protected areas within the current network. Further, we identified two priority sites for reintroductions on Leyte and one on Luzon, along with three recommended sites for new protected designations on Mindanao. Due to the Philippine Eagle's reliance on tropical dipterocarp forest, we recommend designating these KBAs as either new protected areas, Indigenous and Community Conserved Areas (ICCAs) or Local Conservation Areas (LCAs). This would connect the remaining habitat patches which are key to the species future survival (Poulsen, 1995; Posa *et al.*, 2008). Further, protecting these key areas of tropical forest habitat should also be beneficial for prioritising reintroduction sites.

An important advantage of using covariates derived from MODIS satellite remote sensing data is that constant

monitoring can be established for changes in vegetation (Perez & Comiso, 2014). New MODIS covariates can then be used in updated models for the important biological and conservation parameters for area of habitat, population size and protected area coverage, meaning rapid action can tackle emerging threats when needed. However, we recognise that new and emerging satellite remote sensing technologies could also be incorporated into our modelling framework and to improve predictions for SDMs in general (Leitão & Santos, 2019). For example, active optical sensors that can capture the three-dimensional structure of vegetation (i.e. NASA Global Ecosystem Dynamics Investigation; Burns *et al.*, 2020), or passive optical sensors with higher spatial resolution (up to 10 m) and higher revisit frequency (i.e. Sentinel 2, Copernicus programme, European Space Agency). Modelling species distributions at a spatial resolution relevant to both organism and conservation-relevant scales might benefit from the use of these rich data sources that are rarely used in conservation biology.

There is no one overriding 'best' method for modelling species-habitat associations but multiple approaches dependent on the purpose of the study (Qiao, Soberón, & Peterson, 2015). Our approach was useful because of its ability to predict beyond the known range limits of the Philippine Eagle, providing a *potential* area of habitat (*sensu* Sutton



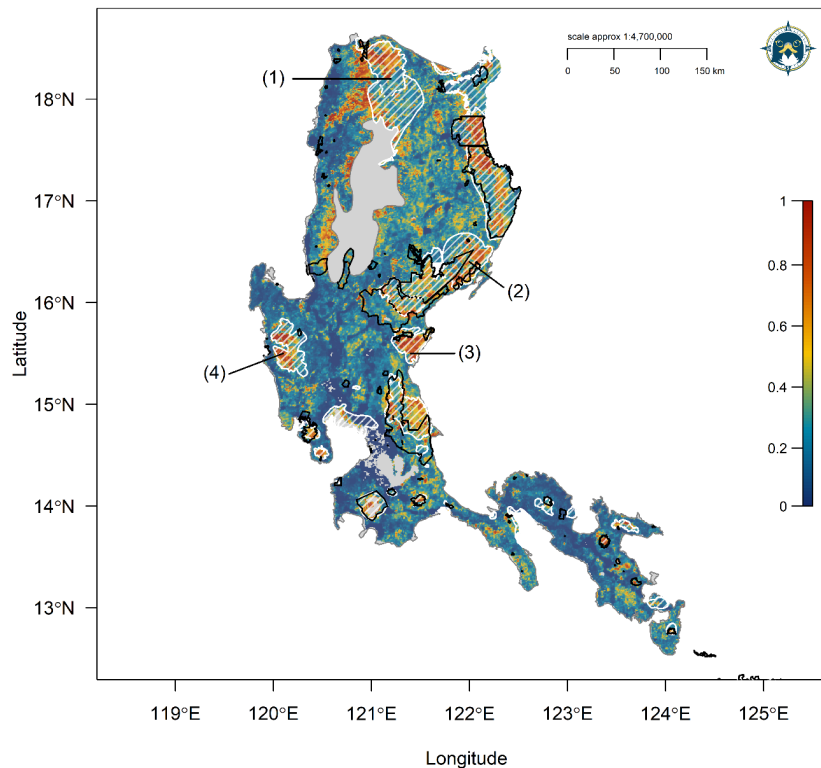
**Figure 6** Gap Analysis for Philippine Eagle habitat on the islands of Leyte and Samar in the Eastern Visayas showing spatial coverage of the World Database on Protected Areas (WDPA) network (black polygons) compared to the Key Biodiversity Area (KBA) network coverage (white hashed polygons) within the continuous model prediction. Map denotes habitat suitability prediction with red areas (values closer to 1) having highest habitat suitability, yellow moderate suitability and blue low suitability (values closer to zero).

*et al.*, 2021a, 2022). This was appropriate in this context when our goal was to provide baseline estimates for global range extent and population size, with geographically biased species locations, rendering standard habitat modelling approaches unsuitable. Further, the standard IUCN approach to estimating AOH uses solely landcover and elevation as covariates (Brooks *et al.*, 2019). Here, along with landcover we also incorporated important predictors for determining species' habitat associations such as those from raw surface reflectance values and human land use (Guisan *et al.*, 2017). This procedure resulted in improved model predictions compared to an initial SDM for the Philippine Eagle using climate and landcover (Sutton *et al.*, 2021b). We recommend that analysts consider remote sensing variables in future area of habitat assessments to fully capture the environmental range limits for a given taxa.

While we envision broad applications for our methodology, we recognise that our spatial workflow is likely most useful for island endemic species with low numbers of occurrences, or with pronounced geographic sampling bias in species locations. Despite potential issues with sampling bias from pooling occurrences from disparate data sources (Fletcher *et al.*, 2019), we were able to use the spatial filter to account for sampling bias and use pooled data because we had no true absences to use in our models, only presences. We sampled pseudo-absences from our study area

but the assumption that all absences would be within that study area (thus approximating the model integral) is difficult to assess (Hefley & Hooten, 2016). Rectifying the issues for this form of sampling bias with an appropriate data model is currently unknown (Hefley & Hooten, 2016). Thus, pooling all the available presence data and then combining with a random sample of background pseudo-absences is justified in this case for a data-poor rare species (Biddle *et al.*, 2021).

Despite this, we recognise the need to find a more efficient observation process when modelling species' distributions using locations from targeted surveys or opportunistically collected community science data (Kéry *et al.*, 2010). Developing robust protocols for structured or semi-structured planned surveys that incorporate true absence observations and observer effort from ground-truthing would be a step forward. Similarly, using existing opportunistic records from community science data to infer absences in a semi-structured observation process accounting for spatial biases would likely improve model predictions (Gorleri, Hochachka, & Areta, 2021; Johnston *et al.*, 2021). Whether locations are opportunistic or from targeted surveys, encouraging recording in the most relevant areas to the specific goal in a biodiversity conservation project would reduce the inherent noise from irregular sampling, especially in community science occurrence data (Callaghan *et al.*, 2019).



**Figure 7** Gap analysis for Philippine Eagle habitat on the island of Luzon showing spatial coverage of the World Database on Protected Areas (WDPA) network (black polygons) compared to the key biodiversity area (KBA) network coverage (white hashed polygons) within the continuous model prediction. Map denotes habitat suitability prediction with red areas (values closer to 1) having highest habitat suitability, yellow moderate suitability and blue low suitability (values closer to zero). Numbered arrows indicate priority KBAs for protection: (1) Apayao Lowland Forest and Balbalasang-Balbalan, (2) North Central Sierra Madre Mountains, (3) Mount Dingalan and Aurora Memorial National Park and (4) Zambales Mountains.

Globally, more than half of all raptor species are declining, largely due to increasing human land use activities, driving habitat loss and degradation (McClure *et al.*, 2018). Quantifying baseline biological parameters such as range extent and population size is key to establishing a solid foundation from which to build effective conservation action (Watson, 2018). With the fundamentals of where a given species occurs and how many individuals exist, conservation planning can be more effectively directed to areas of high conservation priority (IUCN, 2001; Rodríguez *et al.*, 2007). Our results demonstrate that even with geographically biased occurrence datasets, SDMs can inform globally recognised range metrics and baseline population estimates. In the absence of widespread occurrence data for many rare species, our method is a promising spatial tool with widespread applications for many taxa, particularly for those island endemic species facing high extinction risk.

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## Author contributions

LJS conducted the analysis and led the writing with support from all other co-authors. Philippine Eagle Foundation staff provided all occurrence data.

## Conflict of interest

The authors have no conflict of interest to declare.

## Data accessibility statement

The raster and shapefile data that support the findings of this study are openly available on the data repository *figshare* <https://doi.org/10.6084/m9.figshare.21311259.v1>. Due to confidentiality of nest locations for this critically endangered species, we are unable to publicly share our occurrence dataset. However, reproducible R code using simulated occurrences in our model workflow is available on a GitHub repository <https://github.com/sutton74/PHEA-SDM>.

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## Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

**Appendix S1.** Supplementary material.