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Estimating ecological metrics for holistic conservation management in a biodiverse but information-poor tropical region

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Abstract

Conservation ecologists face the dual challenge of working with difficult-to-study species and providing ecological metrics that support conservation management at global, regional, and local levels. We present metrics identifying distributions, site-level and global abundance, site-contextualized habitat requirements, and threats for seven dry forest endemic birds (two threatened, one Near Threatened) in the globally important Tumbes region of Peru. Extents of occurrence ranged from 36,000 to 152,000 km^2, and while broad distributions were generally congruent, nearly half of species overlapped <50% of their range with other species. Population sizes ranged from the low thousands in the threatened/Near Threatened taxa to >150,000. Site-level population estimates varied hugely, reflecting size of site and extreme variation in local abundances. Large tree girths and dense low cover generally promoted bird abundance, but stem density acted in opposite directions for different species, implying the need for site- and species-specific habitat management. Habitat quality varied across sites, further complicating management options at the local level (e.g., reduced grazing). We highlight the suitability of our methods in providing useful conservation metrics for data-poor regions, and demonstrate their application. Importantly, we propose key sites and priority actions for the region, including extensions of existing protected areas.

KEYWORDS

abundance, Aves, birds, conservation areas, density, distribution, dry forest, habitat management, Peru, priority area selection

1 | INTRODUCTION

Metrics expressing abundance and distribution of species are essential building blocks for global conservation instruments such as IUCN Red Lists (IUCN, 2016a) and priority area designation in the form of Key Biodiversity Areas (IUCN, 2016b; Rodrigues, Pilgrim, Lamoreux, Hoffmann, & Brooks, 2006). To gain maximum return from investments in obtaining such measures, metrics should also be useful at multiple scales, such as to inform

site-level habitat management prescriptions, or siting of regional networks of protected areas (Poiani, Richter, Anderson, & Richter, 2000). The same applies to temporal scales; metrics should be able to provide immediate results, as well as being components of long term monitoring schemes. Conversely, a lack of quantitative data on populations, range sizes or trends over time often hamper conservation management, an issue for the majority of the world's species, including birds, one of the best known taxonomic groups (Clark & May, 2002). For example, 121 birds are currently listed as threatened (critically endangered [CR], endangered [EN], or vulnerable [VU]) in South America, based, in part, on past reductions of population size, however, data come from direct observation in just five of these species, and from abundance indices in 18 (IUCN, 2015).

Remotely sensed data is increasingly used for conservation planning in data-poor regions, for example, to model habitat type or species richness to prioritize conservation interventions (Buchanan & Leidner, 2018; Moilanen, 2012). However, at a regional level, between continent-wide and site level analyses, methods to estimate abundance from the field and to model distributions represent key techniques to provide evidence for conservation measures. Where occurrence data are available for rare species (something that is increasingly the case with growing data availability from citizen science initiatives; Graham, Ferrier, Huettman, Moritz, & Peterson, 2004; Soberón & Peterson 2004), species distribution models (SDMs) represent efficient ways of providing information for conservation management (Guisan et al., 2013). The decision on whether and how to collect presence/absence or abundance data is informed by the purpose of the analysis, costs and time demands, and probability of occurrence of the target species (Joseph, Field, Wilcox, & Possingham, 2006). At smaller scales, and with species which co-occur within areas and habitats, data on occupancy rates or actual abundance become more practicable, especially as a basis for identifying important areas for local conservation. As such, distance sampling techniques that take into account variation in detectability, have become one of the most widely used methods to estimate animal abundance in the Neotropics and elsewhere (Thomas et al., 2010). However, despite analytical advances in tools such as SDMs, abundance estimation, and habitat modeling that have fed into mainstream academic studies (Zimmermann, Edwards, Graham, Pearman, & Svenning, 2010), they remain under-used in conservation-orientated studies, especially those aimed at priority areas (Meyer, Kreft, Guralnick, & Jetz, 2015; Veloz et al., 2015) or threatened taxa (Butchart et al., 2005; Marsden & Royle, 2015).

Across the world, dry forest ecosystems, including those within the Neotropics, are a particularly threatened and poorly studied habitat type, but also highly coveted by humans for settlement, not least due to their environmental suitability for agriculture (Miles et al., 2006; Hoekstra, Boucher, Ricketts, & Roberts, 2005; Banda et al., 2016). The endemic-rich dry forests of the Tumbes region are an international conservation priority (Mittermeier, 2004; Stattersfield, Crosby, Long, & Wege, 1998). The region has suffered massive deforestation, making it one of the most severely threatened areas on earth in terms of biological extinction (Portillo-Quintero & Sánchez-Azofeifa, 2010), evidenced by its designation within a global biodiversity hotspot (Mittermeier, 2004). In the region, efforts to protect biodiversity have included several priority setting exercises (e.g., Fajardo, Lessmann, Bonaccorso, Devenish, & Muñoz, 2014; Rodríguez & Young, 2000), results of which are gradually being incorporated into regional networks of protected areas (GORE Lambayeque, 2009; GORE Piura, 2009). However, north Peru's dry forests still lack conservation investment, with only 4,380 km^2 (6%) of their area protected, well below the 17% aim under Aichi Target 11, even though this target has been met at the national level (CHM, 2018). The challenge in the Tumbes region is to implement conservation management actions both inside formally protected areas, and across the wider landscape to maintain local livelihoods such as goat grazing in tandem with the ecosystem services upon which communities also depend (Maestre, Salguero-Gómez, & Quero, 2012; Pennington, Lehmann, & Rowland, 2018). Therefore, modeling methods to estimate distributions across the whole landscape are suited to providing metrics for conservation management in this region.

This paper synthesizes a set of metrics quantifying distribution, abundance and habitat associations into an efficient toolkit to inform conservation activities at global, regional, and local scales within a biodiversity hotspot. Specifically, for seven dry forest endemic birds, with ranges almost entirely restricted to the north of Peru, we (a) model distributions using existing data to estimate range sizes, (b) present abundance estimates for each species at individual sites and across the region as a whole, (c) assess habitat associations for species at individual sites, and (d) combine the above results with existing data to evaluate threats and risks to key species. The information we produce can be used to assess global IUCN Red List status (IUCN, 2016a), identify areas of interest within the Key Biodiversity Area framework (IUCN, 2016b), and provide guidelines for habitat management at individual sites of use to both protected area managers and local communities.

2 | METHODS

2.1 | Study area, species, and site selection

The study area was located along the north Peruvian coast, from approximately 3.5° to 9°S, representing a distance of over 600 km (Figure 1). The seven species with their IUCN Red List status are Peruvian Plantcutter *Phytotoma raimondii* (Vulnerable; VU), Grey-and-white Elaenia *Pseudelaenia leucospodia* (Least concern; LC), Tumbes Tyrant *Ochthoeca salvini* (Near threatened; NT), Rufous Flycatcher *Myiarchus semirufus* (VU), Tumbes Sparrow *Rhynchospiza stolzmanni* (LC), Cinereous Finch *Piezorina cinerea* (LC), and Sulfur-throated Finch *Sicalis taczanowskii* (LC). They are endemic to the Tumbes dry forests and have almost their entire distributions within Peru below an elevation of 500 m. Habitat for the study species consists mainly of dry forest and scrub savannah amongst larger desert areas, located in a narrow band between the Andes and the coast (CDC, 1992). We undertook surveys at 26 sites, selected randomly from two strata: the highest relative probability of obtaining species records (using a preliminary SDM) within each 50 × 50 km grid across the study area (see methods in Devenish, Buchanan, Smith, & Marsden, 2017; Figure 1).

2.2 | Distribution and range sizes

2.2.1 | Extent of occurrence

Point locality species occurrences were taken from observations and museum specimens, collated through literature searches, museum visits, and online databases (principally VertNet, Xenocanto, and eBird; Table S1 in
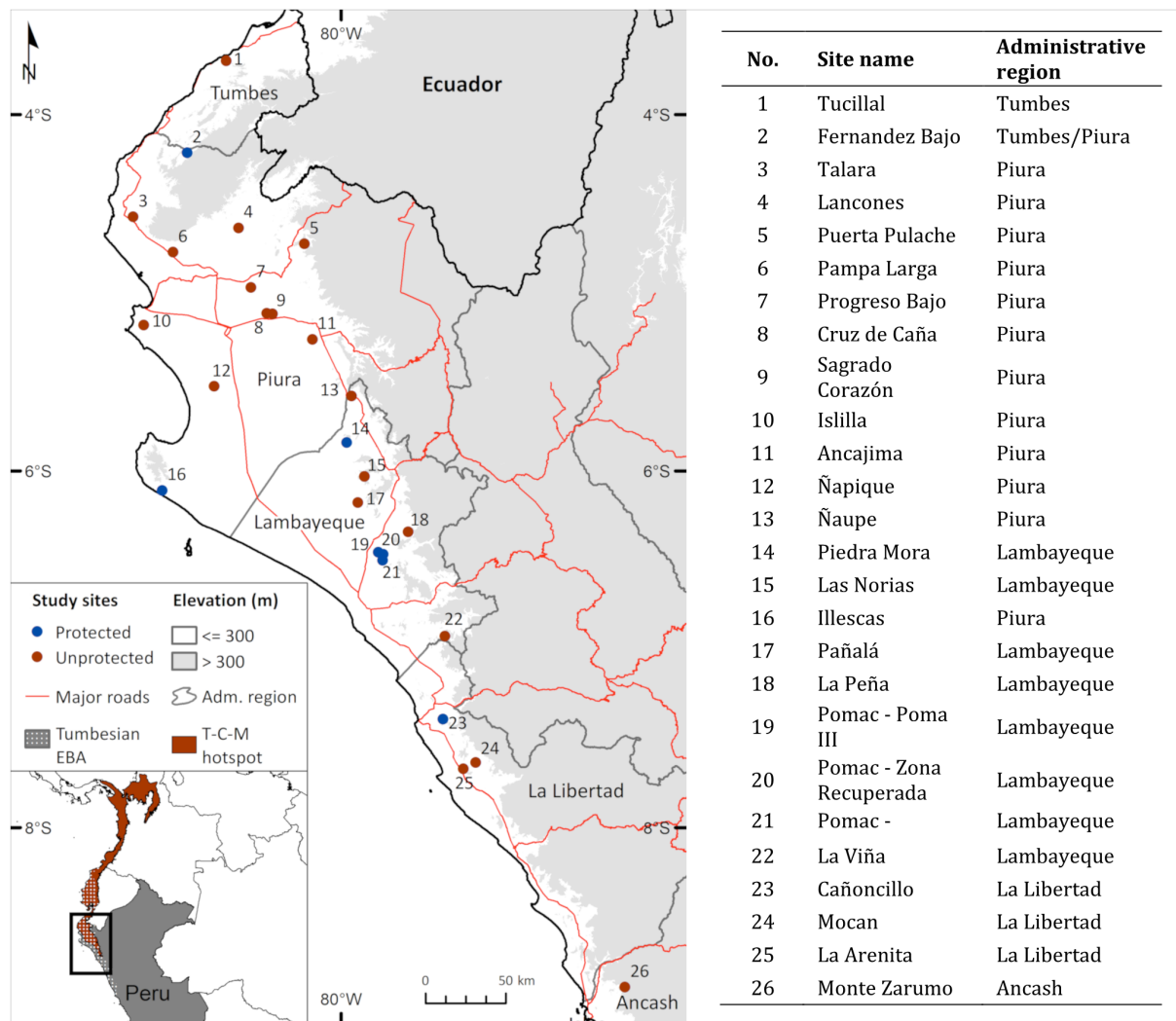

No.	Site name	Administrative region
1	Tucillal	Tumbes
2	Fernandez Bajo	Tumbes/Piura
3	Talara	Piura
4	Lancones	Piura
5	Puerta Pulache	Piura
6	Pampa Larga	Piura
7	Progreso Bajo	Piura
8	Cruz de Caña	Piura
9	Sagrado Corazón	Piura
10	Islilla	Piura
11	Ancajima	Piura
12	Ñapique	Piura
13	Ñaupe	Piura
14	Piedra Mora	Lambayeque
15	Las Norias	Lambayeque
16	Illescas	Piura
17	Pañalá	Lambayeque
18	La Peña	Lambayeque
19	Pomac - Poma III	Lambayeque
20	Pomac - Zona Recuperada	Lambayeque
21	Pomac -	Lambayeque
22	La Viña	Lambayeque
23	Cañoncillo	La Libertad
24	Mocan	La Libertad
25	La Arenita	La Libertad
26	Monte Zarumo	Ancash

FIGURE 1 Study site locations in north Peru, showing protection status. The study area is within the global conservation priorities of the Tumbesian Region Endemic Bird Area and the Tumbes-Chocó-Magdalena (T-C-M) hotspot

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Supplementary Information). In the case of eBird, observations were excluded where survey effort exceeded 5 km (linear route) or 500 ha (area count), given that a single location is given for the whole survey (Johnston et al., 2019). Where occurrence records did not have geographic coordinates, but contained detailed locality data, an attempt was made to georeference the records using online tools (e.g., GEOLocate), gazetteers for Peru (Stephens & Traylor, 1983) and Ecuador (Paynter, 1993), national digital cartography and georeferenced records at the same locality. Occurrence records were checked for correct positioning of coordinates using ArcGIS and R (e.g., lying within country land boundaries, first degree administrative boundaries where known, or broad elevation limits). Records were also checked with known species distributions, for example, distribution shapefiles (BirdLife International & NatureServe, 2015) and guidebooks (Schulenberg, Stotz, Lane, O'Neill, & Parker III, 2007). Extent of occurrence (EoO) was calculated as a convex hull around all occurrence points, following IUCN guidelines (IUCN, 2016a).

2.2.2 | Species distribution models

Species occurrences were used to model species' geographical distributions based on environmental predictors. To avoid sampling bias, exact spatial duplicates and records within 1 km of each other were removed so that only one record per grid cell was used in the models given that the predictors were at 1 km resolution (Graham et al., 2004; Stockwell & Peterson, 2002). Spatial duplicates do not necessarily correspond to areas with higher frequency of occurrence of birds, but may represent areas most visited by collectors or birdwatchers (e.g., close to roads). Spatial filtering of data, by removing observations within a certain distance of each other, has been shown to improve model performance by counteracting the inflation of validation metrics such as area under the curve (AUC) due to spatial autocorrelation of presence points (Boria, Olson, Goodman, & Anderson, 2014; Radosavljevic & Anderson, 2014). Occurrence records prior to 2000 were excluded in order to match the temporal scale of predictors based on remotely sensed images. A total of 36 candidate environmental predictors (Table S3) were collated from three sources: climate indices based on monthly precipitation and temperature data (Hijmans, Cameron, Parra, Jones, & Jarvis, 2005); topographic variables, such as elevation, slope and aspect, derived from a digital elevation model (Shuttle Radar Topography Mission [SRTM]; Jarvis, Reuter, Nelson, & Guevara, 2008); and indices calculated from annual variation in remotely sensed Normalised Difference

Vegetation Index (NDVI), from MODIS product, MOD13A3, averaged across the period 2010–2015. Six predictors were selected using three criteria: first, in terms of ecological significance for the species, for example, areas retaining some moisture may be important to dry forest birds, and minimum annual rainfall and NDVI may provide an indication of this. NDVI was also assessed for its ability to separate between natural and agricultural land cover using boxplots and Kruskal Wallis tests (Figure S1 in Supplementary Information); second, for their predictive ability, variables were prioritized by ranking averaged explained deviance per species from univariate Generalised Linear Models (binomial with logit link); third, to avoid multicollinearity, potential predictors were checked using scatterplots and one of each pair removed where Spearman's correlation coefficients were greater than 0.7 (Dormann et al., 2013; Table S3, Figure S2).

Ensemble SDMs were built from the raw average of four modeling methods with predicted values normalized between methods. Two regression based techniques were used, regularized Generalized Linear Models (GLM) in the R package glmnet (Friedman, Hastie, & Tibshirani, 2010) and Generalized Additive Models (GAM), implemented in R package mgcv, using thin plate regression splines with a modified smoothing penalty allowing the whole term to be shrunk to zero (Wood, 2006), thus allowing a degree of variable selection. A machine learning technique, "Maxent" (Phillips & Dudík, 2008), and the climate envelope, or similarity metric-based method "Domain" (Carpenter, Gillison, & Winter, 1993) were implemented through the dismo package (Hijmans, Phillips, Leathwick, & Elith, 2016). For all modeling methods, a species-specific study area was constructed from which to select background points. A convex hull, with a 25 km buffer, was drawn round all presence points, representing the species' effective area utilized (Barve et al., 2011; Peterson et al., 2011). Then, 5,000 background points were selected randomly from this area for all modeling methods except for Domain, which uses presence records only. For each modeling method, fivefold cross validation was performed and the validation metric (Area under the Receiver Operating Curve—AUC) averaged across all folds. Each fold was chosen with the same proportion of presences and absences as in the full data set. For the final prediction, all presence points were used to build the model.

To identify priority regions for conservation, where high habitat suitability/relative probability of occurrence coincides across species, a standardized threshold was applied to each ensemble model, and the subsequent binary models summed. We avoided using threshold methods that include absences, given that a random background was used instead of true absences in the

models (Peterson et al., 2011). Therefore, a threshold of the minimum predicted model value corresponding to a 5% omission rate was used, that is, a threshold that omits the lowest 5% of the presence points in terms of their probability of occurrence. Pairwise overlap between all species' modeled ranges was calculated as the number of shared pixels divided by total number of pixels in both models.

2.3 | Population size estimates

Local abundances of seven species, without known seasonal movements and with small ranges ($<115,000$ km^2), were estimated using covariate Distance Sampling (Buckland et al., 2001). Fieldwork was only conducted during the dry season (outside the main breeding season) to avoid environmental seasonality affecting bird abundance as a result of changing resources within their habitat (Tinoco, 2009). Survey design consisted of four 2.5 km parallel, straight transects (mainly oriented north–south), off tracks and paths, separated by 500 m at each site. Habitat characteristics were taken every 200 m within a 10 m radius circular plot, equating to 12 vegetation plots per transect. Metrics included tree species present; percentage vegetation cover at two vertical strata (<3 m, >3 m; estimated visually); diameter at breast height (dBH; with tape measure), height of lowest branch, and height (estimated visually) of three largest trees; total number of stems with dBH > 10 cm; and topographic measurements (slope, elevation). Bird density was estimated at the site level, using a global detection function, adjusted with the site-level covariates in the Distance 6.0 software (Thomas et al., 2010). The suitability of habitat variables as candidate covariates was assessed with respect to collinearity, effect on detection distance and variability across sites (see methods in Devenish et al., 2017).

Population sizes were calculated for species at each field site by multiplying local densities (individuals km^{-2}) by site area. The area of each site was determined as the suitable habitat (i.e., not urban or agricultural; MINAM, 2012) within a delimited protected area; within a clearly delimited vegetation patch (e.g., valley, forest surrounded by agriculture or desert) or, where the study site was part of a larger area of relatively homogenous vegetation, within a buffer of 10 km. This approach is precautionary and provides a minimum population size summed across the study sites.

2.4 | Habitat associations

Habitat associations were evaluated at both broad and local scales. For the broad scale associations, modeled values from the individual species SDMs were summarized by broad habitat types (MINAM, 2012) using a geographic overlay in the R raster and sf packages. Results were evaluated graphically with boxplots. Local scale habitat associations were evaluated with linear models using bird density per site as the response, and predictors consisting of four vegetation characteristics summarized by site (across approximately 48 habitat plots): Average dBH, average number of stems; % low cover; height of lowest branch. Predictors were chosen by avoiding collinearity and through exploratory univariate models, and constrained to four to avoid having a low ratio of observations to predictors. Site level was chosen for modeling given the relatively homogenous nature of habitat within sites, and that birds will move around most of the site (transect area: 2.5×2 km). This was evidenced by the response of species occupancy to habitat variables at plot level being driven by site as a random effect in exploratory mixed models (not shown here). Model averaging was performed with all possible combinations of predictors, and variable importance in models (sum of Akaike weights over all models in which the variable is present) and model-averaged, standardized, coefficients were examined to evaluate the effect of habitat on species abundance. Analysis was performed with MuMIn package in R (Barton, 2018).

2.5 | Threat analysis, potential key biodiversity area identification and red list categories

To show exemplary issues faced in the task of conserving bird diversity across the Tumbes region, study sites were classified in terms of biodiversity importance and presence or degree of threats. For biodiversity importance, densities of the seven key bird species were ranked by quintiles across all sites (i.e., $1 =$ sites with lowest density, $5 =$ highest density) and ranks were summed separately for two groups of species at each site. Vulnerable or Near Threatened species were given double the importance of Least Concern species. Thus, our importance index favors sites with higher abundance of species of conservation concern. Each site was categorized according to the following pressures: lack of protection status; threat of large-scale agriculture projects; presence of mining or mineral extraction; percentage of agriculture currently occupying a 10 km radius circle around the site centroid according to a recent habitat map (MINAM, 2012); the proportion of all vegetation plots at the site with selective logging (mainly Prosopis spp.); and a grazing index, calculated as the standardized dung count averaged over the vegetation plots.

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Data on population and range sizes (see above) were applied to IUCN red list criteria (IUCN, 2001, 2016a) to determine potential changes in red list category for the globally threatened species in the study. In addition, assessment of how many subpopulations exist was made from site occupancy data from this study. Key Biodiversity Areas (KBAs) represent globally important sites for species and ecosystem conservation, and are identified using recently standardized criteria based on threat category, geographic range, behavior (where species are used to define the areas) and manageability (IUCN, 2016b). For species in this study, listed under the Vulnerable threat category, ≥1% of the global population, representing at least 10 pairs, must be present at a site in order to qualify. Criteria for identifying potential KBAs (IUCN, 2016b) were applied to data on population sizes at field sites across the study area, with preliminary boundaries defined by existing protected areas or homogenous habitat, including a consideration of management capacity.

3 | RESULTS

3.1 | Distribution models and extent of occurrence

Numbers of non-duplicated occurrence records ranged from 68 for Sulphur-throated Finch to 157 for Cinereous Finch. EoOs from convex hulls ranged from 36,329 km^2 for Tumbes Tyrant, to 151,560 km^2 for Grey-and-white Elaenia (Table S2). Of the four individual modeling techniques, GAMs scored highest mean AUC, followed by Maxent, GLM and finally Domain, although the ensemble model scored highest consistently (Table S4). AUC of ensemble models was not significantly correlated with numbers of species presence points used in models ($r_s = 0.22$, $p = .64$, $n = 7$), with Peruvian Plantcutter and Tumbes Tyrant both scoring high AUC values but with low numbers of presence points (Table S4).

At the broad scale, there were similarities across the ranges of the seven species (Figure 2, Figure S3). A wide area, extending from Tumbes department in the north as far south as La Libertad and bordered to the east by the base of the Andean Cordillera, held all seven species (Figure 2d). The main differences in ranges across species were the degree to which species extend southwards and the distribution of ranges towards the coast or inland. Tumbes Sparrow and Tumbes Tyrant have predominantly inland ranges, except in the extreme north. Proportion of overlap in distributions was greatest for Cinereous Finch with both Peruvian

Plantcutter (0.80) and Rufous Flycatcher (0.77) and lowest for Peruvian Plantcutter with both Tumbes Sparrow (0.30) and Tumbes Tyrant (0.30). Average overlap was 0.52 and 9 of 21 pairs had scores lower than 0.5 (Table S5).

3.2 | Population size estimates

Proportions of the 26 study sites occupied ranged from over 80% in Grey-and-White Elaenia and Cinereous Finch to around 40% for Peruvian Plantcutter and Tumbes Tyrant. Local abundance at sites varied greatly within and between species, with non-zero values ranging from 0.9 to over 340 individuals km^{-2} (Figure S4). The lowest mean density estimates were from two threatened flycatchers, Tumbes Tyrant and Rufous Flycatcher (Table 1). The latter had low density estimates across almost all sites, although its distribution is widespread. Minimum global population sizes were also highly variable, ranging from the low thousands in the three threatened/Near Threatened taxa to one or two magnitudes greater for the other species (Table 1). Underpinning these population estimates are site-based estimates (Table S6) and these show huge ranges based both on the size of the area, the species concerned, and the variability in densities within-species across sites. Importantly, local populations of Rufous Flycatcher and Tumbes Tyrant rarely reached the low hundreds at individual sites and were usually much lower. In contrast, both Tumbes Sparrow and Sulphur-throated Finch had estimated population sizes over 10,000 at five different sites (Table S6).

3.3 | Habitat associations

At a broad scale, all bird species were more associated with forest types (riverine Algarrobo stands, slopes dry forest and plains dry forest) than coastal desert, scrub and agriculture (Figure S5), although differences between species exist. Peruvian Plantcutter showed a stronger association with slopes forest than those on the plains, although its main populations are now within this forest type.

Site-level habitat characteristics varied greatly in their importance as predictors of local abundance across species, although number of stems and percentage low cover were the most important predictors for three species, average dBH for just one, and lowest branch for none (Table S7, Table S8). Species were either positively associated with larger tree girths (Rufous Flycatcher, Tumbes Tyrant, and to a lesser extent, Grey-and-White Elaenia)

FIGURE 2 Species distribution model for (a) Rufous Flycatcher *Myiarchus semirufus*, (b) Peruvian Plantcutter *Phytotoma raimondii*, and (c) Tumbes Tyrant *Ochthoeca salvini*. (d) Shared ranges across all seven species (from summed modeled ranges). See Figure S3 in supporting materials for remaining SDMs
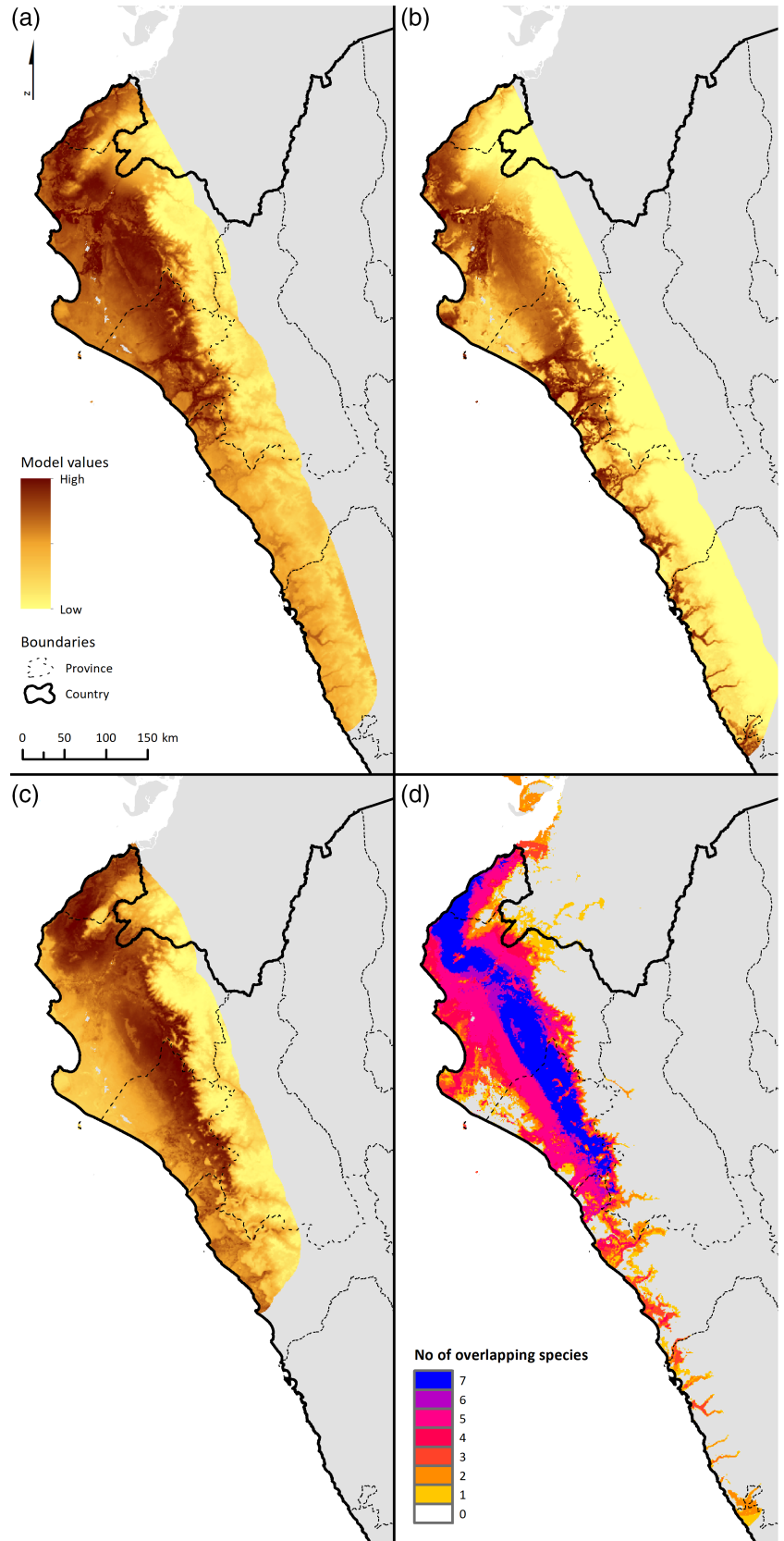
or neutral, while there was a general tendency for species to be associated with dense low-level cover (Figure 3). However, direction of response to predictors also differed across species. A high number of stems at breast height was positively correlated with abundance of Peruvian Plantcutter, but negatively associated with local

TABLE 1 Summary of range-wide density estimates (individual's km^{-2} ± coefficient of variation, range) for seven endemic bird species from north Peru, with site occupancy and minimum global population sizes

| Species (no. of encounters) | No. sites/26 | Density estimates (ind. km^{-2}) | | Minimum population size (95% CI) |
		Combined ± CV	Min–max	
Peruvian Plantcutter *Phytotoma raimondii* (n = 379)	13	27.5 ± 18.3	1.8–104.7	3,333 (1,865–5,511)
Grey-and-white Elaenia *Pseudelaenia leucospodia* (n = 876)	25	44.5 ± 6.3	3.0–103	20,887 (15,408–27,473)
Tumbes tyrant *Ochthoeca salvini* (n = 103)	14	4.1 ± 18.1	0.9–38.4	1,575 (638–3,185)
Rufous flycatcher *Myiarchus semirufus* (n = 70)	23	5.9 ± 19.9	1.9–44.6	1,592 (399–3,398)
Tumbes sparrow *Rhynchospiza stolzmanni* (n = 443)	15	77.4 ± 7.2	5.0–345	58,707 (42,468–76,876)
Cinereous finch *Piezorina cinerea* (n = 811)	23	65.1 ± 5.0	4.4–162	29,225 (19,882–38,613)
Sulfur-throated Finch *Sicalis taczanowskii* (n = 201)	16	342 ± 24.4	6.6–3,060	169,988 (45,988–339,644)

abundance in Rufous Flycatcher and Sulphur-throated Finch. To put the above relationships into a local context, especially given that the distribution of the habitat variables themselves differed significantly between sites (Anderson Darling multi-sample test, $p < .001$) for all four habitat variables, it is necessary to consider the current habitat condition at a site level. By comparing how the local habitat compares to the "mean" across all sites for each of the four predictors, interventions can be assessed (Figure S6). Taking the example of low cover, the Talara and Islilla sites appear to be in need of habitat management to increase levels of low cover, which in turn may benefit three of the seven species considered.

3.4 | Threat analysis, KBAs identification

Two of the top three ranked sites (Ñaupe and Ancajima) held all seven endemic species, but one, Cañoncillo, had just three, but with very high densities, especially of two species of conservation concern (Table 5). Just 6% of dry forest endemic birds' ranges (using threshold models) are currently covered by protected areas and with several hotspots of local abundance for key species occurring at unprotected sites (Figure 4(a)). Of the 10 top ranked sites, just two are protected within reserves covering just 7,200 ha. The region's largest protected areas covering over 100,000 ha protect two of the lowest ranked sites for birds. At two sites (Talara and Illescas), key populations are just outside the protected area limits (or proposed

area limits). The potential KBAs were generally among the top ranked sites (Table 2), with the lower ranked potential KBAs meeting the population criteria for one of the two threatened species but having lower overall endemic species richness. The potential KBAs are grouped as follows: Cañoncillo; Monte Zarumo; Piura Plains (Progreso Bajo/Cruz de Caña/Sagrado Corazon/Ancajima); Paiján (La Arenita/Mocan); Islilla; and Illescas.

Large-scale agricultural schemes fed by water piped from the Amazonian slope of the Andes will supply export agriculture on the dry coastal plains. These schemes affect, or will affect, seven sites, of which five are in the top 10 ranked sites (Table 2). Nine sites had agriculture (small-scale, rain-fed, or locally irrigated) occupying more than 25% of a 10 km radius, and 12 sites are within community farming lands, including six of the 10 top ranked sites. One site, Pomac, a particularly important plains dry forest protected area, is almost totally surrounded by agriculture. In contrast, only two of the top 10 sites have any active mineral extraction (Figure 4(b)). Selective logging and grazing, while almost ubiquitous, affected sites to different degrees. Proportions of plots with presence of cut stumps ranged from 96% (at second ranked Cañoncillo) to just 6%, with an overall average of just less than half. The grazing index was positively skewed, four of six sites with values higher than 0.5 lie within the largest extent of dry forest on the north coast, all of which is within subsistence farming community lands and outside protected areas (Figure 4(c)).
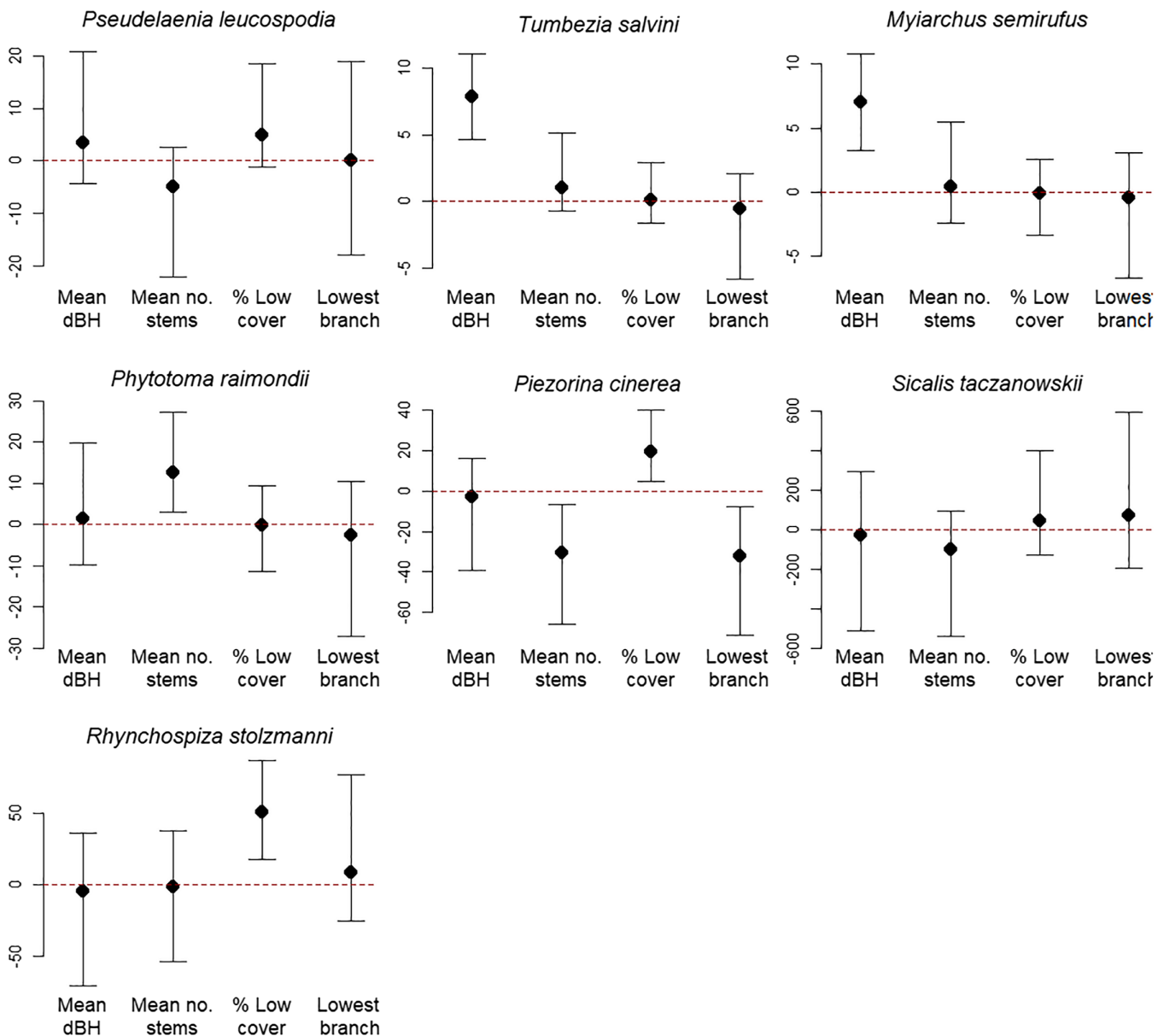
FIGURE 3 Model averaged coefficients, with 95% confidence intervals, from linear regression of individual species density against four habitat variables (averaged over full set of candidate models—where variable is not present it is taken as zero)

4 | DISCUSSION

4.1 | Appropriate methods to provide conservation metrics in data poor regions

This study has highlighted how combining results from field methods and desk-based analyses can provide crucial information for conservation management at multiple scales. A key feature is the suitability of methods for conservation science where resources are scarce, and management is often reactive rather than proactive, precipitating fast decision making with incomplete data (Cook, Wintle, Aldrich, & Wintle, 2014). Field methods presented here are relatively quick, supplemented by

increasingly available online data. The study took around 150 days of field data collection by two people for the 26 sites (including preparation time), 60 days of data collation of bird occurrence records from online and museum sources, and 12 months of data analysis. Results are immediately useful, but could also be incorporated into longer-term monitoring schemes.

SDMs can play a key part in providing conservation metrics, such as estimating range sizes and identifying distribution hotspots and priority areas (Guisan et al., 2013). One vital advantage is their use of existing species occurrence records, often collected without sampling protocols and their performance with rare species. This study has shown that careful compilation of data from the field
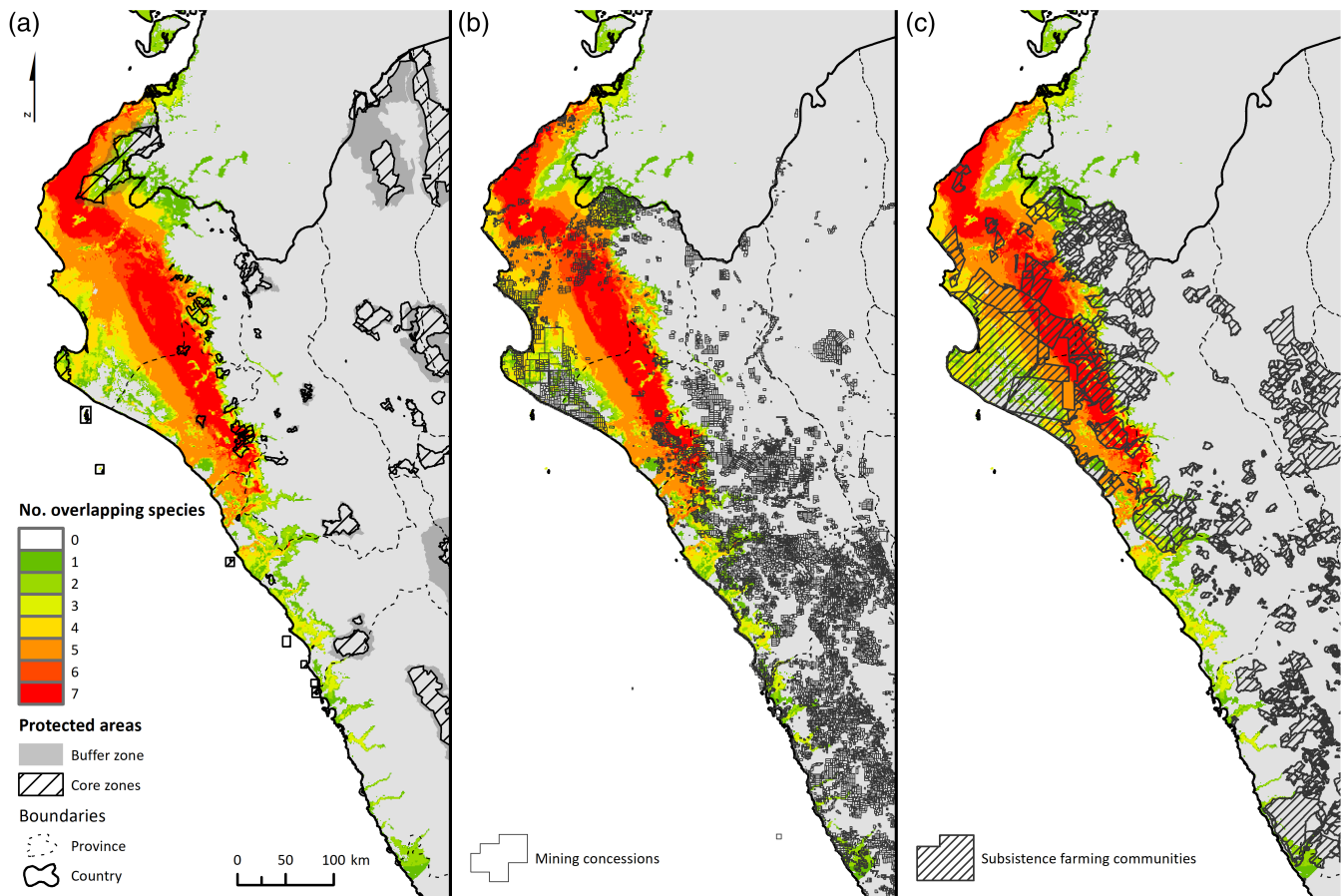
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FIGURE 4 Conservation opportunities and threats for endemic dry forest bird species: (a–c) summed model values for seven study species, showing priority conservation regions in the north of Peru, overlaid with (a) protected areas, (b) mining concessions, and (c) farming community territories

and from museums has provided sufficient data to model a suite of rare, poorly studied species. Good model performance can be obtained from as few as 30–50 presence records (e.g., Hernandez, Graham, Master, & Albert, 2006; Stockwell & Peterson, 2002), with Maxent and Domain performing especially well with lower sample sizes (Wisz et al., 2008). All species in the present study had >60 records (Table S2) with a median of 140, implying that most species were also well over the 10-1 observation-to-predictor ratio recommended for standard regression techniques (Harrell Jr., Lee, & Mark, 1996). When obtaining range sizes from SDMs, a threshold must be applied to convert the continuous probability of occurrence into a presence/absence distribution. The choice of threshold can greatly influence the resulting range size. We consider that using a minimum omission error of 5% as a threshold balances a robust occurrence data verification protocol, whilst allowing for some location errors and vagrancy (Peterson, Papeş, & Soberón, 2008), avoiding the need to use absence data in the threshold calculation (pseudoabsences were used in our models;

Franklin, 2009; Peterson et al., 2011). It has also been used previously to define range sizes for red listing purposes (Fivaz & Gonseth, 2014). Stacking SDMs to identify priority areas not only identifies areas of highest species richness, but can also provide an indication of where suites of species are most abundant given that SDM occupancy probabilities are likely positively correlated with local abundance (Devenish 2017, Weber, Stevens, Diniz-Filho, & Grelle, 2017).

Field survey techniques for birds in biodiverse tropical countries are challenging (Robinson, Lees, & Blake, 2018) and distance sampling is no exception. Taking account of detectability, as distance sampling does, is highly desirable for multiple reasons (Buckland et al., 2001). First, rather than indices of abundance, the method allows estimation of actual population sizes, a cornerstone of red list assessment. Second, it attempts to control for differences in detection across habitat types, important especially in situations where animals are more detectable in open, anthropogenic habitats (Buckland, Marsden, & Green, 2008). Distance sampling

TABLE 2 Sites ranked by species importance, showing protection status, identified threats, and potential Key Biodiversity Area (KBA) status

Name (KBA status)[a]	Site importance rank (no. species present)	Protection status (area in ha)[b]	Large-scale agriculture	Active mineral extraction[c]	% agriculture[d]	Logging (proportion of plots)[e]	Grazing index ($\pm$ SE)[f]
Ñaupe*	1 (7)	U	Y	N	4.9*	54.2	0.52 $\pm$ 0.04
Cañoncillo	2 (3)	PP (1,310)	N	N	34.5	95.8	0.35 $\pm$ 0.03
Monte Zarumo	3 (4)	U	N	Y	9.2*	37.5	0.42 $\pm$ 0.08
Ancajima	4 (7)	U	Y	N	27.6	41.7	0.58 $\pm$ 0.05
Mocan	5 (4)	U	Y	N	27.1	79.1	0.15 $\pm$ 0.03
Progreso Bajo	6 (5)	U	Y	N	29.8*	68.8	0.12 $\pm$ 0.01
Las Norias	7 (6)	U	Y	N	6.7*	37.5	0.42 $\pm$ 0.04
Pomac*	8 (6)	NP (5,890)	N	N	62.7	53.5	0.21 $\pm$ 0.03
Islilla	9 (4)	U	N	Y	0*	6.3	0.22 $\pm$ 0.04
Sagrado Corazón	10 (6)	U	Y	N*	1.7*	54.2	0.91 $\pm$ 0.05
La Peña (San Francisco de Asís)	11 (5)	Proposed PP (10,790)	N	N	22.9*	16.7	1.00 $\pm$ 0.07
Piedra Mora (Huacrupe)	12 (5)	RP (7,270)	N	N	29.2*	43.8	0.75 $\pm$ 0.07
Lancones	13 (6)	U	N	N	4.7	31.3	0.28 $\pm$ 0.03
Puerta Pulache	14 (4)	U	N	Y	33.5	66.7	0.43 $\pm$ 0.09
La Arenita	15 (3)	U	N	N*	48.1	45.8	0.05 $\pm$ 0.02
Talara*	16 (4)	Proposed RP (24,240)	N	Y	0	75.0	0.05 $\pm$ 0.01
Cruz de Caña	17 (5)	U	Y	N*	0*	45.8	0.79 $\pm$ 0.06
Ñapique	18 (3)	U	N	N*	38.5*	34.8	0.23 $\pm$ 0.02
Tucillal	19 (4)	U	N	N	0.11	10.4	0.21 $\pm$ 0.03
Fernandez Bajo (El Angolo)	20 (4)	NP (65,000)	N	N	0	48.9	0.21 $\pm$ 0.02
Pañalá	21 (4)	U	N	N	1.91*	60.4	0.34 $\pm$ 0.03
La Viña	22 (4)	U	N	Y	12.6	10.4	0.00 $\pm$ 0.00
Illescas	23 (4)	NP (37,450)	N	Y	0*	20.8	0.08 $\pm$ 0.01
Pampa Larga	24 (5)	U	N	Y	1.36	51.0	0.07 $\pm$ 0.01

[a]Potential KBAs are shown in **bold**. An asterisk signifies Important Bird Area status (not itself a protection category). Pomac protected area is shown as a single site for clarity.
[b]Protection status: U—Unprotected; PP—Private Protected Area; NP—State National Protected Area; RP—State Regional Protected Area.
[c]Sites marked with an asterisk lie within a mining concession but are not currently being exploited.
[d]Percentage of agriculture within a 10 km radius of field site, asterisks show sites lying within community farming territories.
[e]Proportion of vegetation plots with evidence of selective logging ($n = 48$).
[f]Standardized mean dung count per vegetation plot ($n = 48$).

does require relatively high numbers of encounters per species (typically 60–80; Buckland et al., 2001), which can be prohibitive when estimating densities of rare species by site. However, advances in techniques, such as using site-based covariates (Buckland et al., 2004), as implemented here, can allow global detection functions to vary at site level. Our 5 months of fieldwork allowed us to estimate local population densities with coefficients

of variation <25% in 14 species at 26 sites, allowing a site prioritization analysis across the region.

Understanding the habitat associations of key species is crucial to guide regional policy on developments such as agricultural expansion, while at the same time informing land use management at a very local level through controls on grazing pressure, selective logging, or replanting on, for example, community lands or individual reserves

(Whittingham et al., 2007). To maximize limited resources, field methods need to be efficient and our habitat surveys focused on metrics that were quick and easy to obtain, showed little autocorrelation, and, importantly, were appropriate for multiple species at both the local and more regional scales (Lee & Marsden, 2008). Amount of low vegetation cover was positively associated with the abundance of several species, and never negatively associated with any, indicating the importance of promoting shrub layer and regeneration right across the region, perhaps by reducing grazing (Wassie, Sterck, Teketay, & Bongers, 2009). This is likely to be even more important in Niño years (Holmgren, López, Gutiérrez, & Squeo, 2006). Experimental exclusion studies are urgently required in the region to confirm this result. In contrast, mean number of stems, showed opposing responses among species. Although these species overlap in their ranges, management prescriptions need not be conflicting given the patchy nature of habitat at a local scale (CDC, 1992). Habitat managers may prioritize denser scrubby patches for sites with Peruvian Plantcutter, as long as some open areas, in many cases, naturally so, are kept for Cinereous Finch.

4.2 | Addressing biodiversity challenges in the region

4.2.1 | Identification of key biodiversity areas

Six new potential KBAs were identified based on the results of our study, adding to the eight dry forest Important Bird Areas (also potential KBAs) already identified in the Tumbes region (Figure 5; Devenish, Díaz, Clay, Davidson, & Yépez, 2009). Given the distribution of the threatened and range-restricted species in the Tumbes area, it would be possible to propose multiple additional potential sites for KBAs across the region. However, following guidelines on manageability (IUCN, 2016b; KBA Secretariat, 2019), for example, avoiding conflicting land uses such as mining, potential KBAs were limited to these six sites. KBAs may aid alternative management regimes where formal protected areas are not appropriate (Donald et al., 2019) (e.g., community farming lands) but may also provide a pathway to more formal protection (Kullberg, Di Minin, & Moilanen, 2019).

4.2.2 | Red list implications

Results from our study do not trigger any change to the Near Threatened status of Tumbes Tyrant or the Least
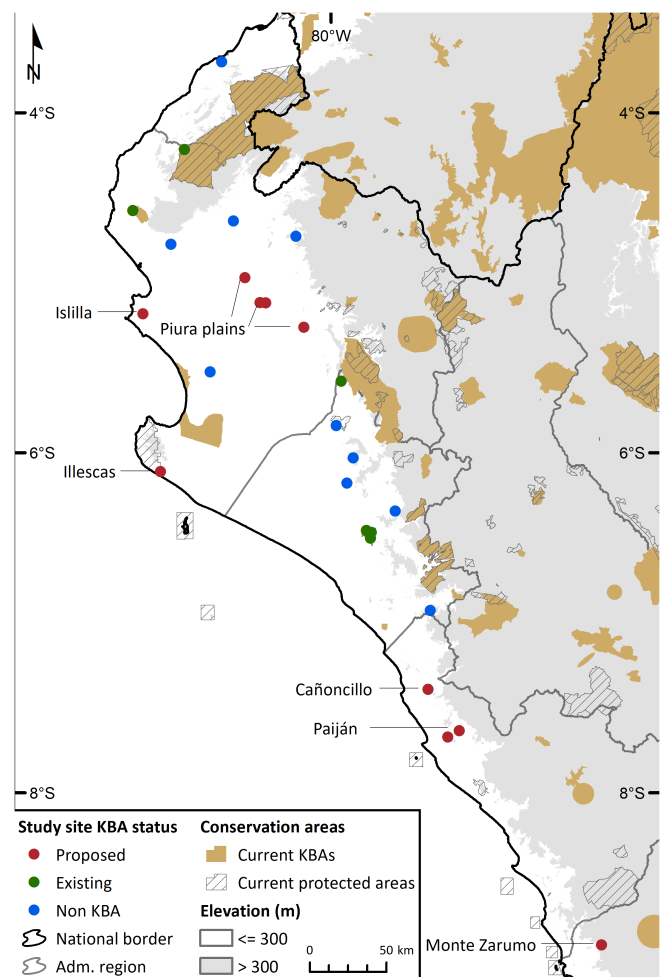

FIGURE 5 Existing and potential Key Biodiversity Areas (KBAs) and currently designated protected areas across the Tumbesian region in Peru. Potential KBAs are: Piura Plains (Progreso Bajo/Cruz de Caña/Sagrado Corazon/Ancajima); Cañoncillo; Monte Zarumo; Paiján (La Arenita/Mocan), Islilla; and Illescas. See Figure 1 for province names

Concern status of those four species currently classified as such. However, our results precipitated changes in Red List status of the two globally threatened species as follows.

Rufous Flycatcher Myiarchus semirufus*: EN to VU*
Our study shows this species to be rare across its range, but that its current EoO is likely to be more than 10 times larger than that previously recognized (BirdLife International, 2016). We estimate that at least 13,000 km^2 of savannah and riverine dry forest, and 13,000 km^2 of desert scrub, suitable habitat for the species, remain across northwest Peru (MINAM, 2012). Our minimum population estimated across the 270 km^2 of (albeit highly suitable) sites surveyed was by itself c.1,500 individuals, which equals the lower bounds of the former global

estimate (1,500–7,000; BirdLife International, 2016). Even using conservatively low levels of occupancy in the above habitats (0.30 and 0.25 respectively) and density (1.5 ind. km^{-2}) in areas we did not survey, a global population in excess of 11,500 individuals is likely. This is beneath the threshold for Vulnerable under criterion C2 (small population). It is possible that when more information on populations in this wider landscape becomes available, its IUCN status will warrant inclusion as Near Threatened.

Peruvian Plantcutter Phytotoma raimondii: *EN to VU*
This study found the Peruvian Plantcutter to have a severely fragmented range, but with high population densities at several sites—more than seven sites had densities exceeding 15 individuals km^{-2}, and four sites >30 individuals km^{-2} (Devenish et al., 2017). Population estimates at sites with presence of the Plantcutter totaled more than 3,000 mature individuals with >50% of the global population likely present at just 10 sites. Although the species is patchily distributed, the present EoO is still too large to meet any IUCN threat criterion, rather, the small population size, with no sub-population larger than 1,000 triggers the Vulnerable threat category.

4.2.3 | Dealing with threats at a regional and local level

Two biomes covering the study area, Equatorial Pacific Coast (dry forests) and Subtropical Pacific (xeric shrubs), have the lowest representation of protected areas in Peru, at 7.6 and 4.4% of their area, respectively. In contrast, 27.4% of the South Amazonia biome is protected (calculated from Stotz, Fitzpatrick, Parker, & Moskovits, 1996). Different strategies are needed to fill gaps in Peru's portfolio of dry forest protected areas (Fajardo et al., 2014). Our study points to prioritizing both small areas, such as Paiján, Islilla, and Monte Zarumo with significant, and geographically separated, Peruvian Plantcutter populations, along with larger areas holding populations of Rufous Flycatcher and other endemics (e.g., potential KBA Piura Plains, west of Old Pan-American Highway between Piura and Chiclayo). Field sites within the latter area scored highly in terms of representing high abundances of endemic species and the area could provide connectivity between northern and mid-region protected areas. Additionally, extensions to existing/proposed protected areas at Illescas, Talara, and Ñaupe may be relatively "easy wins" for conserving currently unprotected populations of Peruvian Plantcutter. We note that private, or regional, conservation areas may be the most suitable protected area categories in Peru, for example, where proposals could be led by local communities (e.g., at Monte Zarumo, following similar initiatives at La Peña—San Francisco de Asís) or by industry (e.g., Islilla, Paiján).

While small irrigation canals feeding coastal agriculture from rivers on the western Andean slope have existed for several millennia (Hocquenghem, 1999), large-scale irrigation projects have recently become a reality, bringing water from the eastern Andes to supply large export agro-businesses on the dry coastal plains. Areas destined for large-scale agriculture include important ecosystems on the Peruvian coast (Olson & Dinerstein, 2002). A worrying aspect of such projects, in addition to the habitat loss, is how mitigation and offsets are managed within the framework of environmental impact assessments. Peru has recently developed legislation requiring ecological equivalence within environmental mitigation measures (MINAM, 2014, 2016). Species reported during impact assessments at Las Norias field site did not include threatened bird species found by this study. Furthermore, mitigation measures, in terms of equivalent area of habitat reforested or protected, may be less than the area impacted and include recommendations for reforestation with species of economic interest for local communities (ECSA Ingenieros, 2011).

Farming communities occupy at least 31,500 km^2 of the Tumbes Endemic Bird Area in Peru, keeping livestock such as goats, and growing rain-fed or locally irrigated crops (Espinosa, 2009). The precise impacts of goats on ecosystems in northern Peru are not completely understood, but habitat degradation appears inevitable where conservation management is lacking (Perevolotsky, 1991; Rodríguez, Alvarez, & Uhlenbrock, 2005). The lack of large trees we found in the region can be attributed to both goat grazing, preventing regeneration, and selective logging for charcoal production, but nonetheless, small-scale agriculture and associated small remnant patches of dry forest can harbor important biodiversity, such as Peruvian Plantcutter (Pollack Velásquez, 2011). Such habitat mosaics within the region's working landscapes are important resources for conservation initiatives outside protected areas if they include locally enforced management such as goat fencing (periodically) and logging quotas.

Additional opportunities for conservation actions outside of protected areas could involve industry. Most of the area under mining concessions is not actively exploited, and forging agreements and long-term commitments on the part of the mining industry, conservation NGOs and regional governments may open up possibilities for habitat protection within concessions (e.g., at Islilla). Similar initiatives have had some success in other countries (Forero-Montaña, Betancur, & Cavelier, 2003). Large agricultural companies could also incorporate set aside areas, or create private reserves for important populations of threatened species (e.g., at Paiján).

4.3 | Key recommendations

- Incorporate key sites (potential KBAs: Talara, Islilla, Illescas, La Arenita/Mocan, Monte Zarumo) for Peruvian Plantcutter into regional government biodiversity strategies as proposed sites for protection (within a variety of conservation measures).
- Engage with industry (e.g., Andalucite Mine, Islilla, Gloria food company—La Arenita/Mocan) to conserve key sites within mining concessions and to incorporate natural habitat patches within large-scale agriculture.
- Work with local farming communities in habitat management (e.g., Piura Plains, La Peña, Monte Zarumo, Pomac), such as restricted grazing by goats, habitat restoration of key plant species, and restricted logging of large trees. Also, implement grazing exclusion experiments.
- Safeguard the area of lowland dry forest savannah (named here as Piura Plains, Figure 5) currently used as grazing areas, through cooperative agreements with farming communities (e.g., with Progreso Bajo, Sagrado Corazon, and Ancajima) and protect from large-scale industrial development.
- Establish a network of protected areas in the southern extreme of the Tumbes region, working with the regional governments of La Libertad, Ancash and Lima (including Monte Zarumo and La Arenita/Mocan).
- Support existing initiatives, such as private conservation areas, conserving key populations of important species, for example, by providing support for the designation or land titling processes and to increase effectiveness of site protection (e.g., in La Arenita/Mocan with industry, or in La Peña, with local communities).
- Improve survey techniques within environmental impact assessments to ensure key species are considered, recorded, and monitored.
- Implement monitoring schemes to assess abundance of key species biannually, based on methods outlined here, outside protected areas, and incorporating ongoing monitoring schemes within protected areas in collaboration with protected areas authority in Peru (e.g., in Pomac, Piedra Mora, Ñaupe).

CONFLICT OF INTEREST
We have no conflicts of interest to declare.

AUTHOR CONTRIBUTIONS
C.D., S.J.M. designed the study, with input from G.R.S. and G.B. C.D. and E.N.C. collected the data in the field. C.D. ran the analyses. C.D. led the paper writing with input and edits from S.J.M., G.R.S., G.B., and E.N.C.

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SUPPORTING INFORMATION

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