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IUCN greatly underestimates threat levels of endemic birds in the Western Ghats

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ABSTRACT

The validity of the threat status assigned to a species by the International Union for Conservation of Nature's (IUCN) Red List relies heavily on the accuracy of the geographic range size estimate for that species. Range maps used to assess threat status often contain large areas of unsuitable habitat, thereby overestimating range and underestimating threat. In this study, we assessed 18 endemic birds of the Western Ghats to test the accuracy of the geographic range sizes used by the IUCN for their threat assessment. Using independently reviewed data from the world's largest citizen science database (eBird) within a species distribution modeling framework, our results show that: (a) geographic ranges have been vastly overestimated by IUCN for 17 of the 18 endemic bird species; (b) range maps used by IUCN contain large areas of unsuitable habitat, and (c) ranges estimated in this study suggest provisional uplisting of IUCN threat status for at least 10 of the 18 species based on area metrics used by the IUCN for threat assessment. Since global range size is an important parameter for assigning IUCN threat status, citizen science datasets, high resolution and freely available geo-referenced ecological data, and the latest species distribution modeling techniques should be used to estimate and track changes in range extent whenever possible. The methods used here to significantly revise range estimates have important conservation management implications not only for endemic birds in the Western Ghats, but for vertebrate and invertebrate taxa worldwide.

1. Introduction

As we move into the Anthropocene, habitat loss and climate change are affecting the distribution of many species at both local and global scales (Steffen et al., 2007; Sodhi et al., 2012). The rapid pace and broad spatial extent of habitat loss and the impacts of climate change, make it immensely difficult to track changes in the distribution of most species. But temporally concurrent citizen science data from geographically widespread sources and substantial advances in spatial and statistical techniques provide new opportunities to accurately estimate contemporary geographic range size, crucial for species conservation management and planning activities.

Geographic range size (in km^2) in the form of Extent of Occurrence (EOO) is an important criterion (B1) used by the International Union for Conservation of Nature (IUCN) for measuring extinction risk for all recognized taxa (IUCN 2016). For example, the level of extinction threat as determined under Criterion B1 suggest that EOOs of $< 20{,}000$ km^2, < 5000 km^2 and < 100 km^2 can lead to an uplisting of threat status to Vulnerable, Endangered and Critically Endangered, respectively, upon satisfying other sub-criteria (such as those related to habitat quality, number of mature individuals, extent of decline in quality of habitat and degree of fragmentation of habitat among others) (IUCN 2016).

Most often, an EOO is calculated by drawing a minimum convex polygon (MCP) around a species range map (IUCN 2016). However, the effectiveness of using the MCP method relies heavily on the accuracy of the species range map (Ostro et al., 1999). For all birds and most mammal species, EOOs have thus far been calculated by simply summing the area of all polygons within a species range map that have been provided to the IUCN by BirdLife International (BLI) and NatureServe (BirdLife International and NatureServe, 2016). Recently, Joppa et al. (2016) proposed that the MCP method should be the standard for future calculations of EOOs of all taxa, thereby warranting the need for accurate species range maps.

Although widely used for conservation planning, most species range maps almost always overestimate the actual distribution of a species by incorporating areas of unsuitable habitat (Hurlbert and White, 2005; Jetz et al., 2007). For example, for all North American breeding birds, Hurlbert and White (2005) showed that bird species were detected in only 40.5% of the range map area. Similarly, Hurlbert and Jetz (2007) showed that up to two-thirds of the range maps for species in global biodiversity hotspots might be gross overestimates of where the species are actually distributed, underscoring the need for more accurate range maps.

Over the past decade, species distribution models (SDMs) have been shown to be a technically more robust means of accurately predicting

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species distributions (Guisan and Thuiller, 2005; Elith and Leathwick, 2009). They do so, by estimating the relationship between a known location of a species and the environmental and spatial conditions that are characteristic of that location (Franklin, 2010). In so doing, SDM techniques have significantly reduced uncertainty in distribution predictions (Elith et al., 2006). With the increasing availability of open access high-resolution land cover maps, environmental variables (e.g. temperature, precipitation), and species occurrence data from citizen science databases, the application of SDMs has become even more nuanced of late, and thus more accurate in estimating species distributions.

The Western Ghats mountain chain (WG) in southwestern India, is a biodiversity and endemism hotspot that is part of the Western Ghats-Sri Lanka biodiversity hotspot (Myers et al., 2000). It hosts 26 endemic bird species with varying IUCN extinction threat levels (Appendix A – Table 1). The current range maps for several of these endemics are coterminous with the entire WG mountain range. However, most of the endemics are evergreen forest and/or high elevation specialists, habitats types which occupy only a small spatial subset of the WG (Ali and Ripley, 1983). Therefore, creating the first accurate range maps for these species, based on detailed observational and ecological data, will likely influence their IUCN threat status and is thus crucial for conservation planning and management.

The citizen science project eBird provides us with a database of bird occurrence covering broad spatial scales (Hochachka et al., 2012; eBird, 2013). Curated eBird species occurrence data can provide the spatially extensive database needed to produce detailed, ecologically relevant SDMs that can render an accurate estimate of spatial extent for WG endemics.

Using eBird data, filtered by regional data reviewers, and freely available landscape scale environmental predictors incorporated into an SDM framework, we: (1) model current extent of suitable habitat for 18 of the 26 Western Ghats endemic birds, and (2) quantify the disparity between ranges estimated by BirdLife International (BLI) and NatureServe for IUCN and ranges estimated using our SDM approach. We demonstrate that remotely sensed data and emerging computational modeling techniques can be used for data rich taxa to significantly improve the accuracy of range maps used by the IUCN to assess the threat status of species. We provide robust evidence that range maps created by BLI and NatureServe for WG include extensive areas of non-habitat/unsuitable habitat for a majority of endemic bird species. For data rich species globally, the latest SDM techniques likely provide a way to realistically assess current extent and track future changes in geographic distribution.

2. Materials and methods

2.1. Study area

The WG (~1600 km long, highest peak 2695 m a.s.l) is topographically complex with a strong precipitation gradient. The annual precipitation varies from over 5000 mm on the west facing slopes and hillcrests to 600 mm on the eastern slopes, which fall in a rain shadow (Gunnell, 1997). The region harbors a wide variety of habitat types ranging from evergreen to sub-tropical broadleaf forests to high elevation *Shola* grasslands (see Roy et al., 2015). In addition, many areas of the Western Ghats are fragmented by anthropogenic landscapes such as plantations, orchards, and other agricultural areas.

2.2. The Western Ghats endemic avifauna

The endemic avifauna of WG varies in habitat preference, from generalist species in orchards and tea plantations to specialist species that exist only in high elevation *Shola* forests and grassland patches. They also differ in their IUCN threat status, with three species listed as Endangered, three as Vulnerable, four as near threatened and 11 as least concern. In addition, three species are listed as not recognized (which is a category used by BLI for species that have had recent taxonomic revisions) and two species are listed as Not Evaluated. Of the 26 endemic bird species in WG, we eliminated the five not recognized/not evaluated species as these species lack BLI range maps for comparison. The Malabar lark (*Galerida malabarica*), Malabar barbet (*Psilopogon malabaricus*), Nilgiri flowerpecker (*Dicaeum concolor*) and Malabar starling (*Sturnia blythii*) were also left out of this study because they are often confused with other species, leading to increased error in citizen science reporting of occurrences. Hence, we considered the 18 remaining endemic bird species, with 2 to 3 representatives in each threat category (Appendix A - Table 1).

2.3. Occurrence data

In this study, we used presence-only data and no information on "true" absences of species was recorded. All occurrence records were obtained from the citizen science database - eBird (eBird, 2013). These records were filtered by date and only those records that occur within the timeframe from 2000 to 2015 were used in the final analyses. Regional data reviewers who are familiar with the ecology of each species eliminated imprecise records. The filtered records were then spatially thinned using the R-based spThin statistical package (Aiello-Lammens et al., 2015), which removes all duplicates and reduces the amount of sampling bias by including only those occurrence records that vary by a particular 'thinning' distance from one another. Thinning distance varied from 100 m to 500 m, based on the dispersal ability of each species and considering the heterogeneity of the habitat between two occurrence records for a single species. We performed 100 iterations for each species and arrived at a final list of "thinned" occurrence points that varied from $n = 35$ (*Trochalopteron cachinnans*) to $n = 780$ (*Leptocoma minima*) (Table 1).

Other thinning approaches, particularly hand-thinning, have been used elsewhere (Radosavljevic and Anderson, 2014). We tested the efficacy of hand-thinning in this study, by applying the Boosted Regression Tree approach, described below, to a hand-thinned dataset for a WG endemic bird species with a broad geographic distribution and one with a narrow distribution. The results of these analyses did not alter the conclusions drawn for these species (see Supplementary data – S2 and Appendix A – Table 3), and so all subsequent spatial analyses reported here are based on spThin occurrence data.

2.4. Environmental data

We initially used 27 environmental variables as potential predictors of a species' distribution (Appendix A - Table 2). We considered these variables based on the ecology of the species and their ability to accurately predict likely habitat for that species (Pearson et al., 2007). Of these 27 predictors, 19 bioclimatic variables were obtained from the WorldClim dataset at a spatial resolution of ~1 km (http://www.worldclim.org/bioclim; Hijmans et al., 2005). In addition, we generated 1 km resolution slope and aspect data using digital elevation model (DEM) data from the WorldClim dataset, which in turn has been interpolated from Shuttle Radar Topography Mission (SRTM) data.

We used a remotely sensed measure of "greenness" known as the Enhanced Vegetation Index (EVI). EVI is correlated to net primary productivity and recent studies suggest that a seasonal estimate of productivity is better at estimating richness of bird communities than annual estimates (Hawkins, 2004; see Hurlbert and White, 2005; Hurlbert and Haskell, 2003). We obtained averaged EVI values from the Moderate Resolution Imaging Spectroradiometer (MODIS) for the months of July, December, February and April to account for a gradient of greenest to driest vegetation. Lastly, we included 35 different land cover types (e.g. Evergreen Forests, Moist-deciduous forests, Orchards) from a high-resolution vegetation type map generated by Roy et al. (2015), using medium resolution IRS-LISS III (Indian Remote Sensing Satellite - Linear Imaging Self Scanner) images that have an overall classification accuracy of 90% (http://bis.iirs.gov.in/).

Table 1
Spatial mismatch between the BLI range maps and the BRT model (thresholded) and the provisional change in threat status implied by this difference.

Species name	BLI range (area in sq. km.)	Current threat status	Model range (area in sq. km)	[a]Proposed revised threat status	Habitat overestimated (in %)	Total number of occurrences
Black and rufous flycatcher (*Ficedula nigrorufa*)	21,356	Near threatened	9300	**Vulnerable**	56	116
Nilgiri pipit (*Anthus nilghiriensis*)	11,558	Vulnerable	1392	**Endangered**	88	53
Broad-tailed grassbird (*Schoenicola platyrus*)	19,731	Vulnerable	8222	Vulnerable	58	55
Gray-headed bulbul (*Pycnonotus priocephalus*)	99,367	Near threatened	29,484	Near threatened	70	276
Kerala laughingthrush (*Trochalopteron fairbanki*)	1098	Near threatened	1789	**Endangered**	− 63[b]	135
Nilgiri flycatcher (*Eumyias albicaudatus*)	32,807	Near threatened	12,376	**Vulnerable**	63	206
Gray-fronted green pigeon (*Treron affinis*)	184,624	Least concern	41,492	**Near threatened**	78	494
Black-chinned laughingthrush (*Trochalopteron cachinnans*)	1286	Endangered	715	Endangered	45	35
Nilgiri shortwing (*Myiomela major*)	1161	Endangered	1050	Endangered	10	43
White-bellied shortwing (*Myiomela albiventris*)	1354	Endangered	1092	Endangered	20	56
Wynaad laughingthrush (*Garrulax delesserti*)	154,095	Least concern	24,557	**Near threatened**	84	97
White-bellied treepie (*Dendrocitta leucogastra*)	107,972	Least concern	24,320	**Near threatened**	78	399
White-bellied blue flycatcher (*Cyornis pallipes*)	44,241	Least concern	43,769	Least concern	1	276
Rufous babbler (*Turdoides subrufa*)	178,046	Least concern	35,962	**Near threatened**	80	394
Nilgiri wood pigeon (*Columba elphinstonii*)	116,465	Vulnerable	37,346	Vulnerable	68	193
Malabar parakeet (*Psittacula columboides*)	121,361	Least concern	38,167	**Near threatened**	69	748
Malabar gray hornbill (*Ocyceros griseus*)	230,696	Least concern	43,060	**Near threatened**	81	774
Crimson-backed sunbird (*Leptocoma minima*)	56,994	Least concern	41,999	Least concern	26	780

[a] Provisional change in threat status is implied based on equating BRT Model range to EOO for a species (similar to the BLI approach, where EOO is the area under the extant distribution map). Bold lettering indicates a provisional upgrading of threat status. Many species require provisional upgrading to the status of Near Threatened, as there has been a dramatic reduction in area in their range.
[b] The Kerala laughingthrush was found to have significantly more habitat than that predicted by BLI.

2.5. Environmental data preparation and exploratory data analysis

For the purpose of modeling suitable habitat, we defined the study area for each species as the cumulative areas that fall under the species' known elevational distribution from published accounts. We then processed all environmental predictors only for areas that satisfied these species-specific elevation constraints. We created random points within the defined study area, known as psuedoabsences, to capture available habitat where a species could be present, though no confirmed presences have been recorded at those points. We based the number of pseudoabsences generated ($n = 5000$ to 20,000) on that required to capture all possible environmental information that exists within the habitats available to a species (Barbet-Massin et al., 2012).

We eliminated correlated environmental predictors with a Pearson's Coefficient > 0.7 (Dormann et al., 2013) and retained only those that had a stronger correlation to the presence records. Additionally, we retained environmental predictors that are relevant to the ecology of the species. The final list of environmental variables chosen for further analyses varied for each species ($n = 14$ to 21), based on the species' ecology.

2.6. Species distribution modeling

We used the Boosted Regression Tree (BRT) approach to determine potential and presently available suitable habitat for each bird. BRTs use regression approaches rooted in classification and regression tree techniques (CART) and boosting algorithms to combine predictions from a number of models. We chose this approach to better parameterize the model in terms of the learning rate, number of trees to be built, number of nodes, and tree complexity (see Elith et al., 2008 for parameter description). Additionally, BRTs do not require the variables to assume a Gaussian distribution.

BRTs are usually overgrown such that there is overfitting of the data, thereby increasing the rate of misclassification of new/withheld data. We dealt with this by using a 10-fold cross validation technique, with each fold containing an equal number of psuedoabsences and presences and hence minimized the rate of misclassification.

These 10 data folds were used to determine key parameters. We tested tree complexity of 5, 8 and 10, number of regression trees within the range 500–2000, in steps of 500, two learning rates of 0.01 and 0.001, and 10 and 20 minimum numbers of observations at each terminal node.

We averaged the resulting 10 BRT models to obtain the final model used to predict suitable habitat for each bird species. To assess the accuracy of the final model and the 10 interim BRT models, we computed the area under the curve (AUC) and the Boyce index accuracy metric (Hirzel et al., 2006).

Lastly, we used the mean predicted probability threshold to convert the probability data to presence/absence only (Liu et al., 2005; Cramer, 2003). By using this approach, we ensured that we removed all areas that have a maximum likelihood of suitable habitat (as produced by the BRT models) lower than the mean predicted probability threshold. The resulting suitable habitat areas obtained from using this threshold were verified by regional data reviewers to check whether they truly bounded each species' known occurrence.

Additional threshold metrics, such as the True Skill Statistic, have been used in other studies (Allouche et al., 2006). We tested this approach, by defining thresholds using the True Skill Statistic on a WG endemic bird species with a broad geographic distribution and one with a narrow distribution. The results of these analyses were extraordinarily close to those using the mean predicted probability threshold (see Appendix A – Table 3 and Supplementary data – S2), and so we report here only the results based on the mean predicted probability threshold.

All environmental data preparation was carried out in ArcMap v10.3.1 (ESRI 2014), chiefly using the Spatial analyst licensed toolbox and R statistical package with contributed packages psych (Revelle and Revelle, 2016), Ecodist (Goslee and Urban, 2007), Caret (Kuhn et al., 2014), PresenceAbsence (Freeman and Moisen, 2008), Ecospat (Hirzel et al., 2006; Franklin, 2010; Broennimann et al., 2016), and raster and rgdal (Hijmans and Van Etten, 2014; Bivand et al., 2014).

2.7. Spatial mismatch calculation

We obtained the latest digital distribution maps prepared by BirdLife International (BLI) and NatureServe (BirdLife International and NatureServe, 2016). We compared the total summed area within a species' published range (polygons) to the cumulative area of the final BRT thresholded model results for that species, and arrived at the extent of spatial mismatch in terms of total difference in cumulative areas between the BRT results and those provided by NatureServe and BLI.

In addition, omission rates of verified eBird occurrences were calculated as the proportion of occurrences outside the BLI range polygon(s). Finally, the proportion of modeled suitable habitat that exists outside the confines of the BLI range polygon boundaries was determined.

3. Results

In 17 of 18 species examined, the BLI range maps overestimate the ranges predicted by our final BRT model, whose AUC and Boyce Index ranged from 0.83 to 0.99 and 0.71 to 0.98, respectively (see Supplementary data – S1). These differences span the Nilgiri pipit (*Anthus nilghiriensis*) with the highest range overestimation at 88% to the White-bellied blue flycatcher with overestimation of 1% of their range. In contrast, for the Kerala Laughingthrush (*Trochalopteron fairbanki*), which has been mapped by BLI using detailed ground survey records, our model estimates a larger range. Of the 18 species modeled, only four species had all occurrences within the BLI range polygons. Omission rates for the remaining 14 species ranged from 0.5% (Nilgiri flycatcher) to 81% (Nilgiri shortwing). The proportion of suitable habitat that exists outside the BLI range polygons ranged from 0.4% (Wynaad laughingthrush) to 62% (Kerala laughingthrush) (Table 2).

If the sum of the area under the BRT thresholded model is equated to an estimate of EOO, which is analogous to what BLI has currently done by summing the areas within the MCPs for a particular species, the threat status of 10 of the 18 endemic species considered in this study should be provisionally uplisted (Table 1). Although there is no change in threat status for the remaining 8 species, based on the geographic range criteria used by the IUCN (Criteria B1), the BLI range maps significantly overestimate ranges for 7 of these 8 species (Fig. 2; Appendix A – Figs. 1 to 16). Additionally, 5 of these 8 species have already been listed by IUCN as Vulnerable or Endangered, and thus likely warrant immediate attention as our SDMs show that most of these endemics are found in a much smaller subset of the range that BLI and IUCN assume.

Table 2
Percent omission rates of occurrences and the percentage of modeled range that falls outside the BLI range polygons.

Species name	Omission rates (in %)	Modeled range outside BLI range polygons (in %)
Black and rufous flycatcher (*Ficedula nigrorufa*)	4.3	3.5
Nilgiri pipit (*Anthus nilghiriensis*)	0.0	2.4
Broad-tailed grassbird (*Schoenicola platyrus*)	16.4	31.1
Gray-headed bulbul (*Pycnonotus priocephalus*)	37.0	28.7
Kerala laughingthrush (*Trochalopteron fairbanki*)	72.6	62.5
Nilgiri flycatcher (*Eumyias albicaudatus*)	0.5	5.6
Gray-fronted green pigeon (*Treron affinis*)	1.0	0.7
Black-chinned laughingthrush (*Trochalopteron cachinnans*)	77.2	56.6
Nilgiri shortwing (*Myiomela major*)	81.4	60.0
White-bellied shortwing (*Myiomela albiventris*)	44.7	50.8
Wynaad laughingthrush (*Garrulax delesserti*)	0.0	0.4
White-bellied treepie (*Dendrocitta leucogastra*)	0.0	0.0
White-bellied blue flycatcher (*Cyornis pallipes*)	23.0	30.0
Rufous babbler (*Turdoides subrufa*)	0	0.8
Nilgiri wood pigeon (*Columba elphinstonii*)	14.5	16.5
Malabar parakeet (*Psittacula columboides*)	3.9	7.8
Malabar gray hornbill (*Ocyceros griseus*)	3.1	3.1
Crimson-backed sunbird (*Leptocoma minima*)	22.8	26.6

4. Discussion

Our modeled range size estimates for the 18 WG endemic birds are significantly smaller than those estimated by BLI for IUCN and provide a more accurate current distribution of each species. We found that BLI range maps include large areas of unsuitable habitat and exclude areas of highly suitable habitat. This range overestimation and underestimation is seen in both high elevation and low elevation species (Fig. 1; Table 1). Additionally, our analysis highlights the use of broad-scale filtered and reviewed citizen science data, freely available geo-referenced environmental parameters, and robust statistical and geospatial techniques for accurate estimation of species ranges, the first of its kind for the Western Ghats endemic avifauna.

Citizen science programs like eBird can provide concurrent, broadly sampled and fine-scaled species occurrence data necessary to produce highly accurate species distribution models. We have incorporated new advances in satellite imagery, the latest geospatial modeling techniques, and open source datasets of vegetation type (see Roy et al., 2015) to greatly boost the accuracy of our distributional range maps. These methods also have the significant added advantage of allowing for frequent (e.g. annual) monitoring of changes in extent of habitat, and correlated threat status, for species of interest with relative ease.

All models come with a certain amount of uncertainty, and although our models might fail to predict every patch of suitable habitat for a particular species, our modeling protocol tries to ensure that few if any areas of unsuitable habitat are included. Furthermore, models are heavily influenced by the input data, in this case citizen science. We have dealt with discrepancies in the citizen science dataset by rigorous filtering of freely available data with the help of regional reviewers. Considering that it is impossible to survey each location in the WG, within a short time span, for each species, citizen science data and SDMs help us make an informed prediction about the likely distribution of species at the scale of the entire WG, a large, remote and rugged region. In this study, we used a presence-only approach, with rigorous filtering of data, to model suitable habitat. But, one could use absences as well, something we hope to do in the future with additional data collection, to further refine range estimates.

IUCN's extinction threat assessments are based on BLI range maps and the species population sizes implied by those ranges. Since our modeled ranges omit large swathes of unsuitable habitats presented in current BLI range maps, we propose that the threat status of WG endemic bird species must be reassessed and in many cases must be uplisted (based on Criterion B1 (Extent of Occurrence)), as a majority of these species lack supplementary information regarding population size estimates (IUCN 2016; Table 1; Fig. 3).

Our results suggest threat status uplisting due to range size overestimation for 10 of the 18 species we analyzed (Fig. 2). Our findings for these 10 species highlight two important modes of range area overestimation, which are relevant for species globally. The first one relates to range-restricted habitat specialists that have endured massive habitat loss in the last few decades. In our analyses, the Nilgiri pipit (*Anthus nilghiriensis*) is one such high elevation grassland specialist that has potentially lost > 88% of its original range as quantified by Robin et al. (2014)and corroborated by our study (1392 km^2 (Model range) vs 11,558 km^2 (BLI range)). For such habitat specialists, based on historical land-cover records, we can directly attribute changes in range size to habitat loss.

The second mode of over-estimation is seen in species that are comparatively widely distributed yet inhabit only a small subset of habitats within that range. In the species we studied, the Malabar parakeet (*Psittacula columboides*) and Malabar grey hornbill (*Ocyceros griseus*) are both examples of species that are found throughout the Western Ghats, but are restricted to the swathes of evergreen forest largely on the west facing slopes and coastal forests of the mountain range. For these species, our analyses reveal that the inclusion of large areas of unsuitable habitat in their range is an important driver of range

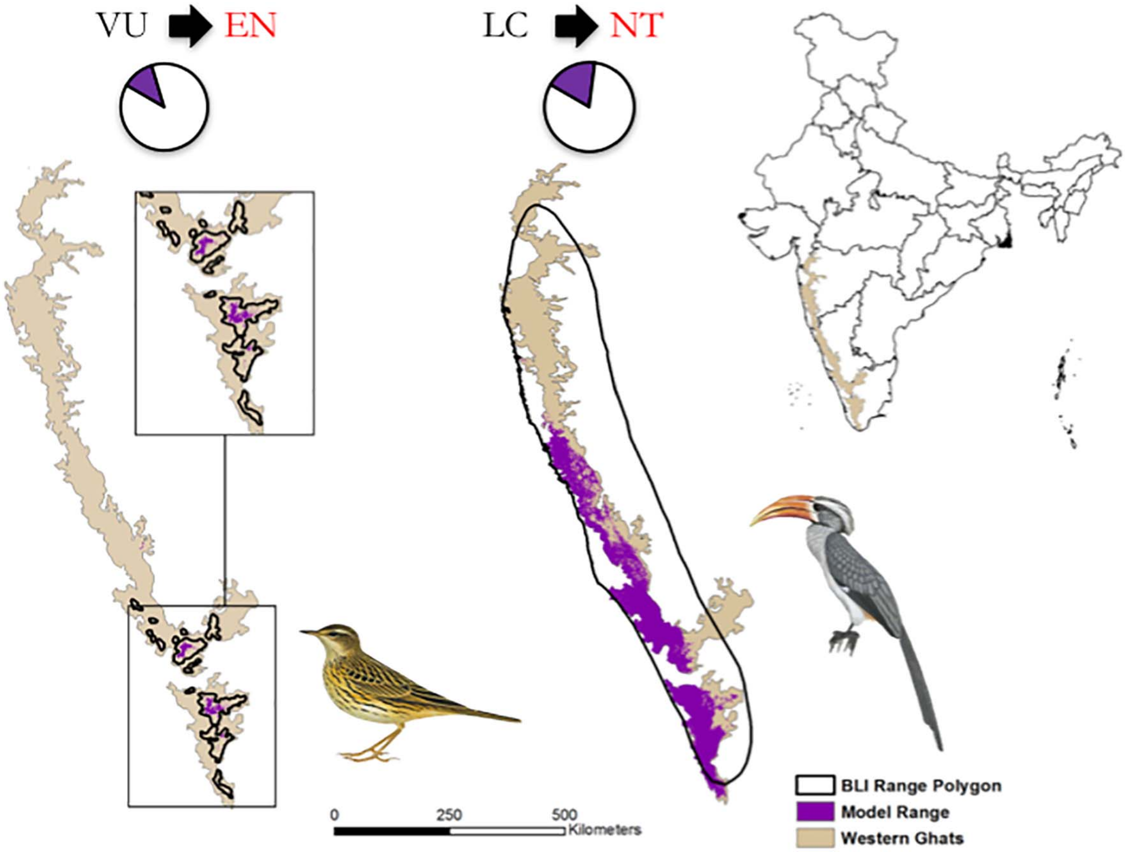

Fig. 1. Range maps have been overestimated by BLI and NatureServe for both high elevation specialists such as the Nilgiri pipit (*Anthus nilghiriensis*) shown on the left to low elevation species such as the Malabar grey hornbill (*Ocyceros griseus*) shown on the right. The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

overestimation in addition to habitat loss. Both of these types of range overestimation - recent habitat loss and inclusion of unsuitable habitat within a broad range - are certainly common for other tropical birds (Hurlbert and Jetz, 2007) and likely for other taxa. By taking an SDM approach, we have minimized the inclusion of unsuitable habitats in current species ranges and provide a basis for tracking habitat loss in the future in known areas of occupancy.

For five of the eight species, for which we do not recommend uplisting threat status based on our models, threat status is already listed as vulnerable or endangered. These species have thus already been identified as needing conservation attention. Our results indicate significant range size overestimation, even for these species, like the Nilgiri wood pigeon (*Columba elphinstonii*), currently listed as Vulnerable on the IUCN Red List, whose range is overestimated by BLI by 68%, or the Black-chinned laughingthrush, whose range is overestimated by BLI by 45%. Both of these species are undoubtedly in need of more urgent conservation action than currently underway, such as population estimation, habitat fragmentation analysis, and landscape management.

We did have one case of range underestimation, the Kerala laughingthrush (*Trochalopteron fairbanki*), for which suitable habitat exists outside the BLI range maps. The proportion of modeled area that exists outside the BLI range maps for this species was 62%, highlighting the inability of the BLI range maps to capture suitable habitat that exists even outside the polygon boundaries (Table 2). This is likely due to the lack of surveys for this high elevation wet evergreen forest species in remote regions where it likely exists but has not been documented. This example, underscores the additional importance of using our data-rich SDM approach in predicting distribution for focused species sampling. Because rigorous distribution modeling techniques were until recently unavailable, very few species range maps produced by BLI and NatureServe map all potential suitable habitat. Instead they are based on the knowledge of a handful of field experts and museum curators. This approach neither helps identify potential areas of un-surveyed but highly suitable habitat, nor does it help track future changes to suitable habitats at the scale of the species range.

Recent studies such as Ocampo-Peñuela et al. (2016) and Li et al. (2016) have shown at continental and regional scales that avian range maps often overestimate habitat, thereby underscoring that there is an increased risk of extinction for avifauna worldwide. However, such studies use an "overly-simple" approach, analogous to BLI's approach, where assumptions have been made on "frequently-missing" information on elevation and land-cover (Peterson et al., 2016). A data-driven approach such as the one shown in this study should be used in the future to arrive at robust range estimates and accurate threat-status for avian taxa worldwide.

Range over-estimation not only introduces inaccuracies to threat status estimation, but it also makes it difficult to track changes in habitat or modify ranges to incorporate effects of climate change, and migratory patterns of hundreds of species worldwide (Runge et al., 2014; Hurlbert and White, 2005). Moreover, while range overestimation is particularly concerning for species with small local ranges that are already listed as endangered or vulnerable, it is also problematic for wider ranging species, where conservation planning to safeguard important habitats and evolutionarily significant units is needed to enhance the chances of a species' survival.

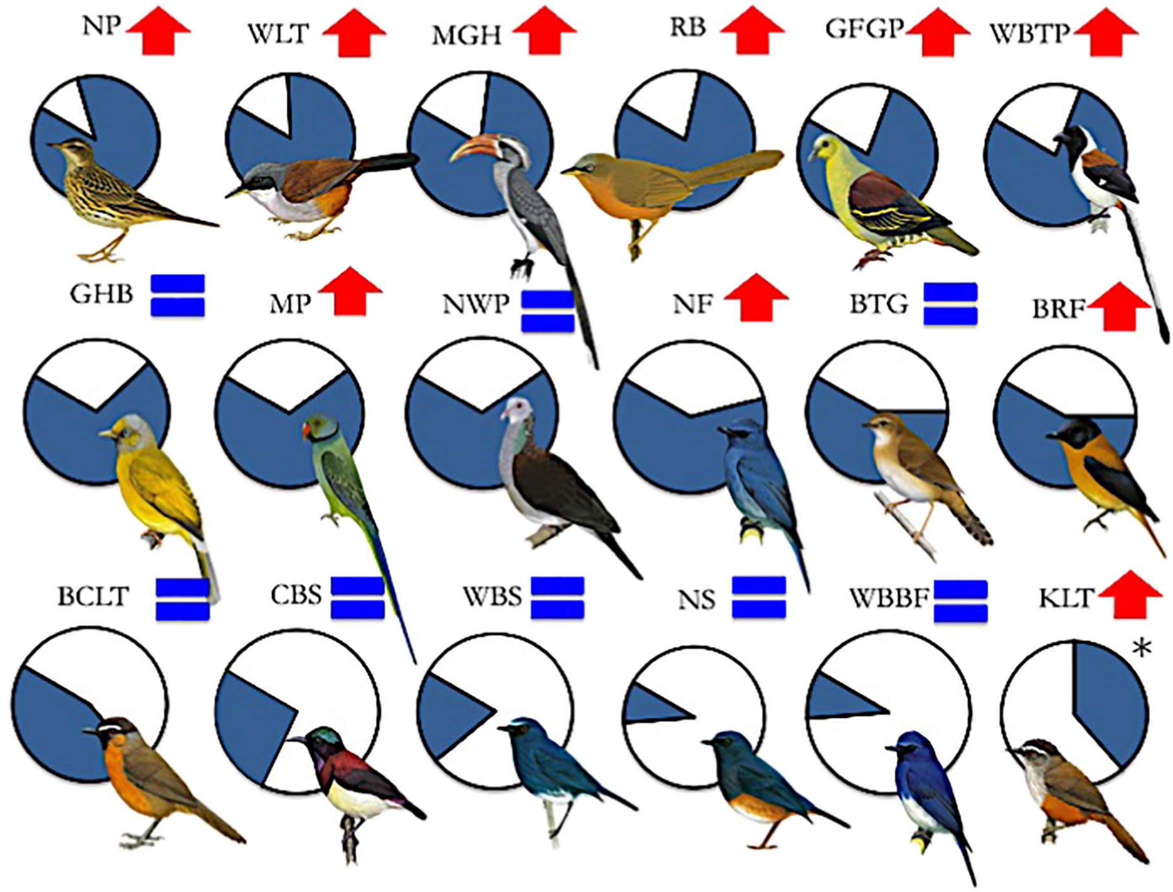

Fig. 2. Range overestimation for 18 species of Western Ghats endemic birds. White portion of pie chart shows percent suitable habitat within IUCN range, blue portion shows percent of the range where unsuitable or no habitats are predicted. Red arrows indicate species with potential need for IUCN threat status uplisting. Blue 'equal' signs indicate species where no uplisting is currently needed. Asterisk for Kerala Laughingthrush (KLT) indicates that it is estimated to be found in an area larger than current BLI range maps.Acronyms used in this figure:NP = Nilgiri pipit, WLT = Wynaad laughingthrush, MGH = Malabar grey hornbill, RB = rufous babbler, GFGP = grey-fronted green pigeon, WBTP = white-bellied treepie, GHB = grey-headed bulbul, MP = Malabar parakeet, NWP = Nilgiri wood pigeon, NF = Nilgiri flycatcher, BTG = broad-tailed grassbird, BRF = black and rufous flycatcher, BCLT = black-chinned laughingthrush, CBS = crimson-backed sunbird, WBS = white-bellied shortwing, NS = Nilgiri shortwing, WBBF = white-bellied blue flycatcher, KLT = Kerala laughingthrush. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

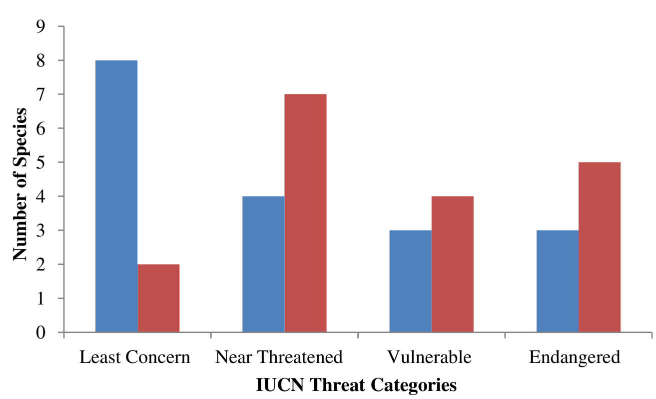

Fig. 3. A comparison of the number of species among the different IUCN threat categories between the current threat status (shown in blue) and the proposed revised threat status (shown in red) for each species. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

We have clearly demonstrated that the current practice of using species range maps provided by BLI and NatureServe grossly overestimate range sizes and underestimate threat status in 17 of the 18 Western Ghats endemic bird species we examined. This resonates with the results of Peterson et al., (2016) and are likely to be true not only of birds, but of other vertebrates and invertebrates, as well.

Using new and comprehensive data-driven approaches, like the citizen science - SDM approach described here, can lead to the creation of more accurate range maps with the added advantage of enabling easy and routine tracking of changes in species distribution in the future. Such an approach can significantly inform current and future conservation assessment and management of endemic and endangered species of birds, mammals, and other organisms worldwide.

Acknowledgements

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Appendix A

Table 1
List of Species considered in this study are marked in black. Species that are often confused with other species in their range are marked in green and were left out of this study. Species marked in red have been listed as Not Recognized/Not Evaluated by IUCN and do not contain any BLI Range maps and were left out of this study.

Species Name	Scientific Name	IUCN Threat Status
Black-and-rufous flycatcher	*Ficedula nigrorufa*	Near Threatened
Black-chinned laughingthrush	*Trochalopteron cachinnans*	Endangered
Broad-tailed grassbird	*Schoenicola platyrus*	Vulnerable
Gray-fronted green-pigeon	*Treron affinis*	Least Concern
Gray-headed bulbul	*Pycnonotus priocephalus*	Near Threatened
Kerala laughingthrush	*Trochalopteron fairbanki*	Near Threatened
Nilgiri flycatcher	*Eumyias albicaudatus*	Near Threatened
Nilgiri pipit	*Anthus nilghiriensis*	Vulnerable
Nilgiri wood pigeon	*Columba elphinstonii*	Vulnerable
Nilgiri shortwing	*Myiomela major*	Endangered
White-bellied shortwing	*Myiomela albiventris*	Endangered
Wynaad laughingthrush	*Garrulax delesserti*	Least Concern
Rufous babbler	*Turdoides subrufa*	Least Concern
Crimson-backed sunbird	*Leptocoma minima*	Least Concern
White-bellied Treepie	*Dendrocitta leucogastra*	Least Concern
White-bellied blue flycatcher	*Cyornis pallipes*	Least Concern
Malabar parakeet	*Psittacula columboides*	Least Concern
Malabar grey hornbill	*Ocyceros griseus*	Least Concern
Malabar Barbet	*Megalaima malabarica*	Least Concern
Malabar Lark	*Galerida malabarica*	Least Concern
Nilgiri Flowerpecker	*Dicaeum concolor*	Least Concern
Flame-throated Bulbul	*Pycnonotus gularis*	Not Evaluated
Malabar Woodshrike	*Tephrodornis sylvicola*	Not Recognized
Vigor's Sunbird	*Aethopyga vigorsii*	Not Recognized
Nilgiri Thrush	*Zoothera neilgherriensis*	Not Evaluated
Malabar Starling*	*Sturnia blythii*	Not Recognized

*This species is often confused with other species of starlings as well.

Table 2
List of environmental predictor variables considered in this study.

Environmental predictor	Data source	Spatial resolution
Annual mean temperature − BIO1	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Mean diurnal range (mean of monthly (max temp − min temp)) − BIO2	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Isothermality (BIO2/BIO7) (∗100) − BIO3	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Temperature seasonality (standard deviation ∗ 100) − BIO4	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Max temperature of warmest month − BIO5	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Min temperature of coldest month − BIO6	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Temperature annual range (BIO5–BIO6) − IO7	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Mean temperature of wettest quarter − BIO8	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Mean temperature of driest quarter − BIO9	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Mean temperature of warmest quarter − BIO10	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Mean temperature of coldest quarter − BIO11	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Annual precipitation − BIO12	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Precipitation of wettest month − BIO13	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Precipitation of driest month − BIO14	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Precipitation seasonality (coefficient of variation) − BIO15	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Precipitation of wettest quarter − BIO16	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Precipitation of driest quarter − BIO17	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Precipitation of warmest quarter − BIO18	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Precipitation of coldest quarter − BIO19	http://www.worldclim.org/bioclim; Hijmans et al., 2005	1 km
Elevation	Interpolated from Shuttle Radar Topography Mission	1 km
Aspect	Derived from Elevation	1 km
Slope	Derived from Elevation	1 km
Enhanced Vegetation Index for the month of February (averaged across 2000–2015)	Obtained from Moderate Resolution Imaging Spectroradiometer (MODIS)	1 km
Enhanced Vegetation Index for the month of April (averaged across 2000–2015)	Obtained from Moderate Resolution Imaging Spectroradiometer (MODIS)	1 km
Enhanced Vegetation Index for the month of July (averaged across 2000–2015)	Obtained from Moderate Resolution Imaging Spectroradiometer (MODIS)	1 km
Enhanced Vegetation Index for the month of December (averaged across 2000–2015)	Obtained from Moderate Resolution Imaging Spectroradiometer (MODIS)	1 km
Vegetation type map (that included 35 predictors such as Evergreen Forests, Moist Deciduous et al.)	http://bis.iirs.gov.in/; Roy et al., 2015	~23.5 m (resampled to 1 km)

Table 3
Additional analyses to compare results of using the True Skill Statistic threshold and manual thinning of occurrence data

Species name	No. of presences (after hand-thinning)	No. of presences (using spThin)	Modeled area (using the True Skill Statistic threshold)	Modeled area (using the Mean probability threshold)	BLI range
Kerala laughingthrush (*Trochalopteron fairbanki*)	138	135	1794 km^2	1789 km^2	1098 km^2*
Grey-headed bulbul (*Pycnonotus priocephalus)*	304	276	31,057 km^2	29,484 km^2	99,367 km^2

* Asterisk for Kerala Laughingthrush (KLT) indicates that it is estimated to be found in an area larger than current BLI range maps (see text).

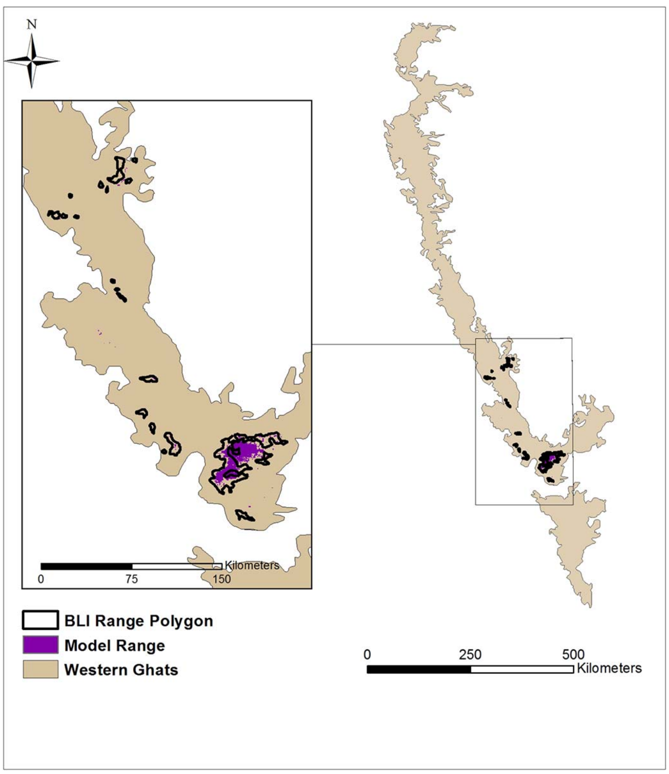

Fig. 1. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the black chinned laughingthrush (*Trochalopteron cachinnans*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

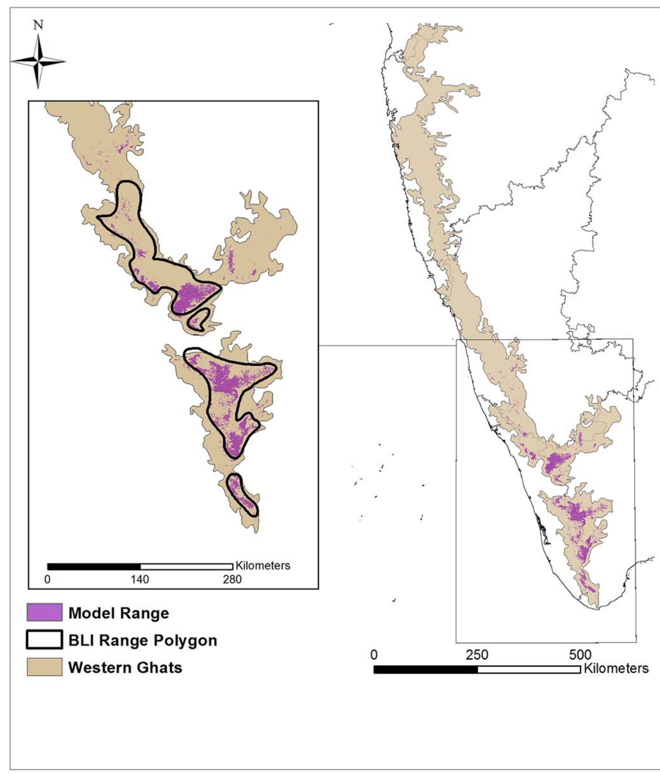

Fig. 2. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the black and rufous flycatcher (*Ficedula nigrorufa*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

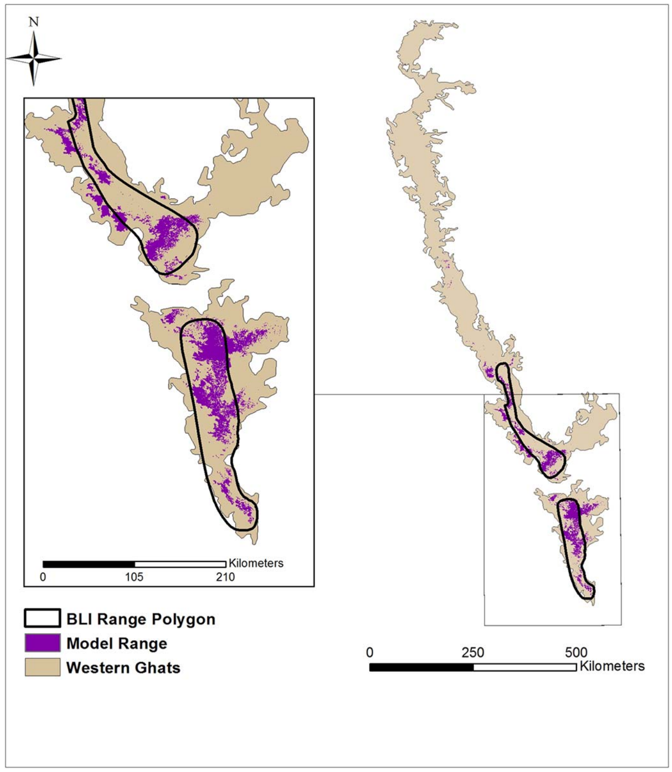

Fig. 3. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the broad-tailed grassbird* (*Schoenicola platyrus*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.*Occurrences for this species were considered only South of Goa, as verified eBird records were not used North of Goa for this study.

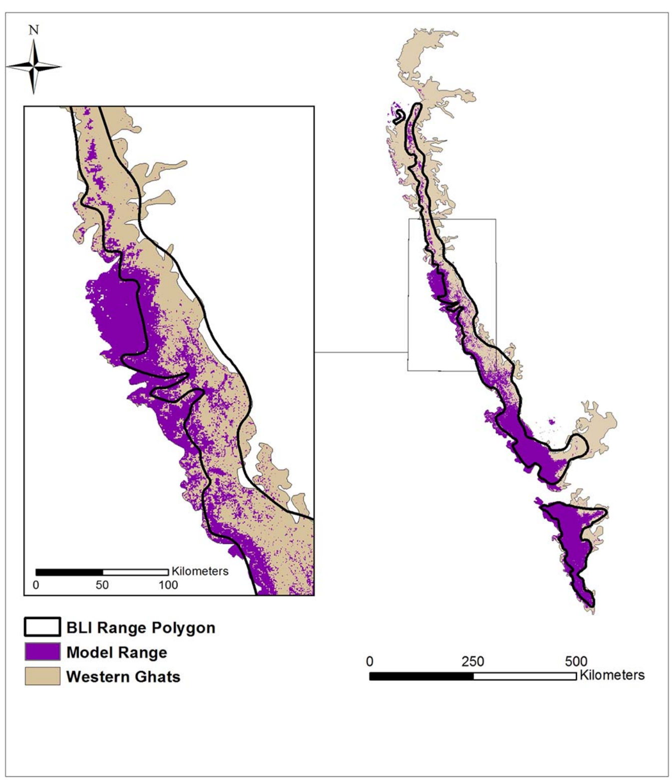

Fig. 4. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the crimson-backed sunbird (*Leptocoma minima*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

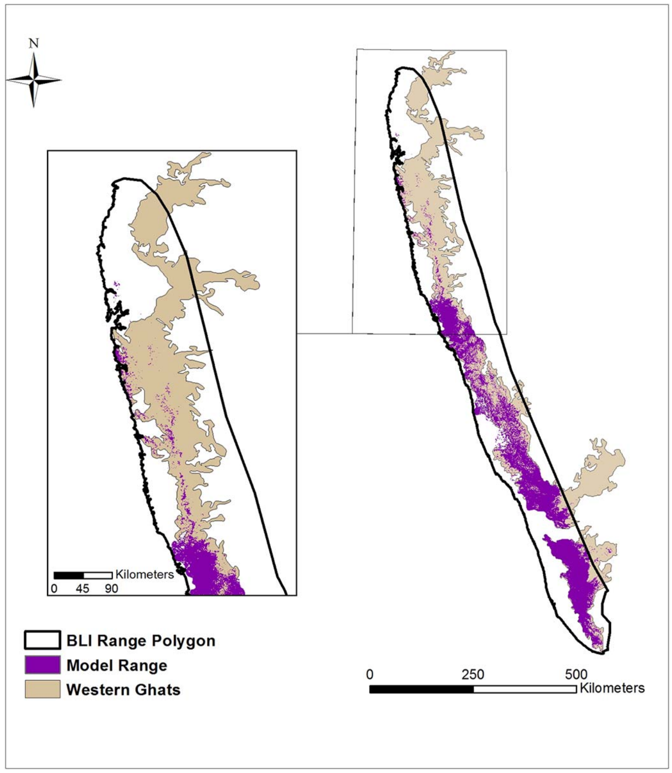

Fig. 5. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the grey-fronted green pigeon (*Treron affinis*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

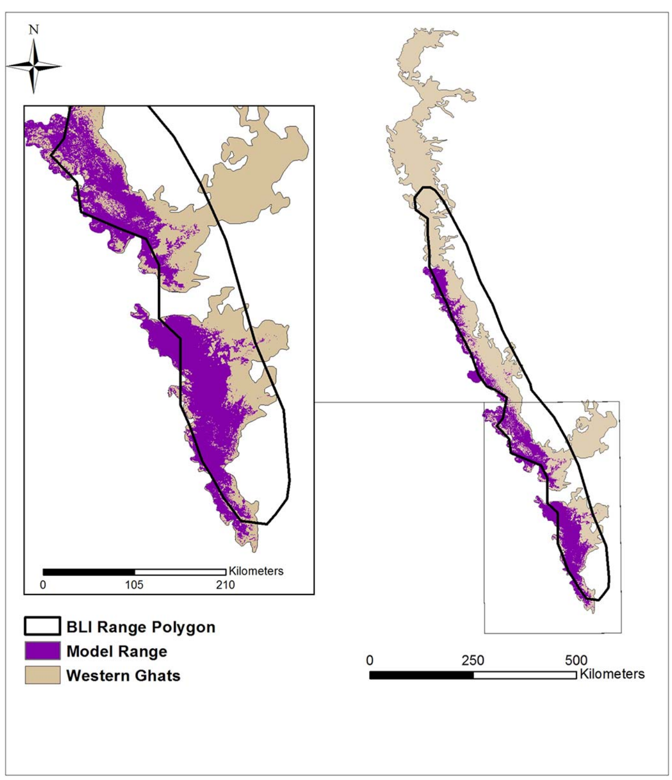

Fig. 6. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the grey-headed bulbul (*Pycnonotus priocephalus*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

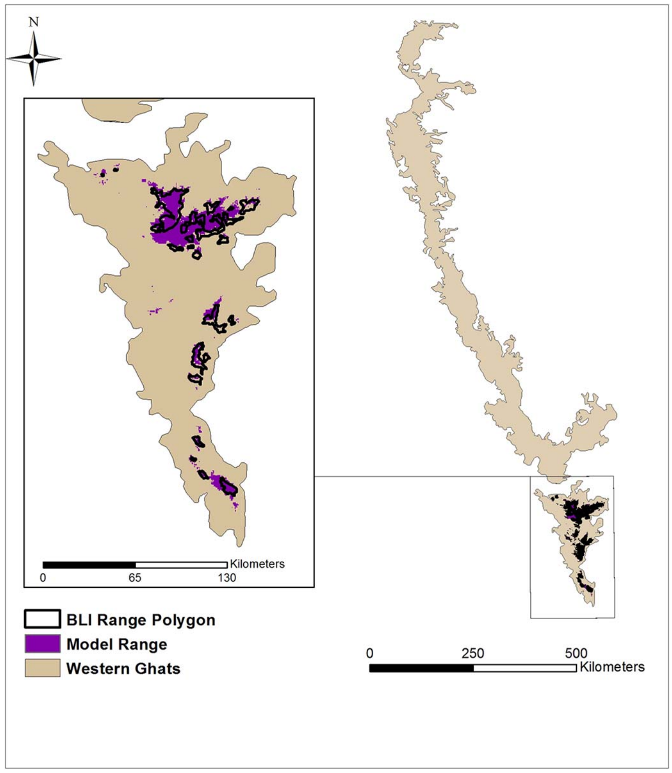

Fig. 7. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the Kerala laughingthrush (*Trochalopteron fairbanki*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

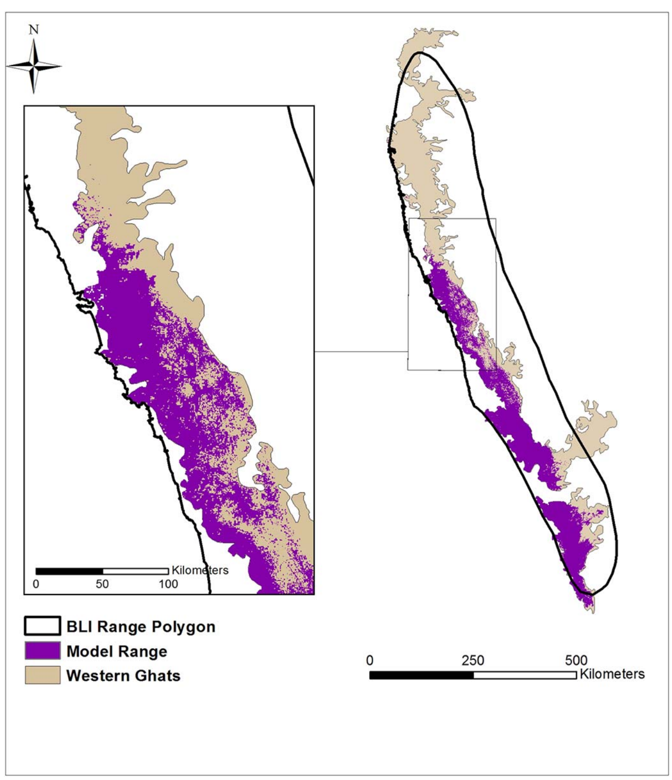

Fig. 8. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the Malabar grey-hornbill (*Ocyceros griseus*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

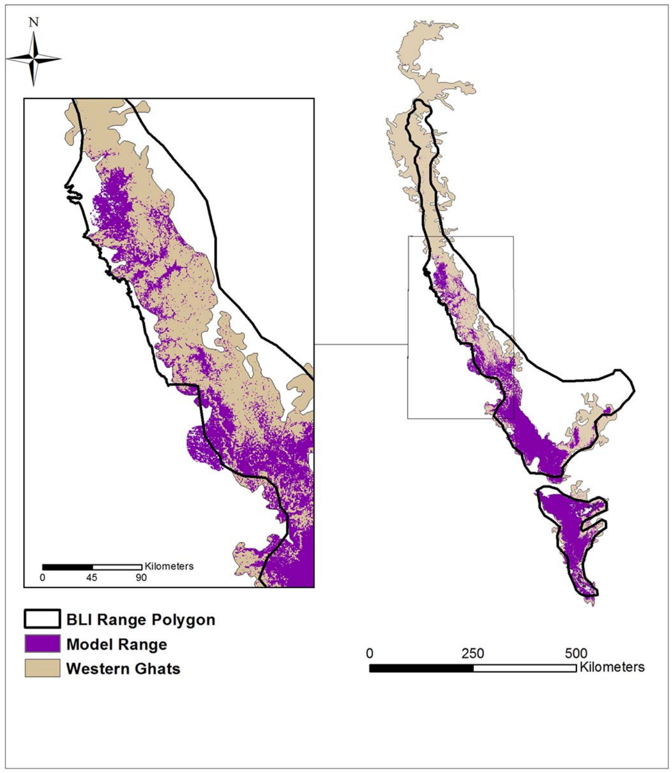

Fig. 9. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the Malabar parakeet (*Psittacula columboides*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

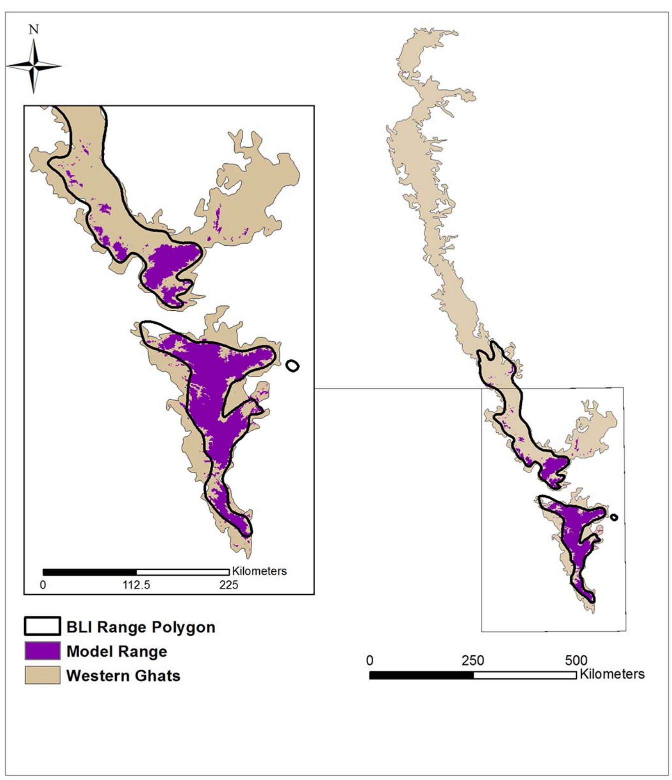

Fig. 10. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the Nilgiri flycatcher (*Eumyias albicaudatus*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

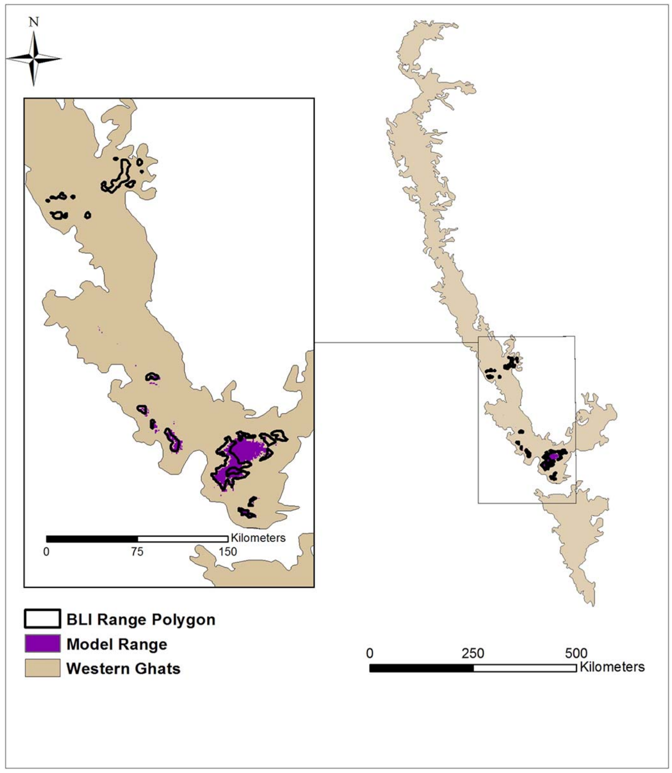

Fig. 11. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the Nilgiri shortwing (*Myiomela albiventris*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

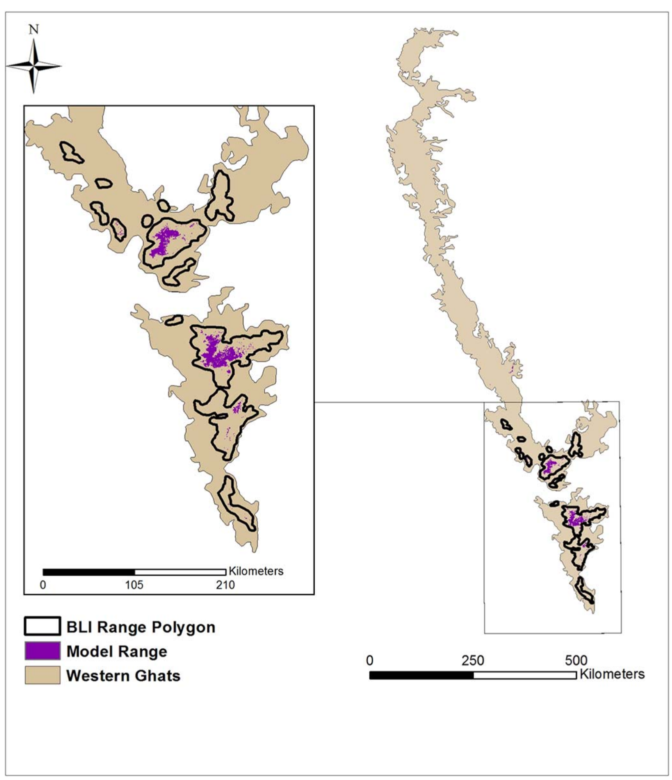

Fig. 12. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the Nilgiri pipit (*Anthus nilghiriensis*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

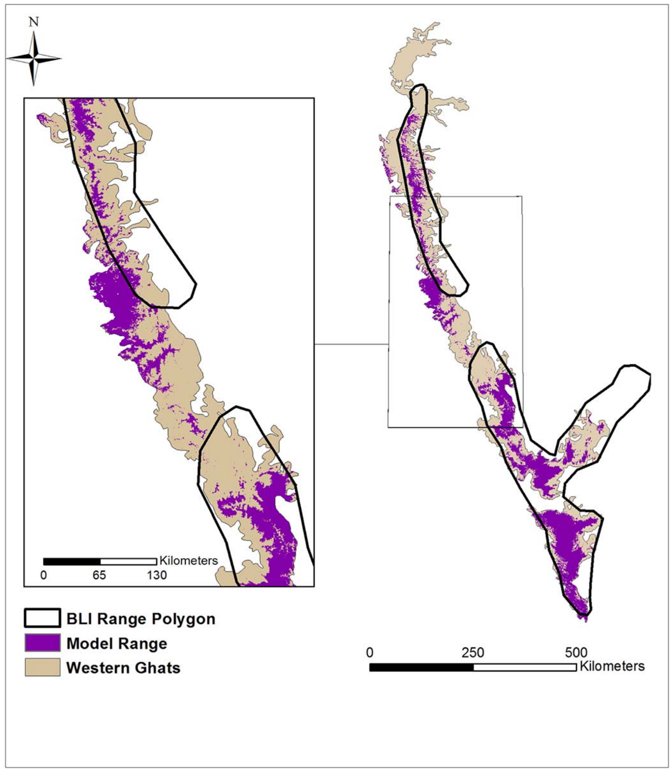

Fig. 13. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the Nilgiri wood pigeon (*Columba elphinstonii*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

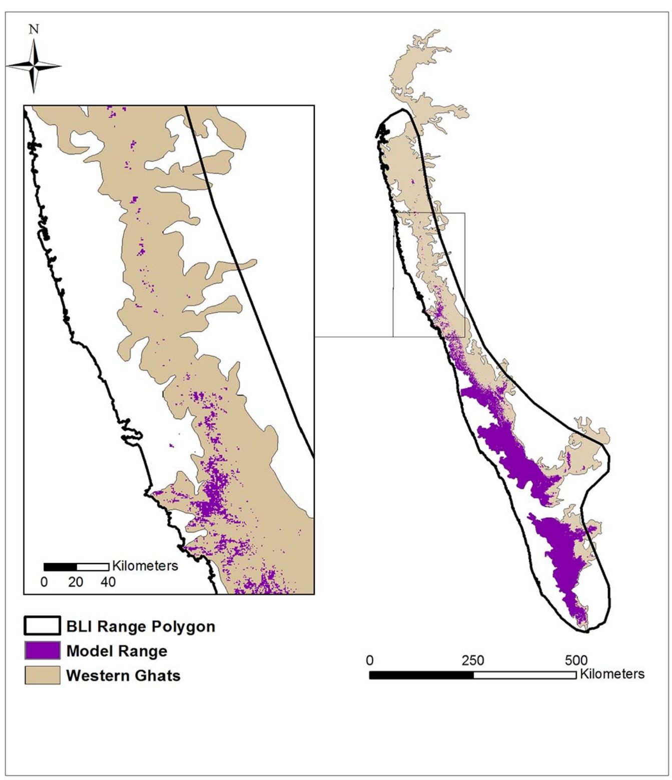

Fig. 14. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the rufous babbler (*Turdoides subrufa*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

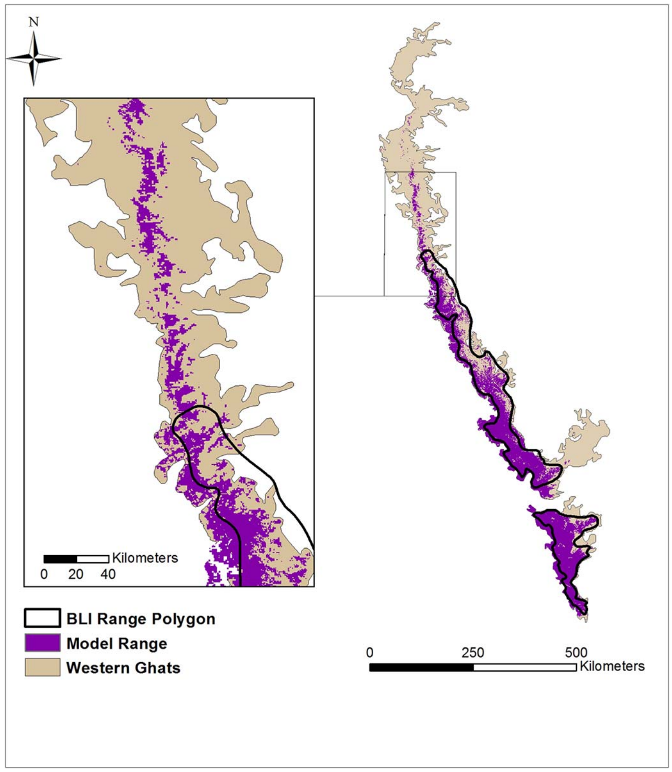

Fig. 15. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the white-bellied blue flycatcher (*Cyornis pallipes*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

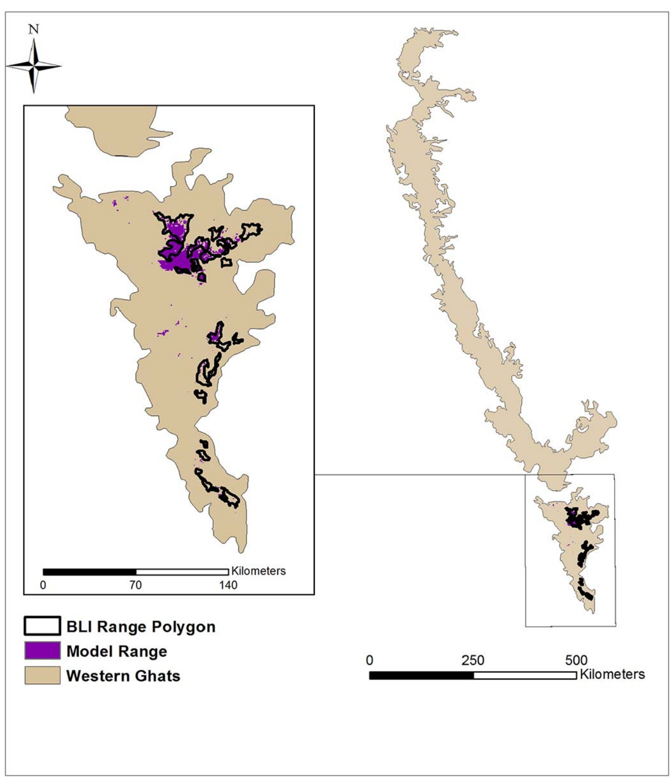

Fig. 16. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the white-bellied shortwing (*Myiomela albiventris*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

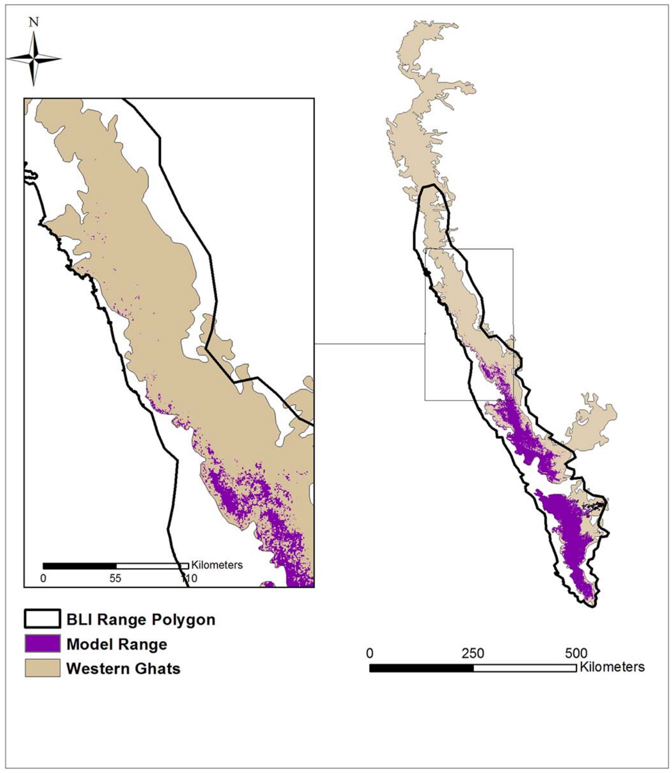

Fig. 17. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the white-bellied treepie (*Dendrocitta leucogastra*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

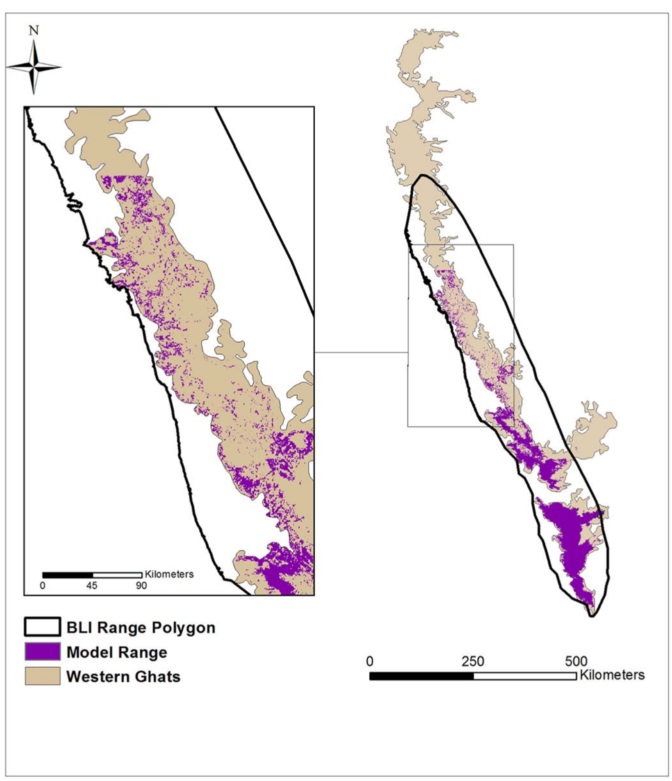

Fig. 18. Spatial mismatch between the BLI and NatureServe range maps and the accurate range modeled in this study for the Wynaad laughingthrush (*Garrulax delesserti*). The black outline represents the range polygon used by IUCN for threat assessment and the range in purple represents the range modeled in this study. The dust brown color represents the boundary of the Western Ghats.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.biocon.2017.03.019.

References

Aiello-Lammens, M.E., Boria, R.A., Radosavljevic, A., Vilela, B., Anderson, R.P., 2015. spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models. Ecography 38, 541–545. http://dx.doi.org/10.1111/ecog.01132.

Ali, S., Ripley, S.D., 1983. Handbook of the Birds of India and Pakistan (Compact Edition). Oxford University Press and BNHS, Mumbai.

Allouche, Omri, Tsoar, Asaf, Kadmon, Ronen, 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the True Skill Statistic (TSS). J. Appl. Ecol. 43 (6), 1223–1232 Blackwell Publishing Ltd.

Barbet-Massin, M., Jiguet, F., Albert, C.H., Thuiller, W., 2012. Selecting pseudo-absences for species distribution models: how, where and how many? Methods Ecol. Evol. 3, 327–338.

BirdLife International and NatureServe, 2016. Bird Species Distribution Maps of the World. Version 5.0. BirdLife International, Cambridge, UK and NatureServe, Arlington, USA.

Bivand, R., Keitt, T., Rowlingson, B., 2014. rgdal: bindings for the geospatial data abstraction library. In: R Package version 0, pp. 8–16.

Broennimann, O., Di Cola, V., Petitpierre, B., Breiner, F., Manuela, D., Randin, C., Engler, R., Hordijk, W., Pottier, J., Di Febbraro, M., et al., 2016. Package "Ecospat." .

Cramer, J.S., 2003. Logit Models From Economics and Other Fields. Cambridge University Press.

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J., Münkemüller, T., McClean, C., Osborne, P.E., Reineking, B., Schröder, B., Skidmore, A.K., Zurell, D., Lautenbach, S., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36, 27–46. http://dx.doi.org/10.1111/j.1600-0587.2012.07348.x.

Ebird, 2013. eBird: An Online Database of Bird Distribution and Abundance .

Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annu. Rev. Ecol. Evol. Syst. 40, 677–697.

Elith*, J., Graham*, C.H., Anderson, R.P., Dudík, M., Ferrier, S., Guisan, A., Hijmans, R.J., Huettmann, F., Leathwick, J.R., Lehmann, A., Li, J., Lohmann, L.G., Loiselle, B.A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J.McC.M., Townsend Peterson, A., Phillips, S.J., Richardson, K., Scachetti-Pereira, R., Schapire, R.E., Soberón, J., Williams, S., Wisz, M.S., Zimmermann, N.E., 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29, 129–151. http://dx.doi.org/10.1111/j.2006.0906-7590.04596.x.

Elith, J., Leathwick, J.R., Hastie, T., 2008. A working guide to boosted regression trees. J. Anim. Ecol. 77, 802–813. http://dx.doi.org/10.1111/j.1365-2656.2008.01390.x.

ESRI, 2014. ArcGIS Desktop: Release 10.3. Redlands, CA: Environmental Systems Research Institute .

Franklin, J., 2010. Moving beyond static species distribution models in support of conservation biogeography. Divers. Distrib. 16, 321–330. http://dx.doi.org/10.1111/j.1472-4642.2010.00641.x.

Freeman, E.A., Moisen, G., 2008. PresenceAbsence: An R Package for Presence Absence Analysis .

Goslee, S.C., Urban, D.L., 2007. The ecodist package for dissimilarity-based analysis of ecological data. J. Stat. Softw.

Guisan, A., Thuiller, W., 2005. Predicting species distribution: offering more than simple habitat models. Ecol. Lett. 8, 993–1009. http://dx.doi.org/10.1111/j.1461-0248.2005.00792.x.

Gunnell, Y., 1997. Relief and climate in South Asia: the influence of the Western Ghats on the current climate pattern of peninsular India. Int. J. Climatol. 17, 1169–1182.

Hawkins, B.A., 2004. Summer vegetation, deglaciation and the anomalous bird diversity gradient in eastern North America. Glob. Ecol. Biogeogr. 13, 321–325. http://dx.doi.org/10.1111/j.1466-822X.2004.00095.x.

Hijmans, R.J., Van Etten, J., 2014. raster: geographic data analysis and modeling. In: R Package Version 2.2–31, URL. http://CRAN.R-project.org/package=raster [accessed 15 March 2014].

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978. http://dx.doi.org/10.1002/joc.1276.

Hirzel, A.H., Le Lay, G., Helfer, V., Randin, C., Guisan, A., 2006. Evaluating the ability of habitat suitability models to predict species presences. Ecol. Modell. 199, 142–152. http://dx.doi.org/10.1016/j.ecolmodel.2006.05.017.

Hochachka, W.M., Fink, D., Hutchinson, R.A., Sheldon, D., Wong, W.-K., Kelling, S., 2012. Data-intensive science applied to broad-scale citizen science. Trends Ecol. Evol. 27, 130–137. http://dx.doi.org/10.1016/j.tree.2011.11.006.

Hurlbert, A.H., Haskell, J.P., 2003. The effect of energy and seasonality on avian species richness and community composition. Am. Nat. 161, 83–97. http://dx.doi.org/10.1086/345459.

Hurlbert, A.H., Jetz, W., 2007. Species richness, hotspots, and the scale dependence of range maps in ecology and conservation. Proc. Natl. Acad. Sci. U. S. A. 104, 13384–13389. http://dx.doi.org/10.1073/pnas.0704469104.

Hurlbert, A.H., White, E.P., 2005. Disparity between range map-and survey-based analyses of species richness: patterns, processes and implications. Ecol. Lett. 8, 319–327.

IUCN Standards, Petitions Subcommittee, 2016. Guidelines for using the IUCN Red List categories and criteria. Version 12. Prepared by the Standards and Petitions Subcommittee. Downloadable from. http://www.iucnredlist.org/documents/RedListGuidelines.pdf.

Jetz, W., Wilcove, D.S., Dobson, A.P., 2007. Projected impacts of climate and land-use change on the global diversity of birds. PLoS Biol. 5, e157. http://dx.doi.org/10.1371/journal.pbio.0050157.

Joppa, L.N., Butchart, S.H.M., Hoffmann, M., Bachman, S.P., Akçakaya, H.R., Moat, J.F., Böhm, M., Holland, R.A., Newton, A., Polidoro, B., Hughes, A., 2016. Impact of alternative metrics on estimates of extent of occurrence for extinction risk assessment. Conserv. Biol. 30, 362–370. http://dx.doi.org/10.1111/cobi.12591.

Kuhn, M., Wing, J., Weston, S., Williams, A., Keefer, C., Engelhardt, A., Cooper, T., Mayer, Z., Kenkel, B., Team, R.C., et al., 2014. caret: classification and regression training. In: R Package Version 6.0–21. CRAN, Wien, Austria.

Li, B.V., Hughes, A.C., Jenkins, C.N., Ocampo-Peñuela, N., Pimm, S.L., 2016. Remotely sensed data informs Red List evaluations and conservation priorities in Southeast Asia. PLoS One 11, e0160566. http://dx.doi.org/10.1371/journal.pone.0160566.

Liu, C., Berry, P.M., Dawson, T.P., Pearson, R.G., 2005. Selecting thresholds of occurrence in the prediction of species distributions. Ecography.

Myers, N., Mittermeier, R.a., Mittermeier, C.G., da Fonseca, G.a., Kent, J., 2000. Biodiversity hotspots for conservation priorities. Nature 403, 853–858. http://dx.doi.org/10.1038/35002501.

Ocampo-Peñuela, N., Jenkins, C.N., Vijay, V., Li, B.V., Pimm, S.L., 2016. Incorporating explicit geospatial data shows more species at risk of extinction than the current Red List. Sci. Adv. 2, e1601367. http://dx.doi.org/10.1126/sciadv.1601367.

Ostro, Linde E.T., Young, T.P., Silver, S.C., Koontz, F.W., 1999. A geographic information system method for estimating home range size. J. Wildl. Manag. 63, 748–755. http://dx.doi.org/10.2307/3802665.

Pearson, R.G., Raxworthy, C.J., Nakamura, M., Townsend Peterson, A., 2007. Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. J. Biogeogr. 34, 102–117.

Peterson, A.T., Navarro-Sigüenza, A.G., Gordillo, A., 2016. Assumption-versus data-based approaches to summarizing species' ranges. Conserv. Biol.

Radosavljevic, Aleksandar, Anderson, Robert P., 2014. Making better maxent models of species distributions: complexity, overfitting and evaluation. J. Biogeogr. 41 (4), 629–643 Wiley Online Library.

Revelle, W., Revelle, M.W., 2016. Package "Psych." .

Robin, V.V., Vishnudas, C.K., Ramakrishnan, U., 2014. Reassessment of the distribution and threat status of the Western Ghats endemic bird, Nilgiri Pipit *Anthus nilghiriensis*. Curr. Sci. 107, 622–630.

Roy, P.S., Behera, Murthy, M.S.R., Roy, A., Singh, S., Kushwaha, S.P.S., Jha, C.S., Sudhakar, S., Joshi, P.K., Reddy, C.S., Gupta, S., Pujar, G., Dutt, C.B.S., Srivastava, V.K., Porwal, M.C., Tripathi, P., Singh, J.S., Chitale, V., Skidmore, A.K., Rajshekhar, G., Kushwaha, D., Karnatak, H., Saran, S., Giriraj, A., Padalia, H., Kale, M., Nandy, S., Jeganathan, C., Singh, C.P., Biradar, C.M., Pattanaik, C., Singh, D.K., Devagiri, G.M., Talukdar, G., Panigrahy, R.K., Singh, H., Sharma, J.R., Haridasan, K., Trivedi, S., Singh, K.P., Kannan, L., Daniel, M., Misra, M.K., Niphadkar, M., Nagabhatla, N., Prasad, N., Tripathi, O.P., Prasad, P.R.C., Dash, P., Qureshi, Q., Tripathi, S.K., Ramesh, B.R., Gowda, B., Tomar, S., Romshoo, S., Giriraj, S., Ravan, S.A., Behera, S.K., Paul, S., Das, A.K., Ranganath, B.K., Singh, T.P., Sahu, T.R., Shankar, U., Menon, A.R.R., Srivastava, G., Neeti, Sharma, S., Mohapatra, U.B., Peddi, A., Rashid, H., Salroo, I., Krishna, P.H., Hajra, P.K., Vergheese, A.O., Matin, S., Chaudhary, S.A., Ghosh, S., Lakshmi, U., Rawat, D., Ambastha, K., Malik, A.H., Devi, B.S.S., Gowda, B., Sharma, K.C., Mukharjee, P., Sharma, A., Davidar, P., Raju, R.R.V., Katewa, S.S., Kant, S., Raju, V.S., Uniyal, B.P., Debnath, B., Rout, D.K., Thapa, R., Joseph, S., Chhetri, P., Ramachandran, R.M., 2015/7. New vegetation type map of India prepared using satellite remote sensing: comparison with global vegetation maps and utilities. Int. J. Appl. Earth Obs. Geoinf. 39, 142–159. http://dx.doi.org/10.1016/j.jag.2015.03.003.

Runge, C.A., Martin, T.G., Possingham, H.P., Willis, S.G., Fuller, R.A., 2014. Conserving mobile species. Front. Ecol. Environ. 12, 395–402. http://dx.doi.org/10.1890/130237.

Sodhi, N.S., Posa, M.R.C., Peh, K.S.-H., Koh, L.P., Soh, M.C.K., Lee, T.M., Lee, J.S.H., Wanger, T.C., Brook, B.W., 2012. Land use changes imperil South-East Asian biodiversity. In: Land Use Intensification Effects on Agriculture, Biodiversity and Ecological Processes. CRC Press, Boca Raton, FL, pp. 39–46.

Steffen, W., Crutzen, P.J., McNeill, J.R., 2007. The Anthropocene: are humans now overwhelming the great forces of nature. AMBIO J. Hum. Environ. 36, 614–621. http://dx.doi.org/10.1579/0044-7447(2007)36[614:TAAHNO]2.0.CO;2.