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Letter to the Editor

Finer spatial resolution improves accuracy of species distribution models in heterogeneous landscapes - A response to Praveen J

In a commentary written to Biological Conservation, Praveen J. questioned the approach of Ramesh et al. (2017) by highlighting the geo-precision of eBird data when modeling the distributional range of a species. He makes a case for using coarse-scale rather than a fine-scale eBird data to model a species' range, as well as correcting for sampling bias in the input of data at any scale. We concur with Praveen J. that there is strong need to account for sampling bias in eBird input data and have previously acknowledged the uncertainty that comes with a modeling approach such as ours ("…*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."*). Here, we clarify the misconceptions that exist with our modeling protocol and argue that rigorously filtered fine-scaled citizen science data can contribute significantly to conserving habitats for the endemic birds of the Western Ghats.

1. The issue of scale

Species Distribution Models (SDMs) estimate the relationship between a known location for a species and the environmental and spatial conditions that are characteristic of that location (Franklin, 2010). In our study, we first collated high-resolution data on Temperature, Precipitation, Land-Cover, Enhanced Vegetation Index (EVI) and Topography for the entire Western Ghats. For each location where a species of interest was reported (eBird checklist Location ID), we extracted information on the above mentioned variables. The data (except for the eBird checklist location) was at a spatial resolution of 1 km^2 (Land-Cover was initially at a resolution of 30 m and was resampled to 1 km for the analyses). It appears that Praveen J. is of the opinion that the eBird data we used in our analyses was also at a spatial resolution of 1 km^2. In fact, for an SDM, the occurrence information is rarely a layer that is defined within a grid, but is defined by a single Latitude and Longitude and hence is a single point in space. Information on environmental variables (e.g. Temperature, Precipitation) is then collated for 1 km^2 grid within which the occurrence record falls.

Praveen (2017) suggests that our analyses should have been done at the scale of 10 km × 10 km, which would have resulted in data points with greater geo-precision (the issue of hotspots and clustering is dealt with below). We maintain that it would be detrimental to use a coarser resolution. To begin with, decreasing the resolution of the input environmental variables 100-fold (1 km^2 vs 100 km^2) would aggregate substantial environmental variation that might otherwise help in differentiating between highly suitable habitat and less suitable habitat patches. For instance, EVI, which is a measure of percent greenness varies significantly even at a 1 km × 1 km scale along elevational and latitudinal axes in the Western Ghats. Modeling at a resolution 100 times coarser will profoundly affect the area of suitable habitat predicted by the model, vastly over-predicting ranges, especially of high-elevation species that live in small, patchy, "sky-island" habitats in the Western Ghats. Another example where a coarser resolution might be deleterious, is the occurrence record of a forest dependent bird at the edge of a forest patch abutting a large tract of agriculture. In a 10 km × 10 km grid, the cropland and other areas unsuitable for a species might be considered suitable habitat. Conversely, as in our case, if unsuitable habitat classes are identified apriori, if the entire grid is predicted to be unsuitable habitat due to the large proportion of cropland, the model would fail to predict the highly suitable habitat that exists within the grid. Such a patch of good quality habitat in a matrix of unsuitable habitat will only be predicted accurately when the spatial resolution of the model is as small as possible.

2. Hotspots and clustering of eBird data

Praveen J points out that observations in and around a 5 km radius of a public birding location (also referred to as 'Hotspots' in eBird) are generally clustered to a particular point. Recognizing this, we re-analyzed the raw data used in our study and calculated the closest neighboring presence record for each presence record that we used for each species. Praveen J. claims that 60% of the data (we assume that the author is referring to the overall data for all 18 species in our study) used in our study came from 'Hotspots'. We would like to remind the readers that in our study, we first removed all duplicates for Location ID and further used spatial thinning of clustered occurrence records (not using points that fall within 100 m–500 m of another record, depending on the dispersal ability for each species) to reduce the influence of a handful of locations on the overall model. Thus, across the 18 species we modeled, the percentage of unique occurrences that fell within 1 km of one another ranged from 14.5% (Wynaad laughingthrush) to 71% (Kerala laughingthrush) (see Table 1). For 16 of the 18 species, the number of unique occurrences that were more than 1 km away from one another was greater than 40%. Hence, the majority of our data actually came from individual observations submitted to eBird and not from 'Hotspots'.

We agree with Praveen J. that a model is only as good as the input data. That is why, in our study, we have taken the utmost care to build models using the finest spatial scale data available in order to minimize over-estimation of the range. We have also ensured removal of duplicates and spatially thinned the occurrence records to ensure that certain locations are not overrepresented in building the models. Our analyses have brought to light the increasingly crucial need to quantify additional variables such as habitat loss over time, the effect of fragmentation relative to dispersal

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Table 1
Percentage of unique occurrences that fell within 1 km of one another.

Species	Percentage of unique occurrences that fell within 1 km of one another
Wynaad laughingthrush (*Garrulax delesserti*)	14.5
Broad-tailed grassbird (*Schoenicola platyrus*)	26.7
Grey-headed bulbul (*Pycnonotus priocephalus*)	34.8
White-bellied blue flycatcher (*Cyornis pallipes*)	37.9
Nilgiri blue robin (*Sholicola major*)	40.7
Nilgiri wood pigeon (*Columba elphinstonii*)	40.9
Grey-fronted green pigeon (*Treron affinis*)	42.0
Rufous babbler (*Turdoides subrufa*)	44.9
Nilgiri pipit (*Anthus nilghiriensis*)	45.8
White-bellied treepie (*Dendrocitta leucogastra*)	47.6
Crimson-backed sunbird (*Leptocoma minima*)	47.9
Nilgiri flycatcher (*Eumyias albicaudatus*)	54.6
Malabar grey hornbill (*Ocyceros griseus*)	55.2
Malabar parakeet (*Psittacula columboides*)	55.5
White-bellied blue robin (*Sholicola albiventris*)	55.8
Black-chinned laughingthrush (*Montecincla cachinnans*)	57.3
Black-and-orange flycatcher (*Ficedula nigrorufa*)	63.7
Kerala laughingthrush (*Montecincla fairbanki*)	71.0

distances of species, and patch size and abundance in order to render our inferences that much more powerful in the conservation management of the Western Ghats endemic avifauna.

References

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