1 **"Tracking the Rain Bird": Modeling the monthly distribution of Pied cuckoo in India**

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Abstract

Pied cuckoo *Clamator jacobinus* (Boddart, 1783) is a migratory, brood-parasitic bird found in the African and Indian Subcontinent. Although the southern Indian population is presumably resident, the North Indian Population migrates from Africa to India during the summer. The arrival of the bird is linked to the onset of monsoon in India from scientific literature to folklore. It is known to make its appearance in central and northern India in the last week of May or early June, indicating the imminent arrival of the monsoon with its unmistakably loud metallic calls. There have been few attempts to compile relevant information on the species migration in the early 1900s and citizen science approach by Bird-count India; little information is available on how environmental factors might be affecting its migration. Here, we have used Maximum Entropy modeling to identify the monthly and seasonal distribution patterns and major bioclimatic factors that might be influencing the distribution of the species in India. We have used E-Bird citizen science platform data, seven bioclimatic variables, and monthly NDVI of respective months for building the models. The predicted output shows the species presence throughout the year in southern India. In contrast, in northern India, the distribution is dynamic, peaking in summers in the Month of May-June and no presence in winter. The influence of bioclimatic variables used in SDM varied monthly; Water vapor pressure was the primary contributing variable in the months prior to species arrival. In July, it was NDVI (Higher NDVI suggests abundance of food resources for the species). In August-September, Windspeed and water vapor pressure (Factors might be responsible for the departure of the species) have contributed highest. Our approach provides a more concise understanding of Pied cuckoo's monthly distributions throughout India, which helps understand the complex seasonal shifts in the distribution of such migratory birds.

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Keywords: Species distribution modeling, Maxent, E-Bird, Migration, Monthly Distribution

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37. Introduction

Birds have been the subject of theoretical developments in behaviour, ecology, and evolutionary biology (Hackett et al., 2008; Schluter, 1996; Sutherland et al., 2004;), and yet their distribution and migration patterns have always been a question with varying hypothesis amidst the ornithological community. Seasonal resource availability results in the varying seasonal distributions of many birds (Engler et al. 2014; Eyres et al. 2017) and seasonal niches in time and space considerations on ecological niches are more complex in organisms with seasonal distributions (Engler et al. 2014; Martínez-Meyer et al. 2004; Nakazawa et al. 2004;). Typical migratory birds demonstrate a breeding and a non-breeding distribution. Due to their large range, migratory birds can either follow their climatic niche from one season to another (so-called 'niche followers' or 'niche trackers'), or they experience varying climatic conditions. (i.e., 'niche switchers'; Joseph and Stockwell 2000; Joseph 1996; Martínez-Meyer et al. 2004; Williams et al. 2017).

Pied cuckoo (*Clamator jacobinus*, Boddart, 1783) (Figure 1) is a type of crested cuckoo (Payne and Juana, 2020) found in the Indian and African Subcontinent and involved in inter and intracontinental migrations (Payne, 2005). This species is a brood parasite to different avifauna (Friedmann, 1964; Gaston, 1976; Johnsingh & Paramanandham, 1982; Payne, 2005) and a summer migrant to India (Friedmann, 1964; Whistler, 1928). There are three subspecies of this bird (Payne and Juana, 2020), viz. i. *C. jacobinus pica* (Hemprich and Ehrenberg, 1833) found in Southern Asia to Pakistan, northern India, Nepal, Tibet, Kashmir and Burma, and Africa south to Tanzania and Zambia (Gaston, 1976); ii. *C. jacobinus jacobinus* (Boddart, 1983); a resident subspecies found in southern India and Sri Lanka (Johnsingh & Paramanandham, 1982), and iii. *C. jacobinus serratus* (Sparrman, 1786); found in coastal South Africa; Zambezi River to the Cape region of South Africa. Pied Cuckoo is a summer migrant to India (Whistler, 1928; Friedmann, 1964) and also a brood parasite to several avifauna (Johnsingh and Paramanandham, 1982; Payne, 2005; Gaston, 1976; Friedmann, 1964). *C. jacobinus* parasitizes several host species (Friedmann, 1964), primarily babblers (genus *Turdoides*) in the plains and laughing-thrushes (genus *Garrulax*) in the hills (Friedmann, 1964; Gaston, 1976). In northern India, the subspecies *C. jacobinus. jacobinus* has been mentioned as resident (Payne, 2005), while the north Indian population is migratory (Ali and Ripley, 1983; Khachar, 1990).

The species is deeply rooted in the regional culture and mythology of India. Historically, the advent of the monsoon for generations has been associated with the appearance of the Pied cuckoo in many parts of India (Ali and Ripley 1989), and the species is mentioned several

71 times in ancient Indian literature and folklores (Kālidāsa and Kale, 1974; Chopra, 2017).
 72 Ancient Hindu poetry refers to Pied cuckoos as '*Chatak*,' who live on drops of rain (Abdulali
 73 1972). In Kalidasa's *Abhijñānaśākuntalam* the bird has been mentioned as "Divaukas," who
 74 said to be present on Earth at certain times of the year (Chopra, 2017), denoting the migratory
 75 behaviour of the species. Nevertheless, unlike most migratory birds arriving in India that
 76 come from the northern hemisphere to winter, the Pied cuckoo is an exception in being a
 77 summer visitor to Northern India. It is known to make its appearance in several parts of
 78 Central and Northern India in the last week of May or early June, announcing the monsoon's
 79 impending arrival with its unmistakably loud metallic call. India is a country with an
 80 agricultural economy; the monsoon is considered one of India's most auspicious seasons. And
 81 so, the Pied cuckoo in North and Central India is a welcome sight. Reports indicate that the
 82 arrival of the Pied Cuckoo, coincides with the variation in the arrival of the monsoon winds
 83 (migrantwatch, 2013, ([http://www.migrantwatch.in/blog/2013/04/04/does-the-pied-cuckoo-](http://www.migrantwatch.in/blog/2013/04/04/does-the-pied-cuckoo-herald-the-monsoon/)
 84 [herald-the-monsoon/](http://www.migrantwatch.in/blog/2013/04/04/does-the-pied-cuckoo-herald-the-monsoon/)). A recent study by Madhusudan (2018) ([https://birdcount.in/rain-bird-](https://birdcount.in/rain-bird-monsoon/)
 85 [monsoon/](https://birdcount.in/rain-bird-monsoon/)) using citizen science data shows the correlation of the bird's arrival in India with
 86 the southwest monsoons winds. Even though being a species with such ecology (Payne, 2005)
 87 and evolutionary history (Friedmann, 1984); apart from folk knowledge about the species, a
 88 few efforts to assemble relevant info in the early 1900s (Betts 1929; Pillai 1943; Simmons
 89 1930; Whistler 1928), and few recent studies (Migrantwatch, 2013; Madhusudan, 2018), a
 90 very little information is available on its migration, monthly distribution pattern, its relation
 91 to the Indian monsoon and allied bioclimatic factors affecting its distribution in India.

92 Species Distribution Modelling (SDM) is used to predict species' distribution across
 93 geographical space and time using species locations with a set of environmental data. It can
 94 help to fill knowledge gaps for poorly understood species by predicting suitable habitats
 95 within an area of interest, providing information about different habitat variables relevant to
 96 the species' distribution, predicting responses to future climate conditions (Elith and
 97 Leathwick, 2009; Pearce and Boyce, 2006). SDM has varied practical applications ranging
 98 from conservation prioritization to effective habitat management of the species (Elith and
 99 Lithwick, 2009; Guisan and Thuiller, 2005; Williams, Willemoes, and Thorup, 2017;). Out
 100 of the many models used in SDM, Maxent (Maximum Entropy Species Distribution
 101 Modelling) (Phillips et al. 2006) is one of the leading algorithms for presence-only data in
 102 contemporary SDMs (Elith et al. 2006) and has outperformed other available presence only
 103 models (Anadón, Wiegand, and Giménez, 2012). There are numbers of studies have been
 104 done on predicting species migration through SDM's using E-Bird, survey data, and satellite
 105 data (Coxen et al., 2017; Gschweng et al., 2012; Thorup et al., 2001; Revell and Somveille,

2017; Peterson, Ball and Cohoon, 2002; Pocewicz et al., 2013). E-Bird data is a high-quality data source for SDMs, and models based on E-Bird data can have high overlap in habitat suitability scores with models based on satellite tracking data (Coxen et al., 2017). The E-Bird data has also sometimes matched or exceeded performance compared to the systematically collected data (Valerie, Elphick and Tingley, 2019)

In this present study, we have used the Maximum entropy modeling approach (MaxEnt) (Philips et al., 2006) using data from EBird, and a set of environmental variables to predict the monthly distribution of *Clamator jacobinus* in India. This study aims to model the distribution pattern of *Clamator jacobinus* in different months and see the influence of environmental and climatic factors on its migration in the Indian Subcontinent.

2. Materials and Methods

2.1. Study Area

For modeling the species distribution, we have used entire India (20.5937° N, 78.9629° E) as our study area (Figure 2). India falls in the oriental biogeographic realm and has ten different biogeographic zones. The country's total geographical area is 3,287,240 sq.km, divided into 28 states and 8 Union Territories. The climate of India is a majorly tropical monsoon type. However, it encompasses a varied range of climate conditions across a vast geographic scale and diverse topography. India experiences an annual mean temperature of 21°C and an average rainfall of 1045mm. India has majorly four seasons, Winter (December-February), Summer (March-May), South-west monsoon season (June-September), Post monsoon season (October-November). The country's climate is influenced by two seasonal winds – the southwest monsoon and the northeast monsoon. The north-east monsoon, generally known as winter monsoon, blows from land to sea. In contrast, the summer monsoon or the southwest monsoon blows from sea to land after crossing the Indian Ocean, the Arabian Sea, and the Bay of Bengal. The southwest monsoon carries most of the rainfall during a year in the country.

2.2. Species occurrence points

E-Bird (Sullivan et al., 2009) is a citizen science platform that exclusively focuses on distribution information about avifauna (Cox et al., 2012; Crall et al., 2010; Jackson et al., 2015; Lin et al., 2015). E-Bird records are submitted in checklist format listing the counts of each species encountered. Checklists include information on observation duration, distance traveled, and other method-related metadata. We obtained these data by directly

downloading the EBird Basic Dataset (<https://ebird.org/science/download-ebirddata-products>) on 30/1/2019.

Overall, out of 21294 downloaded occurrence points for the entire world, we clipped 8930 points for the year 2017-18 for India (Figure 2). However, citizen science data sometimes leads to spatial-clustering due to biased sampling (Zhang and Zhu, 2019). Thus, it is vital to remove the autocorrelated points (Boria et al., 2014; Fourcade et al., 2014). To minimize the error, the occurrence data were filtered and organized in sequential steps to improve quality. We rarefied occurrence data in ArcGIS using the Spatial Distribution Modeling toolbox (SDM toolbox v2.2.) (Brown, 2014) to spatially filter the data to a single point per 1 km² grid and removed duplicate and spatially autocorrelated presence points. The filtered data was split for 12 months for running the models. We split the locations randomly in equal halves: one set of locations for calibration and another set for independent evaluation. The calibration data was split into two random subsets, training data (50%) and testing data (50%) (Supplementary figure. 1).

2.3. Bioclimatic variables:

For modeling the distribution of *C. jacobinus*, we have used a set of environmental variables (Table 1) based on the available data, knowledge of species ecology, and potential factors affecting the species distribution. We have used WorldClim data V2.0 (Fick and Hijmans, 2017) for seven monthly bioclimatic variables, viz, Monthly minimum temperature (°C), maximum temperature (°C), average temperature (°C), Precipitation (mm), and water vapor pressure (kPa). Solar radiation (kJ m⁻² day⁻¹) and monthly Normalized Difference Vegetation Index (NDVI) (Didan, 2015) (Table 1). The Bioclimatic Data for each month were obtained from the WorldClim database version 2.0 (Fick and Hijmans, 2017, available at <http://worldclim.org/version2>) at 30-seconds (Approx. 1km²) resolutions. Monthly NDVI layers were extracted from the USGS Earth-Explorer database at a resolution of 250m. The geographic dimensions of all the downloaded layers were made similar (Pixel size 1 Km²) using the "SDM toolbox" (Brown, 2014) and "export to Circuitscape tool" by Jeff Jenness (http://www.jennessent.com/arcgis/Circuitscape_Exp.htm) in ArcGIS 10.7. Here we have not excluded any layers by correlation test as we intended to check the changing contribution of the bioclimatic variables with each month.

2.4. Maximum entropy modeling

Maxent (Maximum Entropy Species Distribution Modelling) (Phillips et al. 2006) is one of the leading algorithms for presence-only data in contemporary SDMs (Elith et al. 2006) and

has outperformed other available presence only models (Anadón et al. 2012; Kaliontzopoulou et al., 2008; and Wen et al. 2015; Wisz et al. 2008; Suárez-Seoane et al. 2008). We used MaxEnt 3.4.1 (Philips et al., 2006) in the R platform for estimating the monthly distribution pattern of Pied cuckoo in India. The calibration phase and choosing the best parameter are critical (Warren et al., 2010). For model calibration, model calibration and selection, final model creation, and evaluation, we have used 'kuenm' toolbox (Cobos, 2019) in R 3.5.0 (R Core Team, 2018).

2.4.1. Model Calibration:

For each month, we created 290 candidate models by combining ten values of regularization multiplier (0.5–5 at intervals of 0.1), and all 29 possible combinations of 5 feature classes (linear = l, quadratic = q, product = p, threshold = t, and hinge = h). We evaluated candidate model performance based on significance (partial ROC, with 500 iterations and 50 percent of data for bootstrapping), omission rates ($E = 5\%$), and model complexity (AICc). Best models were selected according to the following criteria: (1) significant models with (2) omission rates $\leq 5\%$. Then, from among this model set, models with delta AICc values of ≤ 2 were chosen as final models.

2.4.2. Final model building and evaluation:

We created final monthly models for Pied cuckoo using the presence locations, selected model parameterizations, ten replicates by bootstrap with logistic output. A model's application has little importance if the accuracy of the prediction is not measured (Pearson, 2010). We evaluated the model using Area under Receiver Operating Characteristics (ROC) in MaxEnt and a partial ROC (pROC) using a Kuenm package script. The ROC considers the sensitivity against the specificity of a model when new data is presented. The area under the Curve (AUC) of this ROC plot is a measure of the model's overall accuracy. It ranges from 0 to 1, with 1 representing a model with perfect discrimination between sites where species are present and absent (Elith et al., 2006). Although widely used in the modeling literature, AUC's effectiveness has been criticized as a way of predicting the accuracy of models (Lobo et al., 2008). As an alternative, the pROC has been proposed as an accurate test for model performance (Peterson et al., 2008). We present here both the AUC obtained from MaxEnt and the pROC results. The final map and AUC value are reported here for the average map of the ten replicates. Additionally, the 'kuenm' package was used to calculate the partial area under the ROC curve (pAUC) ratio to evaluate the performance of all models (Cobos et al. 2019). A pAUC ratio >1 indicates that the model has performed better than random chance.

The pROC test was performed for each of the replicates and the average final map. Finally, we have used minimum training presence logistic threshold for creating binary maps (0 and 1) of the predicted distributions.

3. Results:

3.1. Data filtering

We have used E-Bird data to model the monthly distribution of Pied cuckoo to predict its distribution throughout India in different months. We downloaded 21294 points downloaded initially for model building. After removing the duplicate and spatially clustered points total 3375 points were left for 2017-18. The data was split into twelve months for building the models (Supplementary Table 1).

3.2. Model Calibration and evaluation

We have initially calibrated 290 models for each month (total 3480 models) (Supplementary tables 2), among which 3453 number of models were statistically significant. Of these significant models, 562 (16%) met the omission criterion of 5% (Table 2). Finally, of the statistically significant, low-omission monthly models, models with the minimum AICc with selected regularization parameter values and features (Table 3) were used to create the final monthly models. The selection criteria values for each final model varied differently. Final models mean AUC ratio ranged from 1.116 to 1.824, omission rate at 5% ranging from 0.037 to 0.057 (Table 3).

3.3. Importance of bioclimatic variables

We have found the species is present throughout the year in southern India, and Northern Indian distribution is dynamic, highest in June (257400 Km²), and lowest in February (Total predicted area: 189638 km²). In Northern India, distribution started to increase from May before the onset of monsoon and after post-monsoon the distribution decreased gradually. The percent contribution of environmental variables differed between each monthly model (Figure 3). Water vapour pressure contributed highest before its arrival (highest 83% in April) and wind speed during the species departure (highest 42.8% in August). Precipitation was an important variable (24.8% contribution) in May, and NDVI contributed highest in July (26.4%).

4. Discussion

In this study, we have used species occurrence points from e-bird and a set of environmental variables to model the monthly distributions of *C. jacobinus* in India. The monthly dynamic

models produced in this study indicates the arrival of the bird to Northern India has a positive correlation with the onset of monsoon. The amount of contribution of the environmental variables varied every month (Figure 3)

Winter distribution (December to February):

In these months, the species distribution (Figure 4) is restricted to Southern India (Majorly within Andhra Pradesh, Karnataka, Kerala, and Tamil Nadu). In these three months, temperature has been the primary contributing variable restricting the species distribution in Southern India, cumulatively contributing 46.4% in December. *C. jacobinus* is known to have a resident population in Southern India, and temperature is a critical factor restricting its distribution during the colder months of the year.

Summer distribution (March to May):

Distributions in these months (Figure 5) shows that the species first enters the coasts of India, following a similar pattern like monsoon South-west monsoon winds, covering the coastal regions of at first and then gradually starts occupying the Northern and Central parts of India (There are anecdotal records of the species observed early in those regions compared to other areas). In May (Figure 5.C), the species reaches Northern India. Major variables contributing to the distribution for these months were water vapour pressure and wind speed (Figure 3). From March, when the species starts to arrive in the Northern Parts of India, the contribution of Water Vapour Pressure increased drastically (Figure 3); contributing as high as 83.8% in April and again starts decreasing (Lowest in July, contributing 6.5%) when the species reaches Northern India. Here, we hypothesize that the species is probably following the water vapour pressure. A high-water vapour value is a forerunner of rainfall, denoting species' arrival in Northern India just before the monsoon.

Monsoon and Post monsoon distribution (June-October):

In these months, monthly models predicted the species presence throughout Northern India, covering almost all the states of Northern India except the alpine regions. In June (Figure 5.A), Precipitation (24.8%) and Water Vapour Pressure (25.2%) have contributed maximum towards predicting the species distribution, representing the presence of Pied Cuckoo during the monsoon in Northern India. When monsoon arrives in India, the species is present the entire Northern plain parasitizing nests of different hosts (Friedmann, 1984) of respective regions. In July (Figure 6.B), however, NDVI contributes maximum (26.4%) (Figure 3) for

predicting the species distribution. Cuckoos are specialist insectivores, specializing in caterpillar-based diets (Payne, 2005). These caterpillars (mainly *Eupterote modliflora* and *Macrobrochis gigas*) are abundant in rainy seasons when vegetation is green, and abundant food sources are available for the caterpillar. A recent study has found that cuckoos track high average 'greenness' (Thorup et al. 2017). Here, NDVI is considered a surrogate for the vegetation 'greenness.' By the August end, they parasitize its host's nests and start preparing return migration. It is assumed that adults start their migration in October. Also, *C. jacobinus* juveniles start their return migration late without their parents, most likely in late October. In November (Figure 6.F), the species retreats from Northern India, leaving its resident population of Southern India (Majorly the states of Andhra Pradesh, Karnataka, Kerala, and Tamil Nadu). From August, the primary contributing variable is windspeed (Figure 3), factor aiding in its return migration.

5. Conclusion:

Here, we have modeled the monthly distribution of the species throughout India for the first time. A *latitudinal effect* could probably be why the species is present in the northern Part during summer but absent in winter. Many assumptions are present for its migration to date. It is assumed that the South Indian subspecies is resident and the northern India population is migratory. However, it could also be possible that the entire Indian population of this species is dynamic, where a part of the African population migrates and replaces the southern Indian population every year during summer, and the Southern India population migrates to Northern India for breeding. To verify these, we have tagged two Pied cuckoo individuals with 2gm satellite transmitters to identify its migration pathway and its population dynamics in the future.

SDM studies focusing on migratory species are infrequent. SDMs may greatly help define the spatial and temporal variation of habitat suitability for migratory avian species, but their use has been restricted to a few cases (Brambilla and Ficetola. 2012, Sardà-Palomera et al. 2012). However, new frameworks that incorporate such diverging species-environment relationships in time and space (Frans et al. 2018) may enable future studies. Ignoring these issues could, in turn induce an underestimation of areas needed for effective conservation (Runge et al. 2016) or an over-prediction of ranges in general (Reside et al. 2010). Hence, a careful selection of presence records is pivotal to limit such risks (Chamberlain et al. 2013). Our study has supported the hypothesis of migration of *Clamator jacobinus* and its link with the Indian monsoon's arrival. Our approach provides a more concise understanding of monthly

distributions of *C. jacobinus* throughout India, which helps understand the complex seasonal shifts in the distribution of such migratory birds.

3036. **Acknowledgments**

The authors would like to thank Dean & Director, WII, for encouragement. We want to thank Anindita Debnath and Anukul Nath for their inputs. Funding for this paper was by the Department of Biotechnology (DBT), India, through "Indian Bioresource Information Network (IBIN) Geoportal Phase III: Enhancing BioResource Services, Institutional Linkages and Outreach (BT/Coord. II/01/04/2016)" project.

309 **7. Author contributions:**

Debanjan Sarkar: Conceptualization, Data curation, Methodology, Analysis, Writing-Original draft preparation. Bharti Tomar: Data curation, Analysis. R. Suresh Kumar: Conceptualization, Supervision. Sameer Saran: Supervision. Gautam Talukdar: Conceptualization, Methodology, Investigation, Supervision, Writing-Original draft preparation.

315 **8. Competing interest**

The authors declare no competing interests.

317 9. References

- 318 Abdulali, H., 1972. Some bird notes by WF Sinclair. J. Bombay Nat. History Soc, 69, pp.422-424.
- 319 Ali, S. and Ripley, S.D., 1983. Handbook of the birds of India and Pakistan (Compact Edition). Oxford
320 University Press and BNHS, Mumbai. Ali, S. and SD Ripley (1995). The Pictorial Guide to the Birds of Indian
321 Sub-continent. Oxford University Press and BNHS, Mumbai.
- 322 Anadón, J.D., Wiegand, T. and Giménez, A., 2012. Individual-based movement models reveals sex-biased
323 effects of landscape fragmentation on animal movement. Ecosphere, 3(7), pp.1-32.
- 324 Betts FN. 1929. Migration of the Pied Crested Cuckoo *Clamator jacobinus*. Journal of the Bombay Natural
325 History Society 33(3): 714.
- 326 Boria, R.A., Olson, L.E., Goodman, S.M. and Anderson, R.P., 2014. Spatial filtering to reduce sampling bias
327 can improve the performance of ecological niche models. Ecological modelling, 275, pp.73-77.
- 328 Brambilla, M. and Ficetola, G.F., 2012. Species distribution models as a tool to estimate reproductive
329 parameters: a case study with a passerine bird species. Journal of Animal Ecology, 81(4), pp.781-787.
- 330 Brown, J.L., 2014. SDM toolbox: a python-based GIS toolkit for landscape genetic, biogeographic and species
331 distribution model analyses. Methods in Ecology and Evolution, 5(7), pp.694-700.
- 332 Chamberlain, D.E., Negro, M., Caprio, E. and Rolando, A., 2013. Assessing the sensitivity of alpine birds to
333 potential future changes in habitat and climate to inform management strategies. Biological conservation, 167,
334 pp.127-135.
- 335 Chopra, C.P., 2017. Vishnu's mount: birds in Indian mythology and folklore. Notion Press.
- 336 Migrantwatch. 2013. Does the Pied Cuckoo herald the monsoon?
337 <http://www.migrantwatch.in/blog/2013/04/04/does-the-pied-cuckoo-herald-the-monsoon/>
- 338 Madhusudan, R. D. 2017. The Rain Bird and the Monsoon. BirdcountIndia. [https://birdcount.in/rain-bird-](https://birdcount.in/rain-bird-monsoon/)
339 [monsoon/](https://birdcount.in/rain-bird-monsoon/)
- 340 Cobos, M.E., Peterson, A.T., Barve, N. and Osorio-Olvera, L., 2019. kuenm: an R package for detailed
341 development of ecological niche models using Maxent. PeerJ, 7, p.e6281.
- 342 Cox, T.E., Philippoff, J., Baumgartner, E. and Smith, C.M., 2012. Expert variability provides perspective on the
343 strengths and weaknesses of citizen-driven intertidal monitoring program. Ecological Applications, 22(4),
344 pp.1201-1212.
- 345 Coxen, C.L., Frey, J.K., Carleton, S.A. and Collins, D.P., 2017. Species distribution models for a migratory bird
346 based on citizen science and satellite tracking data. Global ecology and conservation, 11, pp.298-311.
- 347 Crall, A.W., Newman, G.J., Jarnevich, C.S., Stohlgren, T.J., Waller, D.M. and Graham, J., 2010. Improving and
348 integrating data on invasive species collected by citizen scientists. Biological Invasions, 12(10), pp.3419-3428.
- 349 Didan, K., Munoz, A.B., Solano, R. and Huete, A., 2015. MODIS vegetation index user's guide (MOD13
350 series). University of Arizona: Vegetation Index and Phenology Lab.
- 351 Elith, J., H. Graham, C., P. Anderson, R., Dudík, M., Ferrier, S., Guisan, A., J. Hijmans, R., Huettmann, F., R.
352 Leathwick, J., Lehmann, A. and Li, J., 2006. Novel methods improve prediction of species' distributions from
353 occurrence data. Ecology, 29(2), pp.129-151.
- 354 Elith, J. and Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across
355 space and time. Annual review of ecology, evolution, and systematics, 40, pp.677-697.
- 356 Engler, J.O., Rödder, D., Stiels, D. and Förchler, M.I., 2014. Suitable, reachable but not colonised: seasonal
357 niche duality in an endemic mountainous songbird. Journal of ornithology, 155(3), pp.657-669.

Engler, J.O., Stiels, D., Schidelko, K., Strubbe, D., Quillfeldt, P. and Brambilla, M., 2017. Avian SDMs: current state, challenges, and opportunities. *Journal of avian biology*, 48(12), pp.1483-1504.

Eyres, A., Böhning-Gaese, K. and Fritz, S.A., 2017. Quantification of climatic niches in birds: adding the temporal dimension. *Journal of Avian Biology*, 48(12), pp.1517-1531.

Fick, S.E. and Hijmans, R.J., 2017. WorldClim 2: new 1 km spatial resolution climate surfaces for global land areas. *International journal of climatology*, 37(12), pp.4302-4315.

Fourcade, Y., Engler, J.O., Rödder, D. and Secondi, J., 2014. Mapping species distributions with MAXENT using a geographically biased sample of presence data: a performance assessment of methods for correcting sampling bias. *PloS one*, 9(5).

Frans, V.F., Augé, A.A., Edelhoff, H., Erasmí, S., Balkenhol, N. and Engler, J.O., 2018. Quantifying apart what belongs together: A multi-state species distribution modelling framework for species using distinct habitats. *Methods in Ecology and Evolution*, 9(1), pp.98-108.

Friedmann, H., 1964. Evolutionary trends in the avian genus *Clamator*. *Smithsonian Miscellaneous Collections*.

Gaston, A.J., 1976. Brood parasitism by the pied crested cuckoo *Clamator jacobinus*. *The Journal of Animal Ecology*, pp.331-348.

Gschweng, M., Kalko, E.K., Berthold, P., Fiedler, W. and Fahr, J., 2012. Multi-temporal distribution modelling with satellite tracking data: predicting responses of a long-distance migrant to changing environmental conditions. *Journal of Applied Ecology*, 49(4), pp.803-813.

Guisan, A. and Thuiller, W., 2005. Predicting species distribution: offering more than simple habitat models. *Ecology letters*, 8(9), pp.993-1009.

Hackett, S.J., Kimball, R.T., Reddy, S., Bowie, R.C., Braun, E.L., Braun, M.J., Chojnowski, J.L., Cox, W.A., Han, K.L., Harshman, J. and Huddleston, C.J., 2008. A phylogenomic study of birds reveals their evolutionary history. *science*, 320(5884), pp.1763-1768.

Jackson, M.M., Gergel, S.E. and Martin, K., 2015. Citizen science and field survey observations provide comparable results for mapping Vancouver Island White-tailed Ptarmigan (*Lagopus leucura saxatilis*) distributions. *Biological Conservation*, 181, pp.162-172.

Johnsingh, A.J.T. and Paramanandham, K., 1982. Group care of white-headed babblers *Turdoides affinis* for a pied crested cuckoo *Clamator jacobinus* chick. *Ibis*, 124(2), pp.179-183.

Joseph, L. and Stockwell, D., 2000. Temperature-based models of the migration of Swainson's Flycatcher (*Myiarchus swainsoni*) across South America: A new use for museum specimens of migratory birds. *Proceedings of the Academy of Natural Sciences of Philadelphia*, pp.293-300.

Joseph, L., 1996. Preliminary climatic overview of migration patterns in South American austral migrant passerines. *Ecotropica*, 2(2), pp.185-193.

Kālidāsa and Kāle, M.R., 1974. The Meghadūta of Kālidāsa: Text with Sanskrit Commentary of Mallinātha, English Translation, Notes, Appendices and a Map. Motilal Banarsidass.

Kaliontzopoulou, A., Brito, J.C., Carretero, M.A., Larbes, S. and Harris, D.J., 2008. Modelling the partially unknown distribution of wall lizards (*Podarcis*) in North Africa: ecological affinities, potential areas of occurrence, and methodological constraints. *Canadian Journal of Zoology*, 86(9), pp.992-1001.

Khachar, S., 1990. Pied Crested Cuckoo *Clamator jacobinus*-the harbinger of the monsoon. *Journal of the Bombay Natural History Society*, 86(3), 448-449.

- 398 Lin, Y.P., Deng, D., Lin, W.C., Lemmens, R., Crossman, N.D., Henle, K. and Schmeller, D.S., 2015.
399 Uncertainty analysis of crowd-sourced and professionally collected field data used in species distribution
400 models of Taiwanese moths. *Biological conservation*, 181, pp.102-110.
- 401 Martínez-Meyer, E., Townsend Peterson, A. and Navarro-Sigüenza, A.G., 2004. Evolution of seasonal
402 ecological niches in the Passerina buntings (Aves: Cardinalidae). *Proceedings of the Royal Society of London.*
403 *Series B: Biological Sciences*, 271(1544), pp.1151-1157.
- 404 Nakazawa, Y., Peterson, A.T., Martínez-Meyer, E. and Navarro-Sigüenza, A.G., 2004. Seasonal niches of
405 Nearctic-Neotropical migratory birds: implications for the evolution of migration. *The Auk*, 121(2), pp.610-618.
- 406 Payne, R. & de Juana, E., 2020. Jacobin Cuckoo (*Clamator jacobinus*). In: del Hoyo, J., Elliott, A., Sargatal, J.,
407 Christie, D.A. & de Juana, E. (eds.). *Handbook of the Birds of the World Alive*. Lynx Edicions, Barcelona.
408 (retrieved from <https://www.hbw.com/node/54785> on 10 April 2020).
- 409 Payne, R.B. and Sorensen, M.D., 2005. *The cuckoos* (Vol. 15). Oxford University Press.
- 410 Pearce, J.L. and Boyce, M.S., 2006. Modelling distribution and abundance with presence-only data. *Journal of*
411 *applied ecology*, 43(3), pp.405-412.
- 412 Peterson, A.T., Ball, L.G. and Cohoon, K.P., 2002. Predicting distributions of Mexican birds using ecological
413 niche modelling methods. *Ibis*, 144(1), pp.E27-E32.
- 414 Phillips, S.J., Anderson, R.P. and Schapire, R.E., 2006. Maximum entropy modeling of species geographic
415 distributions. *Ecological modelling*, 190(3-4), pp.231-259.
- 416 Pillai NG. 1943. Migration of Pied Crested Cuckoo [*Clamator jacobinus* (Boddaert)]. *Journal of the Bombay*
417 *Natural History Society* 43(4): 658.
- 418 Pocewicz, A., Estes-Zumpf, W.A., Andersen, M.D., Copeland, H.E., Keinath, D.A. and Griscom, H.R., 2013.
419 Modeling the distribution of migratory bird stopovers to inform landscape-scale siting of wind
420 development. *PloS one*, 8(10).
- 421 Reside, A.E., VanDerWal, J.J., Kutt, A.S. and Perkins, G.C., 2010. Weather, not climate, defines distributions
422 of vagile bird species. *PloS one*, 5(10).
- 423 Revell, C. and Somveille, M., 2017. A physics-inspired mechanistic model of migratory movement patterns in
424 birds. *Scientific reports*, 7(1), pp.1-10.
- 425 Runge, C.A., Tulloch, A.I., Possingham, H.P., Tulloch, V.J. and Fuller, R.A., 2016. Incorporating dynamic
426 distributions into spatial prioritization. *Diversity and Distributions*, 22(3), pp.332-343.
- 427 Sardà-Palomera, F., Puigcerver, M., Brotons, L. and Rodríguez-Teijeiro, J.D., 2012. Modelling seasonal
428 changes in the distribution of Common Quail *Coturnix coturnix* in farmland landscapes using remote
429 sensing. *Ibis*, 154(4), pp.703-713.
- 430 Schluter, D., 1996. Ecological causes of adaptive radiation. *The American Naturalist*, 148, pp. S40-S64.
- 431 Simmons RM. 1930. Migration of the Pied Crested-Cuckoo (*Coccyzus jacobinus*). *Journal of the Bombay*
432 *Natural History Society* 34(1): 252-253.
- 433 Steen, V.A., Elphick, C.S. and Tingley, M.W., 2019. An evaluation of stringent filtering to improve species
434 distribution models from citizen science data. *Diversity and Distributions*, 25(12), pp.1857-1869.
- 435 Steen, V.A., Elphick, C.S. and Tingley, M.W., 2019. An evaluation of stringent filtering to improve species
436 distribution models from citizen science data. *Diversity and Distributions*, 25(12), pp.1857-1869.

- 437 Suárez-Seoane, S., de la Morena, E.L.G., Prieto, M.B.M., Osborne, P.E. and de Juana, E., 2008. Maximum
438 entropy niche-based modelling of seasonal changes in little bustard (*Tetrax tetrax*) distribution. ecological
439 modelling, 219(1-2), pp.17-29.
- 440 Sullivan, B.L., Wood, C.L., Iliff, M.J., Bonney, R.E., Fink, D. and Kelling, S., 2009. eBird: A citizen-based bird
441 observation network in the biological sciences. Biological conservation, 142(10), pp.2282-2292.
- 442 Sutherland, W.J., Newton, I. and Green, R., 2004. Bird ecology and conservation: a handbook of
443 techniques (Vol. 1). OUP Oxford.
- 444 Team, R.C., 2018. R Foundation for Statistical Computing; Vienna, Austria: 2015. R: A language and
445 environment for statistical computing, p.2013.
- 446 Thorup, K. and Rabøl, J., 2001. The orientation system and migration pattern of long-distance migrants:
447 conflict between model predictions and observed patterns. Journal of Avian Biology, 32(2), pp.111-119.
- 448 Thorup, K., Tøttrup, A.P., Willemoes, M., Klaassen, R.H., Strandberg, R., Vega, M.L., Dasari, H.P., Araújo,
449 M.B., Wikelski, M. and Rahbek, C., 2017. Resource tracking within and across continents in long-distance bird
450 migrants. Science Advances, 3(1), p.e1601360.
- 451 Warren, D.L., Glor, R.E. and Turelli, M., 2010. ENMTools: a toolbox for comparative studies of environmental
452 niche models. Ecography, 33(3), pp.607-611.
- 453 Wen, L., Saintilan, N., Yang, X., Hunter, S. and Mawer, D., 2015. MODIS NDVI based metrics improve habitat
454 suitability modelling in fragmented patchy floodplains. Remote Sensing Applications: Society and
455 Environment, 1, pp.85-97.
- 456 Whistler, H., 1928. The migration of the Pied Crested Cuckoo (*Clamator jacobinus*). J. Bombay nat. Hist.
457 Soc, 33, p.46.
- 458 Williams, H.M., Willemoes, M. and Thorup, K., 2017. A temporally explicit species distribution model for a
459 long-distance avian migrant, the common cuckoo. Journal of Avian Biology, 48(12), pp.1624-1636.
- 460 Williams, H.M., Willemoes, M. and Thorup, K., 2017. A temporally explicit species distribution model for a
461 long-distance avian migrant, the common cuckoo. Journal of Avian Biology, 48(12), pp.1624-1636.
- 462 Wisz, M.S., Hijmans, R.J., Li, J., Peterson, A.T., Graham, C.H., Guisan, A. and NCEAS Predicting Species
463 Distributions Working Group, 2008. Effects of sample size on the performance of species distribution models.
464 Diversity and distributions, 14(5), pp.763-773.
- 465 Zhang, G. and Zhu, A.X., 2019. A representativeness-directed approach to mitigate spatial bias in VGI for the
466 predictive mapping of geographic phenomena. International Journal of Geographical Information
467 Science, 33(9), pp.1873-1893.

Figure Legends:

Figure 1. Photograph of a pied Cuckoo (*Clamator jacobinus*)

Figure 2. Study area for modeling the distribution of the Jacobin Cuckoo (*Clamator jacobinus*). Point locations denote the species presence (obtained from E-Bird). Native resident denotes resident species within the country whereas the migratory denotes the migratory population (Species range source: Birdlife International)

Figure 3. Percentage contribution of the bioclimatic variables used for monthly models of the Pied Cuckoo (*Clamator jacobinus*)

Figure 4. Winter distribution (4.A. December; 4.B. January, 4.C. February) of the Pied Cuckoo in India. Red colour denote higher value whereas blue is the lowest. The distribution of the species is limited in the Southern India in winter, lowest in February (4.C)

Figure 5. Predicted summer distribution (5.A. March; 5.B. April, 5.C. May) of the Pied Cuckoo (*Clamator jacobinus*) in India. Red colour denote higher value whereas blue is the lowest prediction.

Figure 6. Monsoon and Post monsoon distribution (6. A June; 6. B. July; 6. C. August; 6. D. September; 6. E. October, 6. F. November; Red colour denote higher value whereas blue is the lowest prediction.

Figure 7. Summary of the migration cycle of Pied Cuckoo (*Clamator jacobinus*) in India and main bioclimatic variables affecting distribution in different months. More details of the contribution of each variable are provided in figure 3

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497 **Table 1.** List of variables used for modeling the distribution.

Bioclimatic variables used	Abbreviations	Unit	Source
Precipitation	Prec	Mm	http://worldclim.org/version2 (Fick & Hijmans, 2017)
Solar Radiation	Srad	$\text{kJ m}^2 \text{ day}^{-1}$	
Average Temperature	Tavg	° C	
Maximum Temperature	Tmax	° C	
Minimum Temperature	Tmin	° C	
Water vapour pressure	Wvap	kPa	
Wind Speed	Wspeed	m/sec	
NDVI, 2018 for 12 months	NDVI_month	Ratio (-1 to 1)	USGS EarthExplorer, eMODIS NDVI (Didan, 2014)

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Table 2. General Statistics of models that met distinct criteria

Model month	All candidate models	Statistically significant models	Models meeting omission rate criteria	Models meeting AICc criteria	Statistically significant models meeting omission rate criteria	Statistically significant models meeting AICc criteria	Statistically significant models meeting omission rate and AICc criteria
January	290	290	257	1	257	1	1
February	290	281	0	1	0	1	0
March	290	290	0	2	0	2	0
April	290	281	0	1	0	1	0
May	290	290	7	2	7	2	2
June	290	281	0	1	0	1	0
July	290	290	223	1	223	1	1
August	290	290	2	1	2	1	1
September	290	290	32	2	32	2	2
October	290	290	7	2	7	2	2
November	290	290	2	1	2	1	1
December	290	290	32	2	32	2	2

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503 **Table 3.** Performance statistics for the best monthly models.

Model month	Mean AUC ratio	Partial ROC	Omission rate at 5%	AICc	Delta AICc	W AICc	Num parameters
January	1.76	0	0.057	6147.78	0	1	17
February	1.62	0	0.051	3248.176	0	1	25
March	1.474	0	0.051	3320.74	0	1	19
April	1.208	0	0.037	13436.16	0	0.987	69
May	1.36	0	0.043	4261.388	0	0.466	13
June	1.208	0	0.037	13436.16	0	0.987	69
July	1.231	0	0.046	12623.6	0	1	67
August	1.116	0	0.038	13046.17	0	1	26
September	1.263	0	0.05	11901.38	0	0.590	84
October	1.208	0	0.037	13436.16	0	0.987	69
November	1.231	0	0.046	12623.6	0	1	67
December	1.824	0	0.036	4985.472	0	1	38

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