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Role of Maximum Entropy and Citizen Science to Study Habitat Suitability of Jacobin Cuckoo in Different Climate Change Scenarios

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Abstract: Recent advancements in spatial modelling and mapping methods have opened up new horizons for monitoring the migration of bird species, which have been altered due to the climate change. The rise of citizen science has also aided the spatiotemporal data collection with associated attributes. The biodiversity data from citizen observatories can be employed in machine learning algorithms for predicting suitable environmental conditions for species' survival and their future migration behaviours. In this study, different environmental variables effective in birds' migrations were analysed, and their habitat suitability was assessed for future understanding of their responses in different climate change scenarios. The Jacobin cuckoo (*Clamator jacobinus*) was selected as the subject species, since their arrival to India has been traditionally considered as a sign for the start of the Indian monsoon season. For suitability predictions in current and future scenarios, maximum entropy (Maxent) modelling was carried out with environmental variables and species occurrences observed in India and Africa. For modelling, the correlation test was performed on the environmental variables (bioclimatic, precipitation, minimum temperature, maximum temperature, precipitation, wind and elevation). The results showed that precipitation-related variables played a significant role in suitability, and through reclassified habitat suitability maps, it was observed that the suitable areas of India and Africa might decrease in future climatic scenarios (SSPs 2.6, 4.5, 7.0 and 8.5) of 2030 and 2050. In addition, the suitability and unsuitability areas were calculated (in km²) to observe the subtle changes in the ecosystem. Such climate change studies can support biodiversity research and improve the agricultural economy.

Keywords: citizen science; machine learning; Indian monsoon; Jacobin cuckoo; Maxent; species distribution model; habitat suitability; range expansion; WorldClim; CMIP

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1. Introduction

The exponential change in the climate has directly affected the spatial distribution of species and communities in ecosystems, which is an essential requirement to understand the functions and processes of the ecosystem. As such, species movement in response to climatic shifts could be projected from species distribution models (SDMs), which provide an empirical way to assess the climatic impacts for the changes of species habitats (for example, reference [1]). A habitat is defined as a particular location where species live and reproduce with certain characteristics, behaviour, interactions and population patterns [2]. A favourable habitat that is significant for the survival of a species is called habitat suitability [3] and has importance in ecological research through habitat suitability modelling, which can help in conservation and protection plans. Several studies have investigated the suitability of species' habitats using maximum entropy (Maxent) [4] for evaluating the species range using geolocation data; for example, references [5–12]. The

Maxent model has gained popularity in the literature for the modelling of species' spatial distributions, and related studies have received over 5000 citations in the Web of Science Core Collection, mostly used by distribution modelers (ca. >60%) [13]. In recent decades, countless studies have been carried out on the suitability of species' habitats using the maximum entropy method for evaluating species ranges using presence-only data [14–19]. Such studies help to derive useful guidelines on the parameterisations of the model, such as the minimum sample size and data sample requirement, selection of random samples from voluminous datasets and the determination of subsampling process for range predictions per species and per sample size [14–16,18,19].

Although such data-intensive modelling approaches can help in identifying the major factors behind species range expansion [20], the occurrences of species, which poses a significant contribution to the model, should preferably be recorded across spatial (species range) and temporal (time of observation) contexts. However, it is intrinsically a problematic and costly task to record geographically varied near-real-time observations, because such activities need the continuous monitoring of species movements, so the species are tagged with tracking devices without causing any harm to them. Therefore, these real-time or near-real-time observations through a volunteering approach for data collection could help in quantifying the species fitness at a large spatial scale and informing about the changes in climatic patterns. The species properties can also be obtained from floras, the literature, herbaria and museums as theoretical data to model the habitat suitability of a species [21]. However, the main challenge remains the spatial uncertainty, which may be sourced from incorrect geotagging or wrong datum information [21,22]. Until recently, the species data were collected and recorded as a textual description in the forms of names and places [22], and digitising the textual information also causes substantial errors and brings spatial uncertainty in the order of several kilometres [23]. Various techniques have been developed to estimate and to document the location uncertainty among species' occurrence records in order to eliminate high errors prior to suitability modelling [22,24].

Trained and untrained volunteers have helped in the data collection processes as a citizen science approach, which may provide robust and rigorous data with qualitative and quantitative attributes. The data collected using citizen science approaches have been applied to ecological niche models in recent years to mitigate the gaps in the quantity and quality of data, which also improved the approximation of the metric of interest [25]. Species distribution modelling for particular species requires a sufficient number of occurrences distributed across its extant [26–28]. Citizen science is a broad concept that can be understood in different forms [29], from highly systematic protocols to opportunistic surveys with no sampling designs [29,30].

In this paper, a ML-based maximum entropy (Maxent) algorithm was applied to Jacobin cuckoo (pied cuckoo or pied-crested cuckoo) occurrences with environmental variables, such as to evaluate the potential habitat suitability in Africa and in India. For the modelling procedure, the birds' occurrences were first divided into three time periods—June–September, which refers to India's southwest monsoon, October–December, which refers to India's northwest monsoon and Africa's wet season, and January–May—to predict the suitability site of the Jacobin cuckoo, as most parts of India have winter and summer seasons. This approach was also used to predict the change in monsoon patterns by modelling how this bird's favourable habitats will shift under different climate change scenarios. For this future prediction modelling, the obtained modelling results of current suitability with the existing environmental variables and species occurrences was projected with future models to observe the probable climatic changes in 2030 (an average of 2021–2040) and 2050 (an average of 2041–2060). In addition, the areas of suitability and unsuitability sites were also calculated to analyse the increase or decrease in the ecological system in response to changes in the monsoon patterns. The first ever Indian monsoon climate change study in terms of Jacobin cuckoos' migration was performed by Singh and Saran [31], in which the geographic occurrences of the Jacobin cuckoo with 19 current bioclimatic variables were modelled using the ML-based Maxent model in R software. This trained

model was then projected with future bioclimatic variables under the RCP8.5 scenario of the Coupled Model Intercomparison Project (CMIP5) to assess the predicted changes in the suitability of Pied cuckoos' habitats by 2050. Specifically, the current and future bioclimatic variables were used at a resolution of 2.5 arc seconds (~4.5 km at the equator) of latitude and longitude. The above-mentioned study signified that the major environmental variables that affect the suitability of the Jacobin cuckoo were isothermality (16.8%), the mean temperature of the warmest quarter (15.7%), annual precipitation, precipitation of the warmest quarter (13.6%) and precipitation of the wettest month (11.3%) during the Indian summer monsoon season, i.e., June–October. As per the current suitability predictions, the states of Southern India—Andhra Pradesh, Goa, Karnataka, Kerala, Maharashtra and Tamil Nadu—and Northern India—Uttarakhand and Himachal Pradesh—showed high, as well as medium, habitat suitability, and the western states (e.g., Gujarat) displayed medium suitability; southern Africa was found unsuitable for this bird, because in the June–October months, a dry and hot climate is experienced there, which is not a favourable habitat. However, according to the future suitability prediction of this bird, the Jacobin cuckoo range contraction could happen in all parts of India except the southern parts of Tamil Nadu due to increased greenhouse gas emissions and a decrease in precipitation of the warmest quarter. In addition, the quantiles (5% and 95%) of the relevant environmental variables were calculated to observe the changes in climates of now and 2050 with respect to Indian monsoon seasons.

2. Citizen Science as a Biodiversity Research Method

The act of engaging volunteers in scientific tasks has proliferated in the past few decades with offered, more pressing opportunities for participants to deliver advanced approaches and make meaningful insights into their collected data. The activity of effectively utilising crowdsourcing, along with the Internet and mobile applications, over large geographic regions is known as citizen science. Citizen science “is a process where concerned citizens, government agencies, industry, academia, community groups, and local institutions collaborate to monitor, track and respond to issues of common community concern” [32] and “where citizens and stakeholders are included in the management of resources” [33,34]. Citizen science involves both professionals and non-professionals participating in both scientific thinking and data collection [33,35] with the support of technological advancements, such as smart phones with location services, camera, accelerometer, etc. [36]. However, based on its nature of engagement and utility in diverse domains, citizen science may have different conceptual definitions and meanings.

According to the nature of engagement, the galaxy of citizen science is categorised into four levels—crowdsourcing, distributed intelligence, participatory science and extreme [37]. Crowdsourcing is the most basic level, where the general public can contribute to science by processing and analysing collected data. The next level is distributed intelligence, in which citizens learn new skills before becoming involved in data collection and interpretation activities. The third level is participatory science, where citizens are involved with research groups for defining problems and data collection. The last level is extreme, where citizens are equipped with full control to define problems, collect data and performing analyses on it.

As per its utility in various projects with different aims, Wiggins and Crownston [38] classified citizen science projects into five mutually exclusive and exhaustive types—action, education, conservation, investigation and virtual projects. The various action projects address local issues with the joint collaboration of citizens and scientists/researchers—for example, references [39–49]—and education projects help in improving the knowledge of citizens as part of the curriculum [50–55]. The conservation projects focus on the management of natural resources—for example, reference [19]—investigation projects emphasise the study of citizen's observations combined with different parameters to answer scientific questions [56,57] and virtual projects involve remote citizen science activities [58–61].

The above classification schemes can be demonstrated with the example of Project PigeonWatch, which is one of the citizen science projects at the Cornell Lab of Ornithology (CLO) and the National Audubon Society that engage many volunteers of all ages and professions throughout the world to collect hands-on data to study and analyse pigeon colour variations. On the basis of the above checklist, this project can be characterised as an “investigation” project, and the utilised approach is “crowdsourcing”.

Amidst various citizen science projects, 72% of the projects relate to the discipline of biology [62], and due to such dominance in this area, the study and research on the diversity and distribution of species [63] advance the rapid need for biodiversity monitoring, conservation planning and ecological research. Many citizen science programs have been realised over the span of years or even decades and are still being carried out to study the patterns of nature on a large spatial scale by collecting data on different locations and habitats of species. The way of collecting such information on the species’ locations, habitats and other related information [63–65] by enlisting the public in scientific activities is now considered the best practice. It is not necessarily true that the scientific output is always benefitted by robust strategies and inferences from highly recognised and peer-reviewed scientific publications; rather, gathering information through public participation could be a better source of scientific information to answer specific questions [66,67]. Higher credit may be given to Cornell University’s Lab of Ornithology, which laid the foundation for volunteer participation in biodiversity observations, monitoring and research [52]. However, there are many other organisations and research groups that have designed various citizen science programs to collect geographically well-distributed and dense data with rigorous spatial sampling, such as Species Mapping through the Indian Bioresource Information Network (IBIN) portal [68], bioblitz [69], the shell polymorphism survey [70], the water quality survey [71] and breeding bird surveys [72]. Such diverse datasets compel the aggregation of observation data from different sources for conventional research, but the major concerns even after data aggregation are data quality [73] and techniques for combining diverse datasets into different schemas [74]. Therefore, apposite planning is required for managing the voluminous dataset integration into a uniform schema with data quality check infrastructure for handling observational biases, “false absences” that yield to inadequate sightings [75] and uneven data distributions [76]. These challenges were addressed by a global concerted effort [77] that began in 2004 and has now resulted into the largest single gateway to observation-based datasets, known as the Global Biodiversity Information Facility (GBIF).

The GBIF is an intergovernmental organisation that provides “an Internet accessible, interoperable network of biodiversity databases and information technology tools” [78] as a “cornerstone resource” [79], with a “mission to make the world’s biodiversity data freely and universally available via the Internet” [79]. Currently, the GBIF portal provides open access to more than 160 million biodiversity occurrences and taxa data from 1641 institutions and volunteered surveying data around the globe. Therefore, the GBIF has become an authentic repository where various organisations/institutes share their data with quality and in large quantity, which are essential for modelling and decision-making purposes. Edwards et al. [77] performed a spatial validation of the third-largest flowering plant family, the Leguminosa, using its taxa and distribution data from the GBIF portal to evaluate the quality and coverage of its geographic occurrences. Similar reviews could be seen by Graham et al. [21] and Suarez and Tsutsui [80] for additional uses of museum specimen data, which facilitated biodiversity policy and decision-making process [80]. Amongst the various other advantages, GBIF data can be used for biodiversity assessments [81], taxonomic revisions [82], compiling red lists of threatened species [83] and habitat suitability modelling [31,84–87]. The latter is one of the prominent examples of climate change studies in which citizen science-based observations from the GBIF are being increasingly used [88–95]. In this paper, different climate change scenarios combined with the GBIF’s observed occurrences of the monsoon favourable bird, *Clamator jacobinus*,

are modelled using the Maxent approach to study the contemporary and future habitat suitability of this bird so that the variations in the Indian monsoon season can be examined.

3. Materials and Methods

3.1. The Jacobin (Pied) Cuckoo Species

As per Indian belief, the arrival of this partially migrated bird, the Jacobin cuckoo (*Clamator jacobinus*) (Figure 1), also known as “Chatak” in India, heralds the onset of the Indian monsoon [96]. During the summer, the bird flies from Africa to India for breeding, crossing the Arabian Sea and the Indian Ocean, as shown in Figure 2. The Jacobin Cuckoo belongs to the cuckoo order of small terrestrial birds with black and white soft plumage and long-wings with a spiffy crest on the head that quenches its thirst with raindrops. The species is also known as a brood parasite, i.e., instead of making its own nest, it lays its eggs in the nest of other birds, particularly Jungle babbler (*Turdoides striata*). This bird of an arboreal nature mostly sits on tall trees but often forages for food in low bushes and, occasionally, on the ground. It prefers well-wooded areas, forests and bushes in semi-arid regions. As widely known, the Jacobin cuckoo maintains their suitability in India in two ways. There is a population that is sighted as residents year-round in the southern part of the country. The Jacobin cuckoo is also sighted in the central and northern parts of India along with summer monsoon winds from just before the monsoon to early winter, i.e., May–August. The reason behind choosing the Jacobin cuckoo was that the arrival time of this bird is directly linked with the monsoon because it only drinks rainwater drops as it pours down and does not utilise any other water sources, such as collected rain waters, rivers, etc., to quench its thirst.



Figure 1. Image of *Clamator jacobinus* (Jacobin cuckoo or Pied cuckoo) (Source: Pied Cuckoo Macaulay Library ML32455551).

3.2. The Species Distribution Data and the Preprocessing

The distribution data was obtained from the GBIF repository that collated geographic records of this bird from surveys, museums, human observations and other data sources. Then, those occurrences recorded through “human observation” were selected for this study, because this research was focused on demonstrating the use of citizen science data for habitat suitability modelling [97]. The institutes/organisations contributed this bird’s data in the “human observation” category through various citizen science programs. These institutes/organisations are the Cornell Lab of Ornithology, FitzPatrick Institute of African Ornithology, South African National Biodiversity Institute, iNaturalist.org, Observation.org, Xeno-canto Foundation for Nature Sounds, naturgucker.de, Kenya Wildlife Service, India Biodiversity Portal and A Rocha Kenya. However, the dataset contained repeated latitude and longitude values, as well as null values (NA: not available). By using a data cleaning algorithm in R, records with NA values and duplicated locations were removed. Since the

Jacobin cuckoos are known for their close association with the onset of monsoon season in India, the compiled GPS records of human observations from 1991 to 2020 were divided into the following monthly sets:

- i. Based on the period of the southwest monsoon season that typically lasts from June to September, the geographic occurrences of the Jacobin cuckoo were filtered for these months starting from the year 1991 to 2020. In this period, the whole country receives more than 75% of its rainfall [98].
- ii. The second input set was filtered using the months of northeast monsoon season, i.e., October–December. This monsoon season is also known as post-monsoon or winter monsoon season, in which the country receives about 60% of its annual rainfall in the coastal areas and about 40% in the interior areas [99]. Additionally, the rainy season starts from October and lasts until April–June in Africa, where the conditions are mostly suitable for its residency.
- iii. The third and final set contains the data of months January–May that denote the mid-rainy period and end of the rainy season in Africa and India, respectively.

Hence, the abovementioned sets of geographic occurrences were combined with environmental datasets to understand their potential suitability ranges, environmental parameters and altered climatic variations in different climate change scenarios.

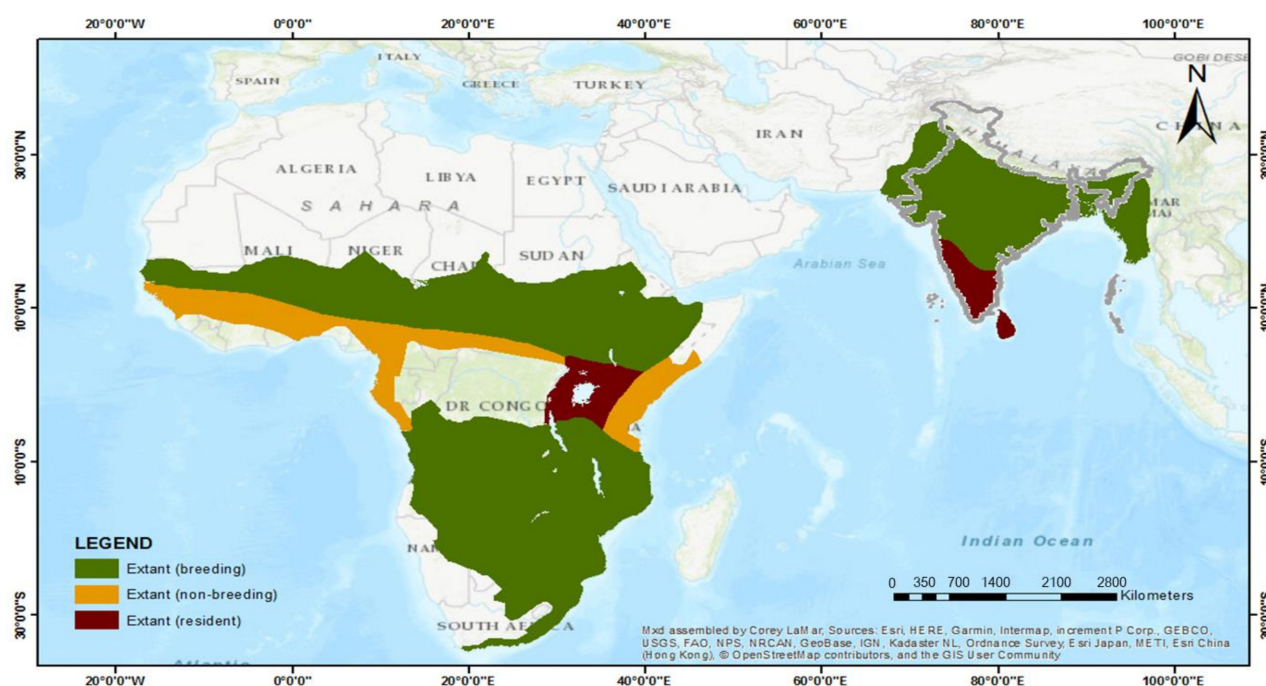


Figure 2. Extant map of *Clamator jacobinus* (Pied cuckoo) (Image Source: reference [30]).

3.3. Environmental Data

3.3.1. Selection of Environmental Variables

This section discusses the selection of environmental data that are assumed to ecologically influence mobile species like birds, particularly the Jacobin cuckoo distribution. These include bioclimatic variables, minimum temperature, maximum temperature, precipitation, elevation and wind at the spatial resolution of 2.5 arc-min from WorldClim. For the present climatic conditions, the bioclimatic variables, which were averaged for the years 1970–2000, were obtained from WorldClim version 2.1, the latest version of climate data launched in January 2020 [100]. As per this study, modelling was carried out for three different time periods; therefore, climatic variables such as precipitation, wind, minimum temperature and maximum temperature were taken and screened for the given three sets.

For future sets, 19 bioclimatic variables (Table 1) for the near-future (2021–2040) and remote-future (2041–2060) projections of the species distribution maps at 2.5 arc-min were obtained from WorldClim [101]. For future climate scenarios, the CIMP's climate data of the CNRM-ESM2-1 [102] global climate model (GCM) for four Shared Socioeconomic Pathways (SSPs): 126, 245, 370 and 585 were obtained from WorldClim's database, which was spatially downscaled and calibrated to reduce the bias.

Table 1. Environmental variables used in the habitat suitability modelling process.

Bioclimatic Variable Code	Bioclimatic Variable Name	Unit
BIO1	Annual Mean Temperature	°C
BIO2	Mean Diurnal Range (Mean of monthly (max temp–min temp))	°C
BIO3	Isothermality (BIO2/BIO7)	dimensionless
BIO4	Temperature Seasonality (Standard Deviation)	°C
BIO5	Max Temperature of Warmest Month	°C
BIO6	Min Temperature of Coldest Month	°C
BIO7	Temperature Annual Range (BIO5–BIO6)	°C
BIO8	Mean Temperature of Wettest Quarter	°C
BIO9	Mean Temperature of Driest Quarter	°C
BIO10	Mean Temperature of Warmest Quarter	°C
BIO11	Mean Temperature of Coldest Quarter	°C
BIO12	Annual Precipitation	mm
BIO13	Precipitation of Wettest Month	mm
BIO14	Precipitation of Driest Month	mm
BIO15	Precipitation Seasonality (Coefficient of Variation)	fraction
BIO16	Precipitation of Wettest Quarter	mm
BIO17	Precipitation of Driest Quarter	mm
BIO18	Precipitation of Warmest Quarter	mm
BIO19	Precipitation of Coldest Quarter	mm

The 2013 IPCC (Intergovernmental Panel on Climate Change) fifth assessment report (AR5) generated climate models from CMIP5, and the 2021 IPCC sixth assessment report (AR6) presented CMIP6 with the 10 Earth system models (ESMs) [103]. CNRM-ESM2-1 is one of the ESMs that contains interactive earth system components such as aerosols, atmospheric chemistry and the land and ocean carbon cycles. In CMIP6, sufficient amounts of data on Carbon Brief were included to analyse the future emission scenarios, such as past and future warming and climate sensitivity since CMIP5. The IPCC AR5 introduced four Representative Concentration Pathways (RCPs) that examined future greenhouse gas emissions in different climate change scenarios: RCP2.6, RCP4.5, RCP6.0 and RCP8.5. These scenarios were updated with the Shared Socioeconomic Pathways (SSPs) scenarios in CMIP6—SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0 and SSP5-8.5. SSP1 is a world of sustainability-focused growth and equality. SSP2 is known as the “middle of the road”, where the historical patterns are followed, SSP3 lies right in the middle of the range of the baseline outcomes produced by ESMs, SSP4 is a more optimistic world that fails to ordain any climate policies and SSP5 depicts the worst-case scenario. These SSPs could examine the demographic and economic factors, as well as how societal picks will have an impact on greenhouse gas emissions. While in RCPs, the socioeconomic factors are not included, but only the pathways are set to examine the greenhouse gas concentrations and the amount of warming that could occur by the end of the century. In this paper, the SSPs 1–2.6, 2–4.5, 3–7.0 and 5–8.5 were used.

3.3.2. Screening of Environmental Variables

The correlation test between the environment variables for each of the three seasonal sets was carried out to retain the ecologically relevant variables in the species' suitability. Spearman's correlation coefficients [104] were applied on the variables set, where, if the

variables had a Spearman correlation < 0.7 , those variables were not highly correlated. Then, the Variance Inflation Factor (VIF) was calculated in R software for each remaining variable using the `vifcor` function of R package `usdm` [105] and eliminated the environmental variables whose VIF values > 3 , because the smaller VIF values hold low correlations. The resulting VIF values were < 3 [106], and therefore, no further variables were eliminated. This correlation test among the environmental variables was performed for India and Africa separately, and these screened environmental variables were then used in the Maxent model to predict the habitat suitability in the abovementioned study areas.

3.4. The Spatial Distribution Model with Maxent

ML-based Maxent modelling [107] is the most popular and a well-established habitat suitability modelling approach [108–116] that predicts probable distributions based on species' occurrences and environmental variables. The advantage of using Maxent is that it uses presence-only data and provides a predictive map within the study area. This works on the principle of maximum entropy that estimates the probability distribution of species' habitats with no constraints and assumes that each feature has the same mean value in the approximated distribution as the species occurrences.

In this study, the maximum entropy algorithm with bird's occurrences and screened predictor variables was modelled to predict the potential suitable habitats and analyse the relative importance of different bioclimatic factors of each point of occurrence for the Jacobin cuckoo. This method was applied on all the three sets of time periods, so that the habitat suitability analysis could be performed to validate the belief that the Jacobin cuckoo are the harbinger of the Indian monsoon and analyse the suitable climates and range of this bird in India, as well as in Africa, during the selected periods. The jackknife test was applied to recognise the importance of the environmental variables. The species occurrences were split as training (75% of the total occurrences) and test (25% of the total occurrences) data for the models' calibration and assessment, respectively. The response curves; jackknife and other features such as linear, quadratic, product, threshold and hinge were set as true parameters in the habitat suitability model. The other model parameters were used as follows:

- i. "replicates = 10" tells the model about the number of replicates that the model executes for cross-validating, bootstrapping or doing sampling with replacement runs;
- ii. "lq2lqptthreshold = 80" is the number of samples at which the product and threshold features start being used;
- iii. "l2lqthreshold = 10" is the number of samples at which the quadratic features start being used and
- iv. "hingethreshold = 15" is the number of samples at which the hinge features start being used.

The predictive performance of the generated model was then assessed by calculating the Area Under the Receiver Operator Curve (AUC) of the receiver operating characteristic (ROC) plot, which ranges between 0 (no discrimination) to 1 (perfect discrimination) [116]. The process of evaluating the model's predictive performance using AUC involves the process of setting thresholds on the model's prediction by generating various levels of false positive rates and then assessing the true positive rate as a false positive rate function. Here, the false positive rate referred to the prediction of a presence for those places where the species is absent, and the true positive rate is the successful prediction of a presence. The AUC range from 0.7 to 0.8 is acceptable, 0.8 to 0.9 is excellent and above 0.9 is an outstanding performance [117]. The dominant environmental variables in determining the species' probable distribution were assessed through the jackknife test (also called "leave-one-out") that gives the permutation importance against the environmental variables [110]. The species response curves were generated by the model to examine how the likelihood of species' occurrences responds to the variations in the changing environmental conditions.

Then, the future climatic variations (2021–2040 and 2041–2060) were also modelled to estimate how the species will respond to changes in ecological systems, as their favourable

habitats will shift under different climate change scenarios (i.e., SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5).

The predicted habitat suitability maps were then reclassified into convenient classes that represented the threshold limits that differentiated the unsuitable and suitable habitats. The reclassified classes of habitat suitability were: the unsuitable conditions with a lower threshold and the suitable conditions that were further categorised into three classes: low, medium and highly suitable. This threshold helped in interpreting the ecological significance by identifying areas that were at least suitable as similar to those areas where the species has been recorded.

4. Results

4.1. Selection of Environmental Variables

To detect the correlations among environmental variables, the Spearman's correlation coefficient threshold was set to 0.7, and then, the vifcor function was performed. From the visual assessment, some variables showed an intercorrelation that was then eliminated if their vif values was assigned as less than 3. This was the case for the minimum temperature, maximum temperature, precipitation, elevation, wind and bioclimatic variables. The final selected set of variables were then used to predict the suitability of the Jacobin cuckoo, given in Table 2.

Table 2. Environmental variables selected after the correlation test.

Time Periods	India	Africa
June–September	bio14, bio15, bio18, bio19, bio2, bio3, bio8, wind7	bio13, bio14, bio19, bio2, bio3, elevation, wind6, tmax9
October–December	bio14, bio15, bio18, bio19, bio2, bio3, wind12, prec12	bio14, bio15, bio19, bio8, bio9, wind 12
January–May	bio14, bio15, bio18, bio19, bio2, bio3, wind2, prec1	bio14, bio15, bio19, bio2, elev

4.2. Performance Evaluation Results of the Maxent Model

After executing the Maxent model on the species' occurrences and environmental variables, its predictive accuracy was evaluated by using AUC plots. As shown in Table 2, environmental variables were selected for India and Africa separately in three different time periods; therefore, the Maxent model was executed by separating the species occurrences of India and Africa into three different time periods. Additionally, the minimum temperature, maximum temperature and precipitation used in the Maxent model were taken according to these three time periods.

The AUC values for the Pied cuckoos' suitability prediction model given in Table 3 depicted that the model's prediction was very good, so that it could effectively predict the species distribution under the current and future climate scenarios.

Table 3. AUC values of the Maxent model's performance.

Time Periods	India	Africa
June–September	0.885	0.908
October–December	0.91	0.947
January–May	0.958	0.908

4.3. Variable Importance and Contribution

Tables 4 and 5 depict the heuristic estimate of the percentage contribution and the permutation importance of the environmental variables used in the Maxent model for three different time periods with species occurrence data from India and Africa. These two tables helped us to interpret the most influential environmental variables that played a significant role in the Jacobin cuckoo's habitat suitability in India and Africa. It is observed

in Table 4 that bio2, bio3, bio14, bio15, bio18, bio19 and wind are common for all the three time periods in India, whereas, in Africa (Table 5), bio 14 and bio 19 are common in all three time periods. In India, wind and precipitation play a minor role, whereas, in Africa, wind and elevation hold major contributions in suitability modelling. Therefore, this section concluded that the environmental variables related to precipitation play a significant role in the distribution of the Jacobin cuckoo and are essentially required in its potential suitable habitats.

Table 4. Percent contribution and permutation importance of the environmental variables in terms of India's suitability.

Time Periods	Selected Environmental Variables	Percent Contribution	Permutation Importance
June–September	bio8 (Mean Temperature of Wettest Quarter)	52.4	40.9
	bio3 (Isothermality)	13.9	11
	bio2 (Mean Diurnal Range)	9.2	14.4
	bio18 (Precipitation of Warmest Quarter)	7.8	5.3
	wind7 (wind of July month)	6.8	9.6
	bio19 (Precipitation of Coldest Quarter)	5.2	10
	bio15 (Precipitation Seasonality)	4.5	7
	bio14 (Precipitation of Driest Month)	0.3	1.7
October–December	bio3 (Isothermality)	69.7	54.7
	bio18 (Precipitation of Warmest Quarter)	9.8	12.4
	bio2 (Mean Diurnal Range)	9.4	17.9
	wind12 (wind of December month)	3.8	5.7
	prec12 (precipitation of December month)	2.6	2.8
	bio15 (Precipitation Seasonality)	2.3	4.5
	bio19 (Precipitation of Coldest Quarter)	2	1.6
	bio14 (Precipitation of Driest Month)	0.5	0.5
January–May	bio3 (Isothermality)	56.2	49.7
	bio19 (Precipitation of Coldest Quarter)	21.7	5.1
	bio2 (Mean Diurnal Range)	13.2	22.8
	prec1 (precipitation of January month)	3.5	4.7
	bio18 (Precipitation of Warmest Quarter)	3.4	9.6
	wind2 (wind of February month)	1.3	6.3
	bio15 (Precipitation Seasonality)	0.7	1.5
	bio14 (Precipitation of Driest Month)	0.1	0.4

Table 5. Percent contribution and permutation importance of the environmental variables in terms of Africa's suitability.

Time Periods	Selected Environmental Variables	Percent Contribution	Permutation Importance
June–September	bio14 (Precipitation of Driest Month)	31.2	26.9
	bio13 (Precipitation of Wettest Month)	23.5	24.3
	wind6 (wind of June month)	15.4	19.2
	bio19 (Precipitation of Coldest Quarter)	11.1	7.2
	tmax9 (Maximum Temperature of September)	8.9	12.6
	bio2 (Mean Diurnal Range)	5.7	3.4
	elev (Elevation)	2.1	4.8
	bio3 (Isothermality)	2	1.6
October–December	bio9 (Mean Temperature of Driest Quarter)	51	30.1
	bio14 (Precipitation of Driest Month)	24.8	20.9
	wind12 (wind of December month)	8.9	18
	bio8 (Mean Temperature of Wettest Quarter)	8.1	20.9
	bio15 (Precipitation Seasonality)	5.5	8.1
	bio19 (Precipitation of Coldest Quarter)	1.7	2
January–May	bio19 (Precipitation of Coldest Quarter)	33.9	38.6
	bio15 (Precipitation Seasonality)	24.8	16.1
	bio14 (Precipitation of Driest Month)	24.6	37.9
	bio2 (Mean Diurnal Range)	15.4	6.3
	elev (Elevation)	1.4	1

4.4. Predicted Habitat Suitability Map of the Jacobin Cuckoo

Using the influential bioclimatic factors in the species distribution, the habitat suitability prediction was performed under the current and future climatic scenarios to estimate the changes in the ecological systems and how the species will respond to the changes in different climatic variations. This section discusses the spatial characteristics of the utilised distribution data, i.e., India's southwest and northeast monsoon seasons and Africa's rainy season, especially in Southern Africa.

4.4.1. Current Habitat Suitability

June–September

The months of June–September are known as India's southwest monsoon period, in which all of India receives more than 75% of its rainfall [118], whereas these months bring the dry season in Central, South and East Africa. Therefore, the recorded occurrences of June–September (separately for India and Africa) with screened environmental variables were supplied to the Maxent model, which resulted in the dominant bioclimatic variables, as well as the prediction of the current habitat suitability of this bird. After evaluating the model's performance, the output was then used to project the future habitat suitability of the Jacobin cuckoo under different climate change scenarios.

The species habitat suitability map shown in Figure 3 depicts that the areas covered with grey colour represent no suitability for this bird, whereas the yellow and brown colours represent good and low habitat suitability of the species, respectively. The species occurrences are plotted with red points on the map, and the habitat suitability ranges can be seen from the probability scale, which depicts the bird's residency. Accordingly, Africa has very low suitability during the June–September period because of its dry season, which might not be a favourable climate for the suitability of Pied cuckoos. However, the model predicted the good and high suitability of these birds in all of India as compared to Africa, because India receives 75% of its rainfall then, and thus, this could be one of the main reasons of their partial migration to India, so that they can get their suitable climatic factors. The results shown in Figure 3 were computed on occurrences from 1991 to 2020 and the climatic variables (tmin, tmax, prec and wind) of the June–September months.

In India, the major suitability predictions under the current scenario can be seen in Northern, Western and Southern India, but Eastern, Central and North-eastern India have shown very low or no suitability predictions. The model predicted the average suitability range of the Jacobin cuckoo in the following Indian states—Uttarakhand and Uttar Pradesh and in Madhya Pradesh of Central India. The reason behind its migration to these parts of India could be because of the wettest features due to the highest rainfall and the maximum number of rivers. A good suitability range was predicted in Western India, such as in Gujarat (sites near to the Gulf of Kachcha and the Gulf of Khambat) and in Maharashtra (sites surrounded by the Arabian Sea) and, also, in Southern India, such as in Western Ghats. The highest suitability of this bird was predicted in a few areas of South India, such as Southern Tamil Nadu, which is Rameswaram, Dhanushkodi and Thoothukodi. Therefore, there is a probability that this bird likes to stay at the wettest sites, which receive the highest amount of rainfall. In Africa, no habitat suitability was predicted for Jacobin cuckoo, because this time period is the dry season, which might force the Jacobin cuckoo's migration to India.

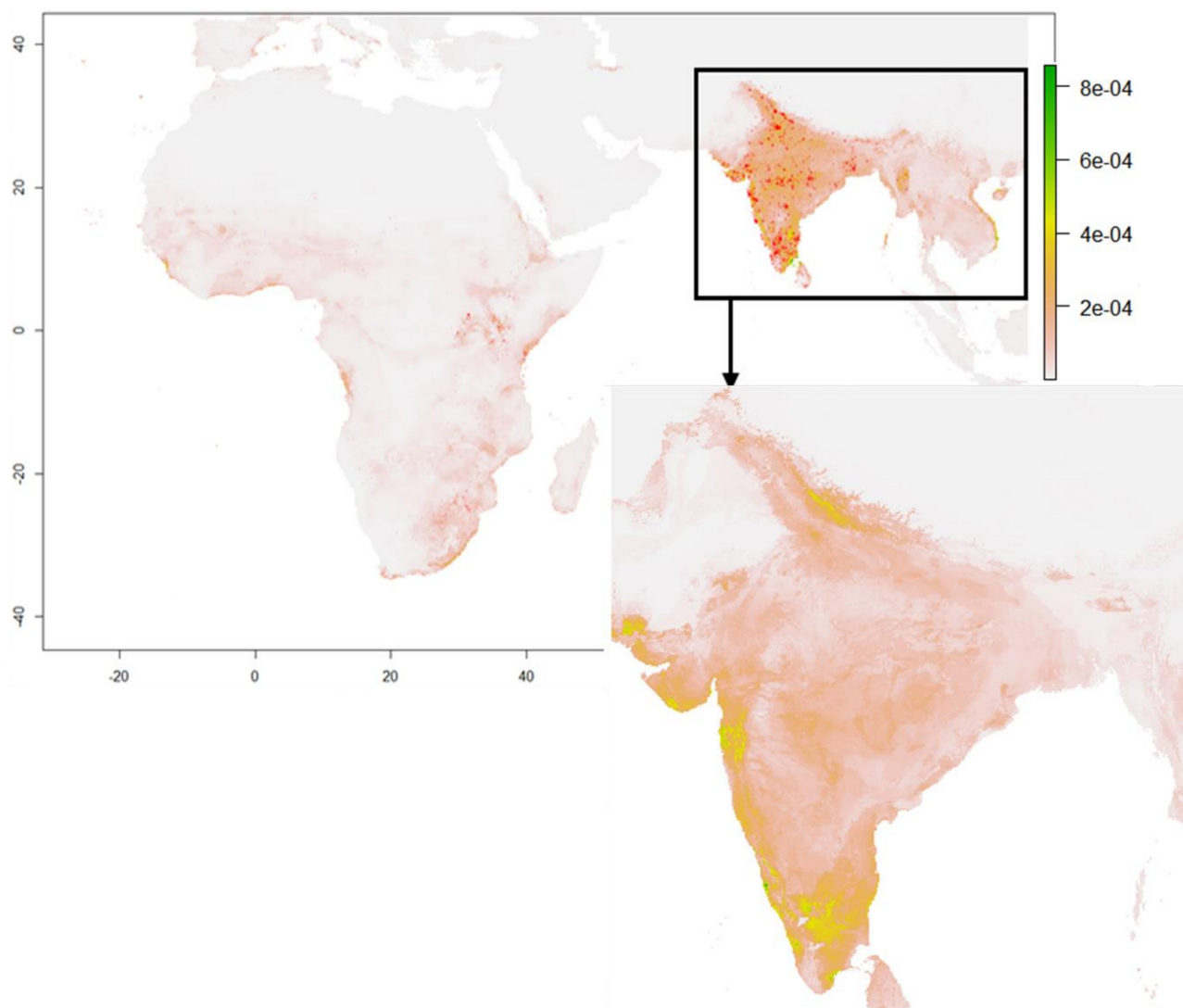


Figure 3. Habitat suitability prediction of June–September for the Pied cuckoo range.

The change in climate, particularly the Indian southwest monsoon patterns, were analysed with respect to the Jacobin cuckoo in the past 30 years by separating the datasets into two subsets—1991–2005 and 2006–2020. For this, the climatic variables were used for these yearly subsets, and their results are illustrated in Figures 4 and 5, respectively. In Figure 4, there is no suitability predicted in Africa in 1991–2006 during June–September because of its dry weather, which is unsuitable for the bird, but, in India, an adequate habitat suitability can be seen in the eastern parts and northern parts but not the southern and western parts, due to the bird’s migration to India in search of a wet climate. When the suitability results of Figure 4 are compared with Figure 5, a decline is observed in the Indian monsoon rainfall in the north and east for the past 15 years in June–September. Additionally, this study on climate change was completely dependent on sightings of the Jacobin cuckoo, so one of the reasons of less suitability in Southern and Western India would be less sightings of the bird due to the unawareness of crowdsourcing. As per Google Trends search records from 2004 to the present (Figure 6), the public interest in the term “crowdsourcing” in India started in 2007.

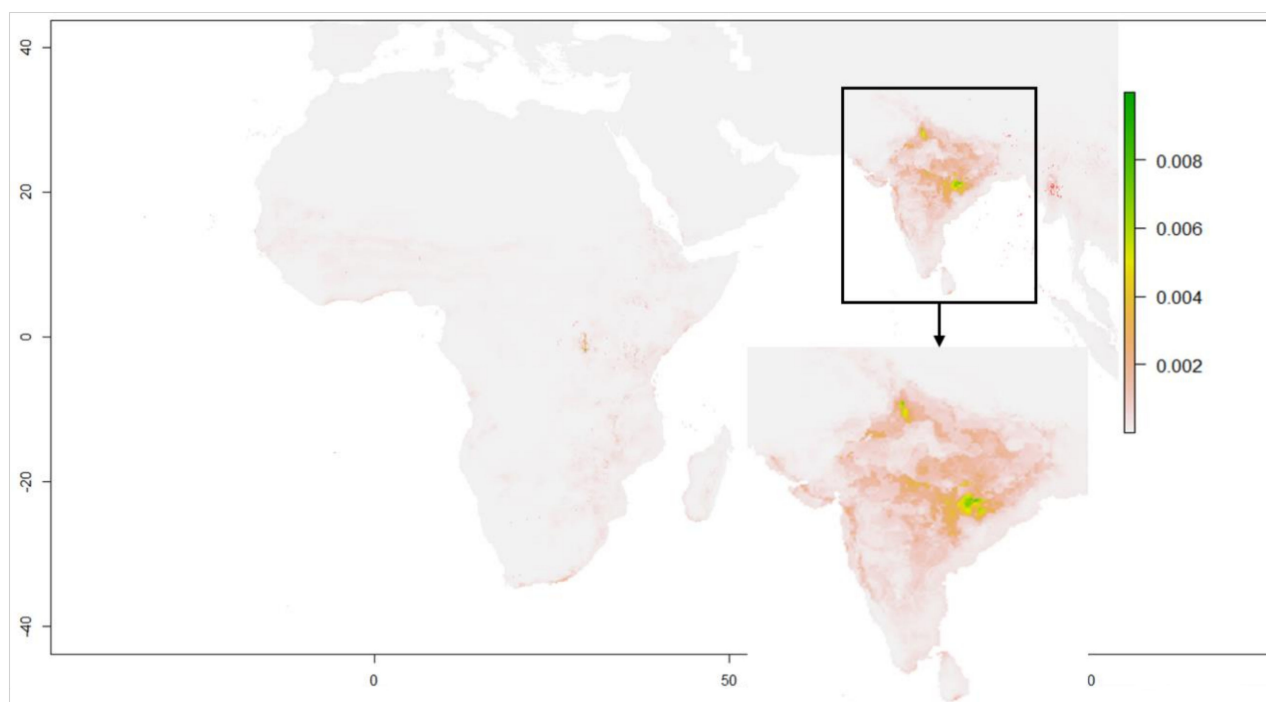


Figure 4. Habitat suitability modelling in 1991–2005 for the June–September period.

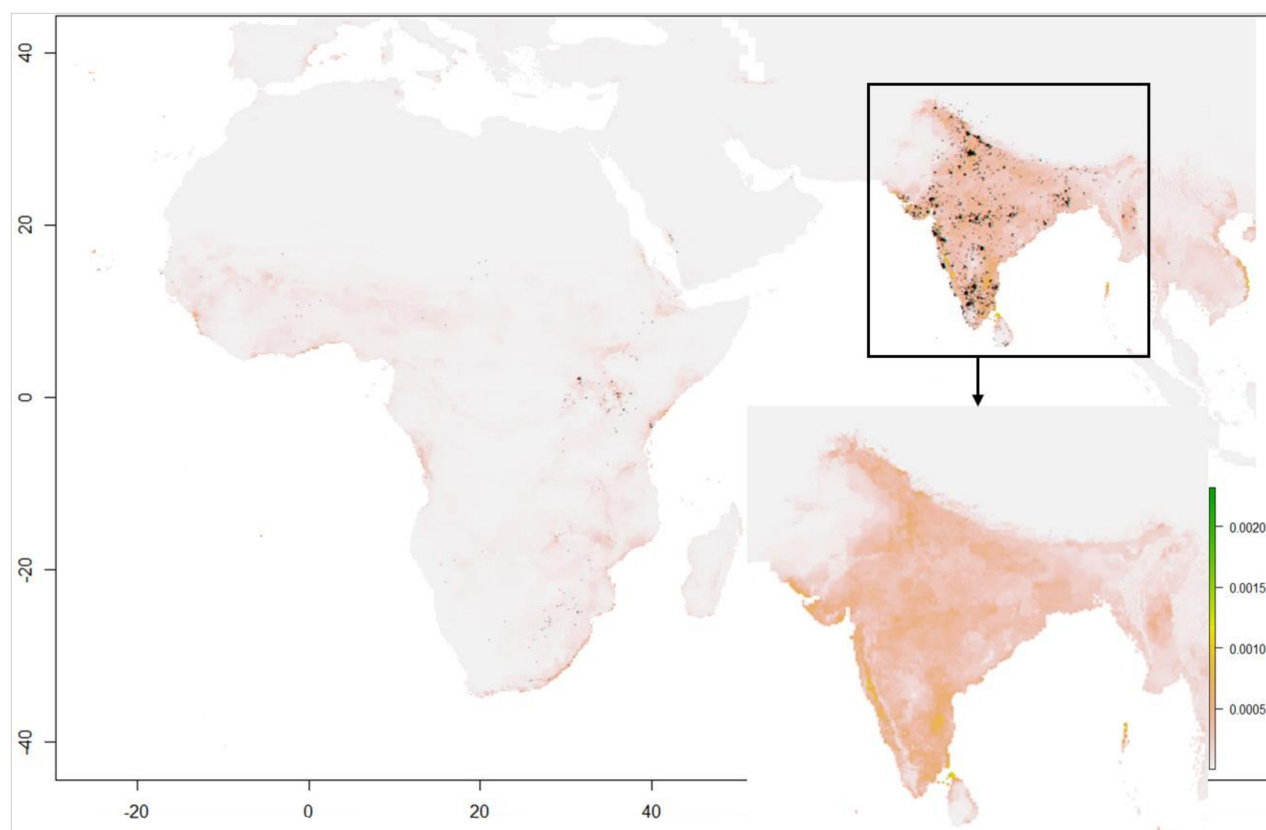


Figure 5. Habitat suitability modelling in 2006–2020 for the June–September period.

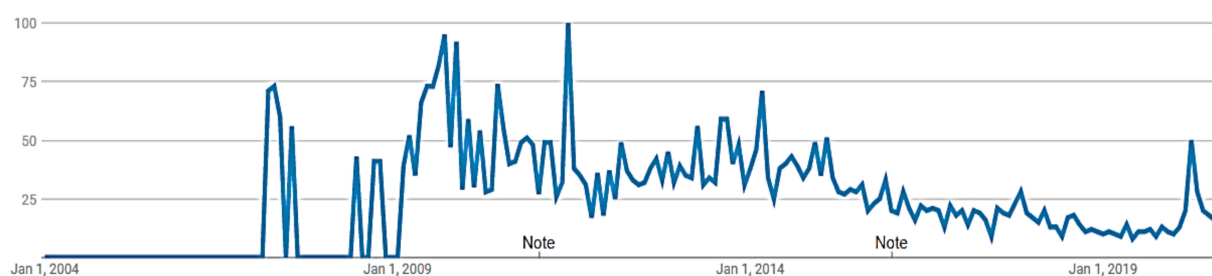


Figure 6. Google trends of “crowdsourcing” based on searches in India.

October–December and January–May

The months of October, November and December are known for the northeast monsoon or winter monsoon in India, as its direction is set from the northeast to southwest of India, and the beginning of rainy and wet season in Africa, which typically lasts until April. As such, this set of months includes monsoons of two different countries. Therefore, the results discussed in this section are divided into two sub-sections: one for October–December and another for January–May.

The northeast monsoon season from October to December in India brings rain to Andhra Pradesh mainly in the coastal regions of Kerala, Puducherry, Rayalaseema, South Karnataka and Tamil Nadu. As compared to the southwest monsoon, this monsoon period gives only 11% of the annual rainfall in India, but in Tamil Nadu, this season gives almost half of its annual rainfall. The habitat suitability map given in Figure 7 depicts that, in India, the highest habitat suitability of the Jacobin cuckoo is predicted in Tamil Nadu, good in Andhra Pradesh and Karnataka and low in Kerala. Considering the model’s predictions on the bird’s habitat suitability, which is correlated with the patterns of the northeast monsoon (i.e., in October, November and December), it can be linked to the belief or fact that the bird’s movements are completely linked with the monsoon rains of the northeast monsoon period.

After verifying and exploring the links of the Indian monsoon arrival with the bird’s sightings, subsequently, the same study was carried out to investigate the major climatic factors that could be the cause behind the bird’s return journey to Africa. Figures 7 and 8 depict that, when the rainy and the wet season starts in October, the Pied cuckoos, residents of Africa, might return to their native lands and reside there until April. Therefore, the sightings of the Jacobin cuckoo were observed in the provinces of Africa, except the Western Cape. However, the highest suitability (green colour) is predicted in the coastal areas of the Eastern Cape and Kwazulu-Natal Provinces. Therefore, the research on the habitat suitability of the Jacobin cuckoo proved the correlation between sighting of the Jacobin cuckoo and the arrival of the monsoon season in India and also gives rise to ancestral tales or traditional beliefs that these Jacobin cuckoos have the magical ability of summoning rain wherever they go, such as all over the Indian subcontinent, as well as in Africa.

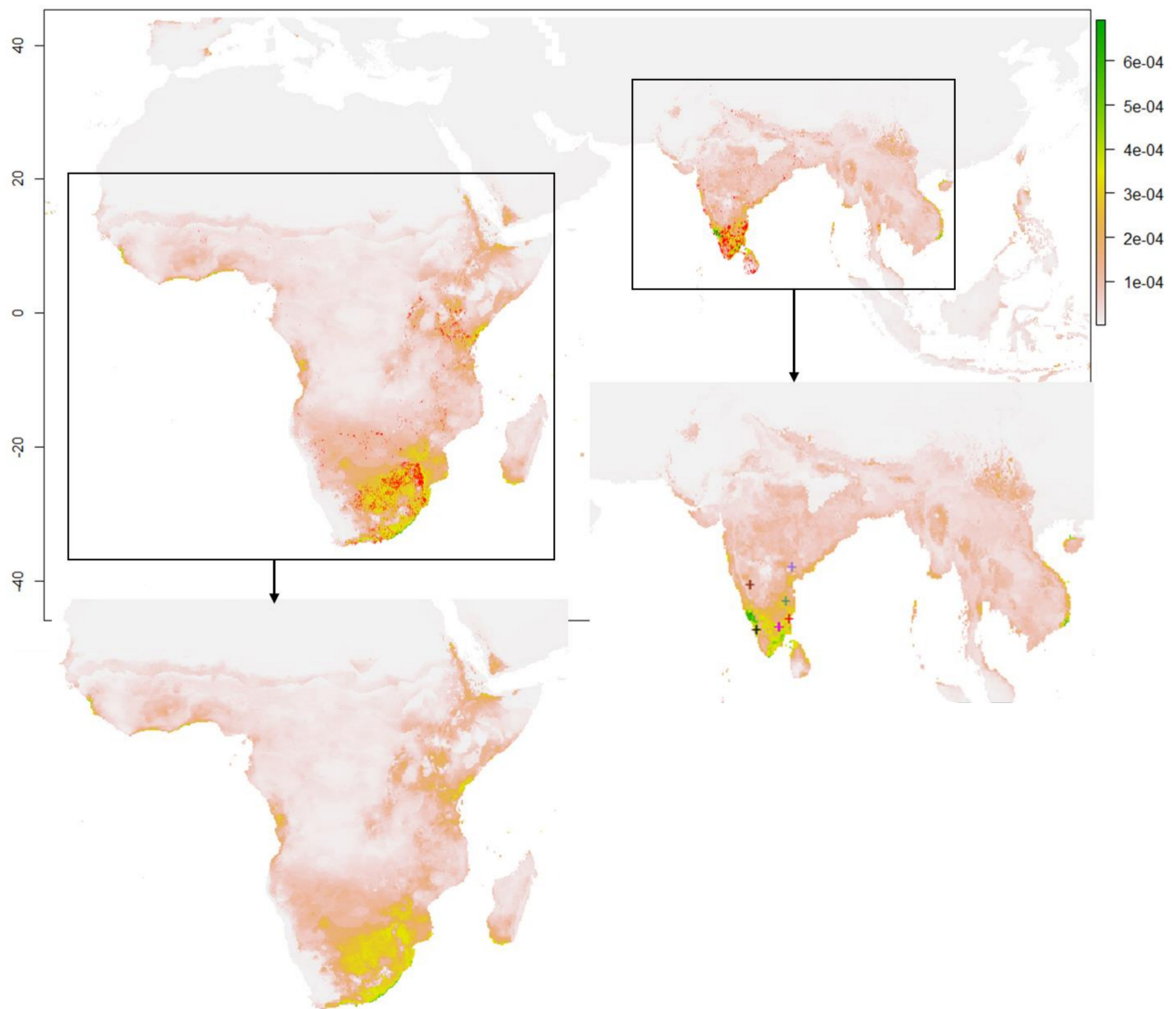


Figure 7. Current habitat suitability predictions of October-December for the Jacobin cuckoo range. The regions marked with a cross sign in the lower right part of the figure are: Andhra Pradesh (blue mark), mainly in the coastal regions, Kerala (black mark), Puducherry (red mark), Rayalaseema (green mark), South Karnataka (marron mark) and Tamil Nadu (pink mark).

4.4.2. Predicted Future Suitability under Different Climate Change Scenarios

This section is related to the modelling of future habitat suitability of the Jacobin cuckoo by using the existing Maxent model, existing occurrences data and existing environmental layers and then projecting them with future environmental variables of the years 2030 and 2050. In addition, the probable increase or decrease in suitable and unsuitable habitats in the current and future years were also estimated for the sites occupied by the species, which can be used in various climate change studies later.

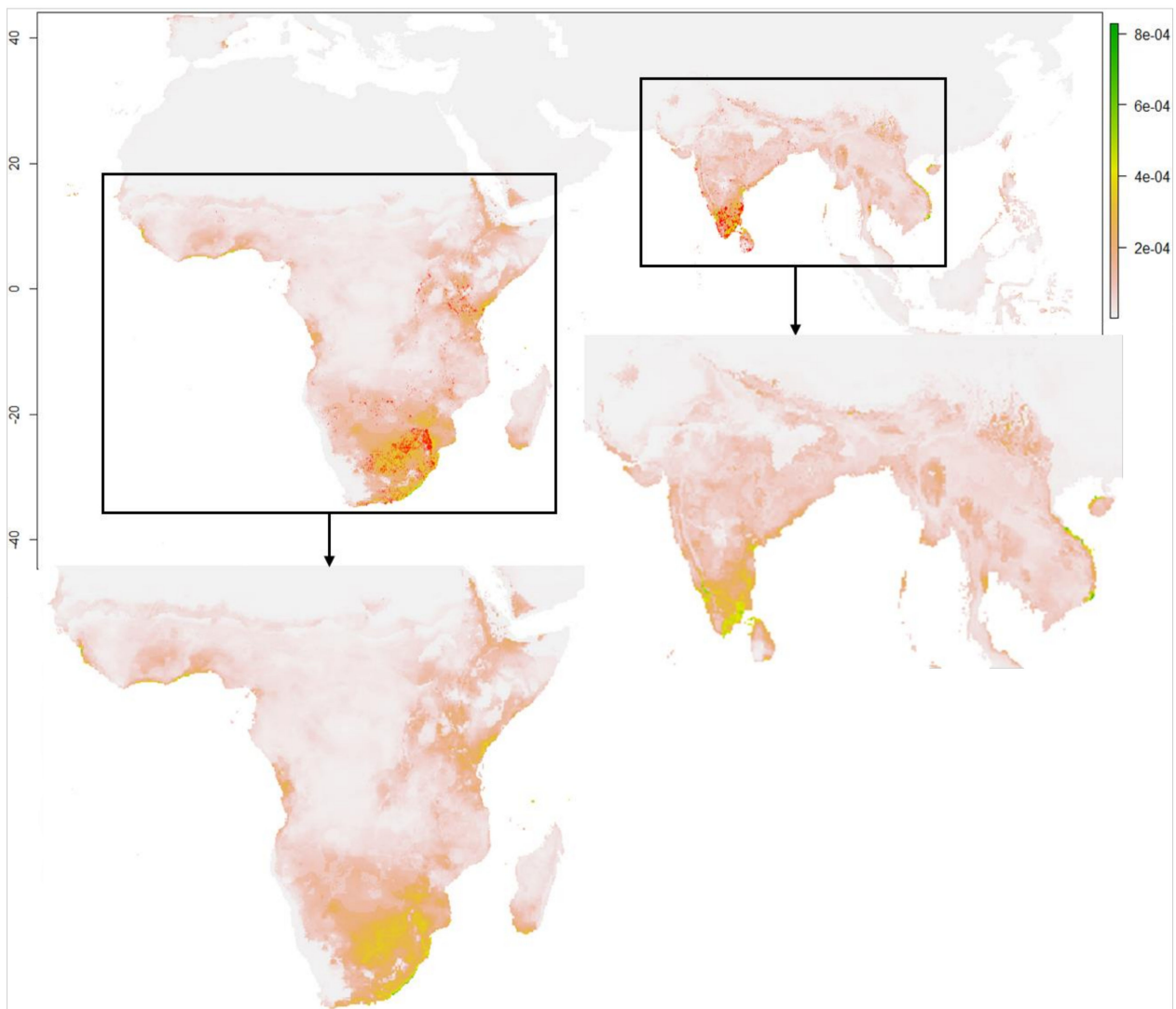


Figure 8. Current habitat suitability prediction of January-May for the Pied cuckoo range.

June–September

The resulting suitability maps were then generated using the selected environmental variables that are given in Figure 9. The figure depicts that the probable habitat suitability conditions of the Jacobin cuckoo have are relatively medium in SSPs 2.6, 4.5 and 7.0 of 2030. As compared to the current predictions in Figure 5, declines are observed in different climatic scenarios of the future years, particularly in SSP 8.5, in which the pixels of good suitability disappeared. This might be due to the estimation of higher CO₂ emissions and the increase in global warming. Table 6 depicts that there is a decline in suitable areas and an increase in unsuitable areas as compared to the current ones.

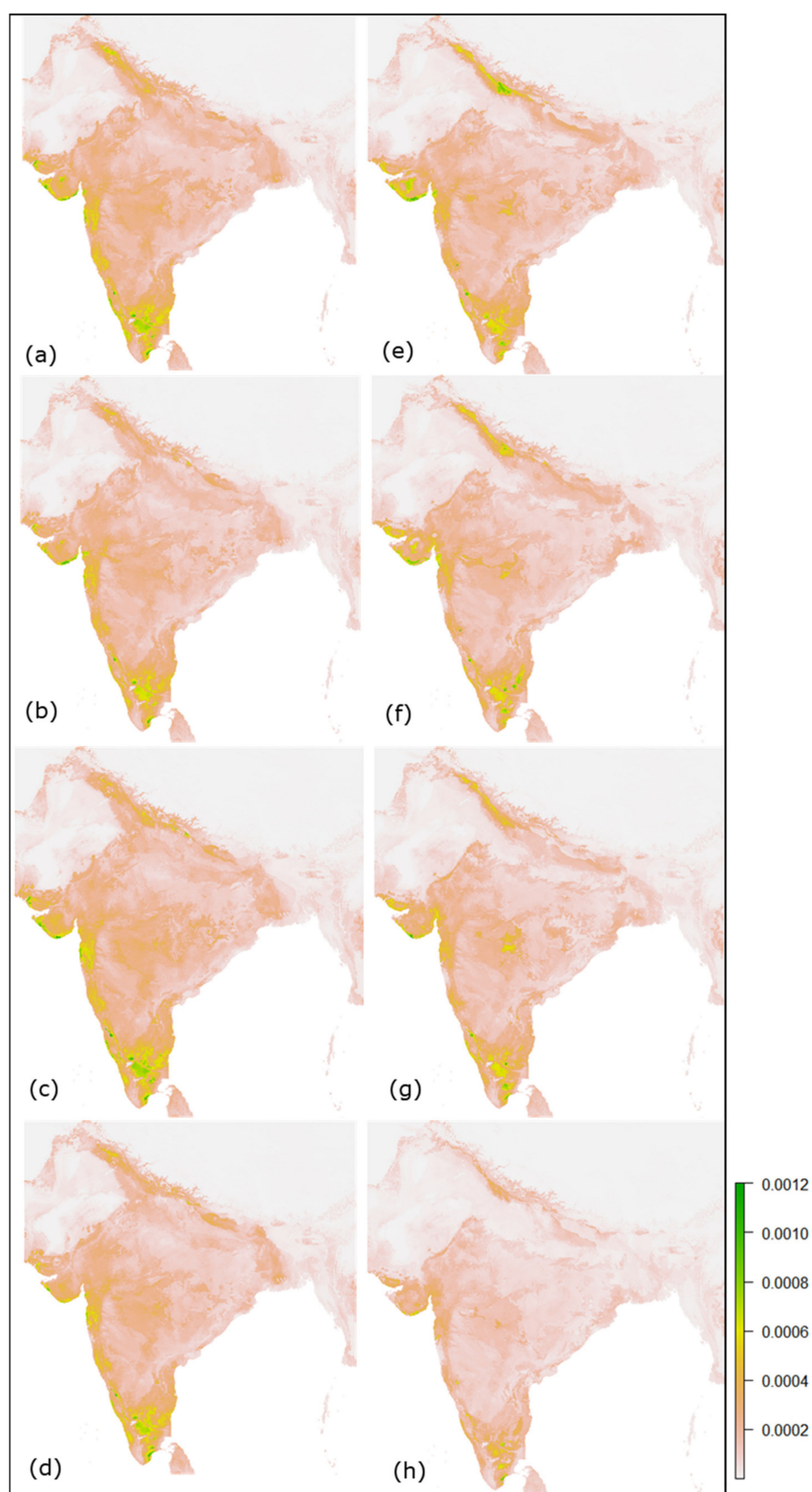


Figure 9. Predicted future habitat suitability maps of the Jacobin cuckoo during June–September of India for the 2030 SSPs 2.6, 4.5, 7.0 and 8.5 (a–d) and 2050 SSPs 2.6, 4.5, 7.0 and 8.5 (e–h).

Table 6. Predicted suitable areas under the current and future climatic conditions during June–September (India).

	Climatic Scenarios	Unsuitability (km ²)	Suitability (km ²)
Current	–	3,903,906.3	1,554,570.5
2030	SSP 2.6	3,917,983.9	1,533,619.6
	SSP 4.5	3,956,603.1	1,492,705.1
	SSP 7.0	3,925,725.7	1,530,059
	SSP 8.5	4,083,028.8	1,371,543.6
2050	SSP 2.6	3,935,078.1	1,514,768.8
	SSP 4.5	4,012,498.1	1,436,972
	SSP 7.0	4,170,800.4	1,281,060.6
	SSP 8.5	4,249,557.4	1,205,204.4

October–December and January–May

This section discusses on how the distribution of potential habitats will shift under different climate change scenarios. According to the model's future predictions for the months of October–December in India (Figure 10) and Africa (Figure 11), the habitat suitability of the Jacobin cuckoo is highly related to the current scenario (Figure 7) under SSPs 2.6 and 4.5 of 2030. However, the suitability conditions under different scenarios such as 7.0 and 8.5 of 2030 and, in 2050, under all climatic scenarios, the probability of occurrence of the Jacobin cuckoo is predicted as quite low when compared with the current one. This can be observed in Tables 7 and 8, which represent the increase in unsuitable and decrease in suitable areas of the Jacobin cuckoo in India and Africa, respectively.

Table 7. Predicted suitable areas under the current and future climatic conditions during October–December (India).

	Climatic Scenarios	Unsuitability (km ²)	Suitability (km ²)
Current	–	4,662,162.9	269,311.2
2030	SSP 2.6	4,772,917.3	198,217
	SSP 4.5	4,773,967.4	197,233.2
	SSP 7.0	4,758,425.3	200,135.6
	SSP 8.5	4,806,362.7	185,111.4
2050	SSP 2.6	4,772,249.1	1,990,134.3
	SSP 4.5	4,804,739.2	183,147.1
	SSP 7.0	4,842,675.4	165,650.5
	SSP 8.5	4,836,618.7	163,666.7

Table 8. Predicted suitable areas under the current and future climatic conditions during October–December (Africa).

	Climatic Scenarios	Unsuitability (km ²)	Suitability (km ²)
Current	–	25,328,121	1,416,705.3
2030	SSP 2.6	25,421,822.1	1,320,241.8
	SSP 4.5	25,402,520.3	1,337,374.5
	SSP 7.0	25,396,134.9	1,344,209.5
	SSP 8.5	25,417,724.7	1,321,503.3
2050	SSP 2.6	25,549,750.9	1,193,954.8
	SSP 4.5	25,598,589.5	1,144,656.8
	SSP 7.0	25,611,813.3	1,132,636.1
	SSP 8.5	25,682,361.4	1,065,214.8

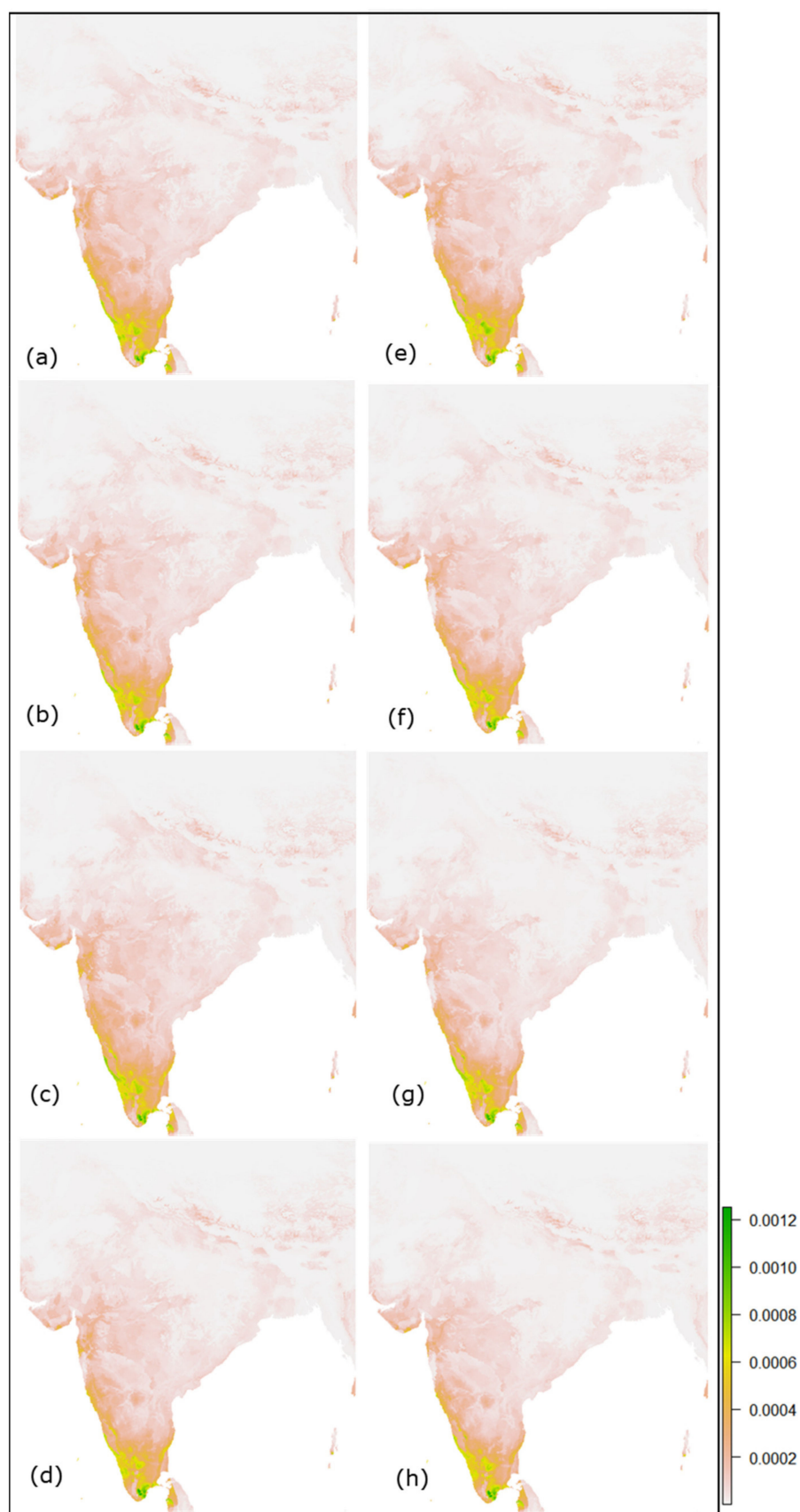


Figure 10. Predicted future suitability maps for Jacobin cuckoos from October to December: (a–d) and (e–h) represent the SSPs 2.6, 4.5, 7.0 and 8.5 for 2030 and 2050, respectively.

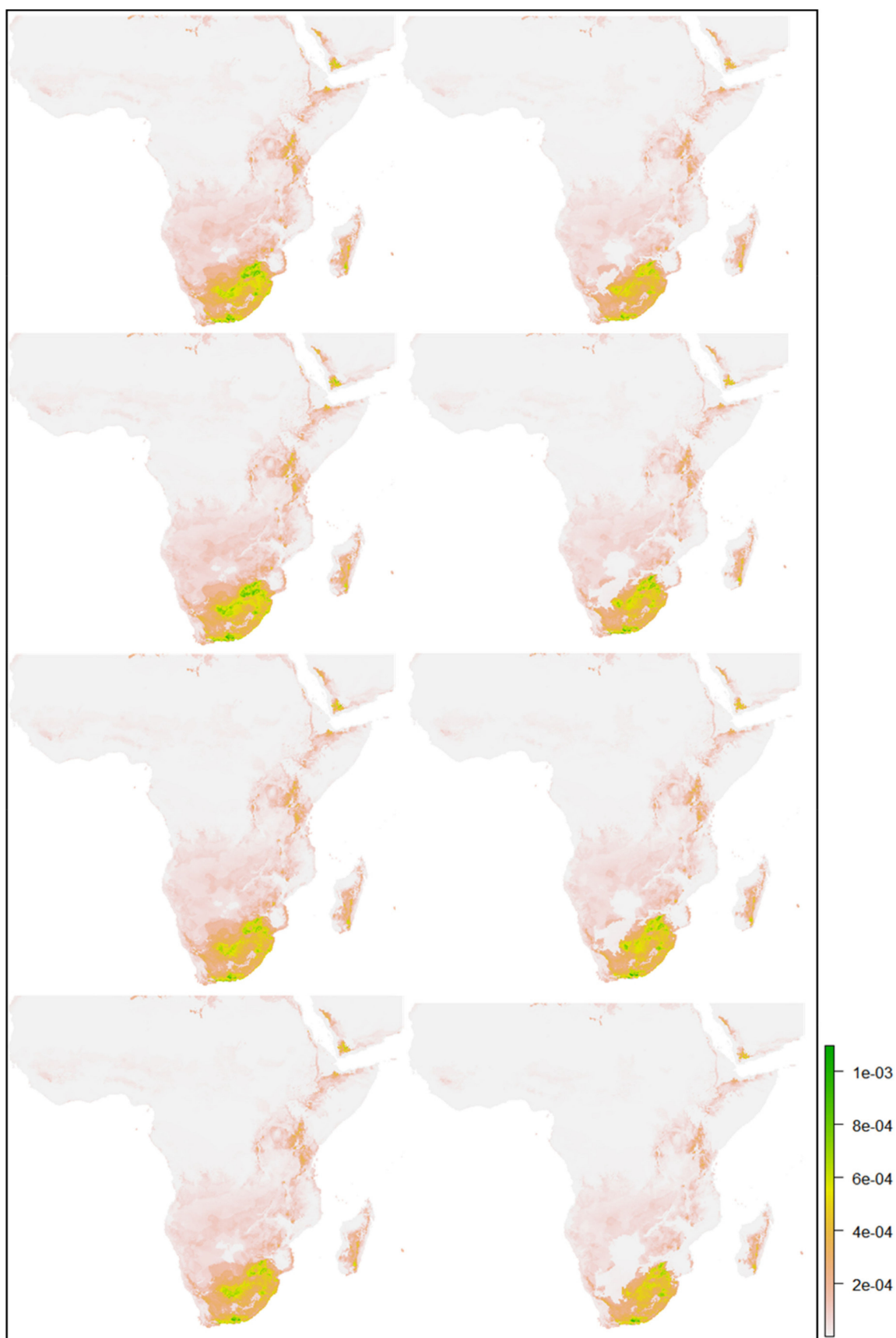


Figure 11. Predicted future suitability maps for Jacobin cuckoos from October to December in Africa: (a–d) and (e–h) represent the SSPs 2.6, 4.5, 7.0 and 8.5 for 2030 and 2050, respectively.

Other future suitability predictions for the January–May months of 2030 and 2050 through the Maxent model are shown in Figures 12 and 13 for India and Africa, respectively, which provides the probability that the bird’s suitability might become low in 2050 under all climate scenarios. Such a decline in habitat suitability of the bird during these months indicates that, in the future, India, as well as Southern Africa, might receive less rain and more dryness, which will result in a decline of the Jacobin cuckoo’s suitability in India (Table 9) and Africa (Table 10). Although incongruities may exist between various climate modelling approaches [119], the strategy of assessing the current suitability and predicting the future changes in the distributions of diverse species, which are influenced by different climatic patterns, is still recognised as an important research area.

Table 9. Predicted suitable areas under the current and future climatic conditions during January–May (India).

	Climatic Scenarios	Unsuitability (km ²)	Suitability (km ²)
Current	–	4,568,739.6	128,897
2030	SSP 2.6	4,585,901.9	114,579.5
	SSP 4.5	4,583,793.4	115,614
	SSP 7.0	4,584,234.3	115,404
	SSP 8.5	4,594,489.4	100,791.9
2050	SSP 2.6	4,573,664.1	121,099.9
	SSP 4.5	4,581,033.1	117,698.1
	SSP 7.0	4,593,339.3	103,510.2
	SSP 8.5	4,600,834.1	94,180.3

Table 10. Predicted suitable areas under the current and future climatic conditions during January–May (Africa).

	Climatic Scenarios	Unsuitability (km ²)	Suitability (km ²)
Current	–	15,137,454	1,205,065.2
2030	SSP 2.6	15,271,158.6	1,150,279.7
	SSP 4.5	15,242,352.7	1,143,199.7
	SSP 7.0	15,275,949	1,170,872.3
	SSP 8.5	15,385,782.4	1,140,142.1
2050	SSP 2.6	15,271,495.7	1,206,615
	SSP 4.5	15,279,882.5	1,115,013
	SSP 7.0	15,200,979.4	1,199,596.5
	SSP 8.5	15,389,258.9	1,125,855.3

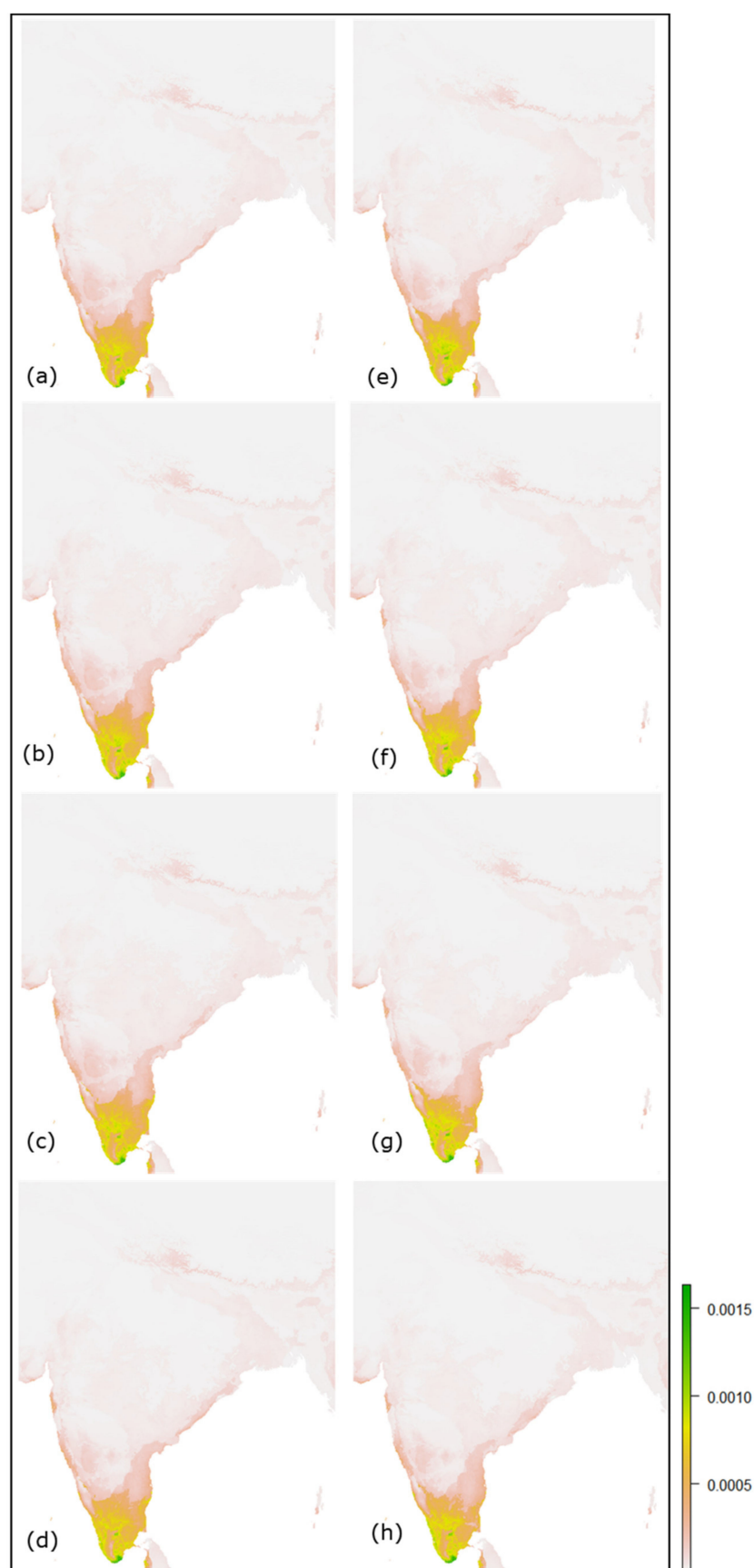


Figure 12. Predicted future suitability maps for January-May in India: (a–d) and (e–h) represent the SSPs 2.6, 4.5, 7.0 and 8.5 for 2030 and 2050, respectively.

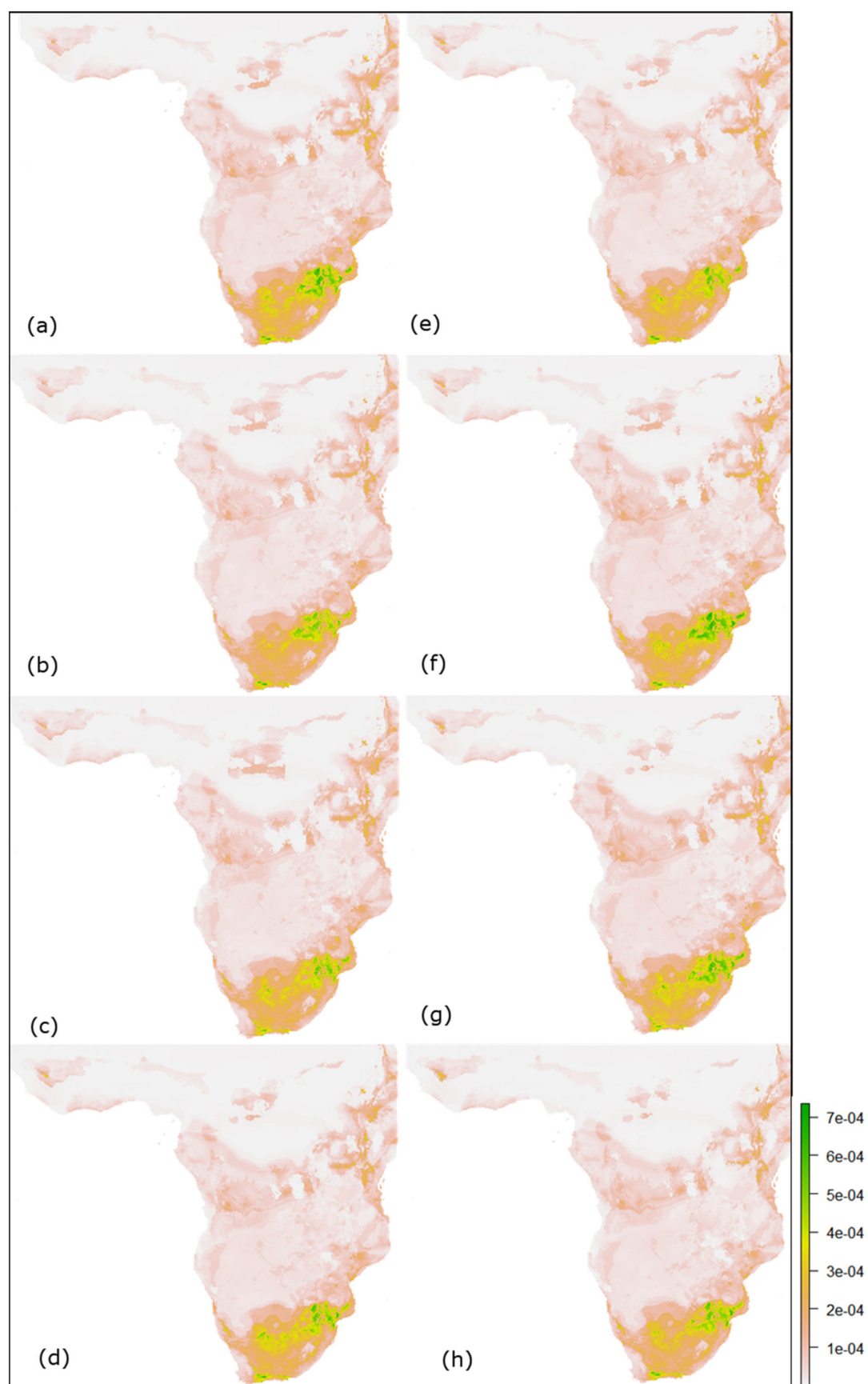


Figure 13. Predicted future suitability maps for January-May in Africa: (a–d) and (e–h) represent the SSPs 2.6, 4.5, 7.0 and 8.5 for 2030 and 2050, respectively.

5. Discussions

The study presented here analysed the habitat suitability for the Jacobin cuckoo in different seasons, with particular reference to India, using the species' occurrences (1991–2020) in the ML-based Maxent model with environmental variables. The occurrences were obtained from the GBIF database, an observatory composed of data from public institutions, e.g., museums, and citizen observations. The Maxent model's predictive performance achieves higher AUC values, which denotes that this model is excellent and accurate. The results obtained using the Maxent method for predicting the potential suitability of the Jacobin cuckoo are different in all three seasons of India, i.e., June–September (the southwest monsoon), October–December (the northeast monsoon) and January–May (winter and summer). The important environmental variables affecting its habitat suitability are the precipitation of the driest month, precipitation seasonality, precipitation of the warmest quarter, mean temperature of the wettest quarter and wind. The model predictions showed that the species suitability followed the same pattern of both Indian monsoon seasons, i.e., southwest and northeast. Therefore, based on the results, the bird's migration can be linked with monsoons in the assessed regions—India and Africa. Nevertheless, in order to examine India's southwest monsoon season, the datasets were divided into two subsets—1991–2005 and 2006–2020, and then, the Maxent model with the environmental data was executed. From the results, it was surprisingly interesting to see that the monsoon patterns started declining in 1991 in a few regions of the northern and eastern parts of India during the June–September period, which might be because of anthropogenic activities, deforestation, etc. However, in Africa, the climatic conditions are always suitable for this bird's residency starting from October and lasting until April. When the rainy and wet season in Africa ends, the birds start migrating to different parts of the world where they get more favourable climate conditions. The future suitability of the Pied cuckoo bird was modelled here with a full set of climatic conditions under four scenarios (SSPs): 2.6, 4.5, 7.0 and 8.5 for 2030 (averaged for 2021–2040) and 2050 (averaged for 2041–2060), using the results of the current suitability and its projected bioclimatic variables. As per the future predictions carried out in this study, the potentially suitable climatic distribution will shrink in the future ($2050 < 2030 < \text{current}$) under different climate change scenarios, indicating that there could be a change in the monsoon season in India, as well as in Africa, which will result in less suitability for the Jacobin cuckoo. Such a direct link of this bird with the monsoon season helps to critically analyse the likely climatic change activities and which environmental variables play an influential role for its suitability and to support its migratory movements.

6. Conclusions

This study concluded that the ecological systems will be altered with respect to the climate changes, and the favourable habitats of species will shift under different climate change scenarios. The present study demonstrated an example of the modelling or the prediction of these shifts by using citizen observations, which provided the required set of data or the observations to apply robust ML models. Thus, the use of citizen science methods was essential for enabling such an analysis. Future suitability modelling using CMIP6 future datasets revealed that the precipitation and wettest climates might decline while warm and dry climates may rise.

The wettest season and precipitation are major elements in Jacobin cuckoos' distribution, and various collaborative programs are required to maintain the suitability of various migratory birds like the Jacobin cuckoo in such a changing and unexpected potential warming of the Earth. However, such predicted changes are based only on climatic factors and are not necessarily related to the distribution of human-occupied land use like urban settlements and dispersal ability.

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References

1. Araújo, M.B.; Guisan, A. Five (or so) challenges for species distribution modelling. *J. Biogeogr.* **2006**, *33*, 1677–1688. [\[CrossRef\]](#)
2. Matthiopoulos, J.; Fieberg, J.; Aarts, G.A.; Beyer, H.L.; Morales, J.M.; Haydon, D.T. Establishing the link between habitat selection and animal population dynamics. *Ecol. Monogr.* **2015**, *85*, 413–436. [\[CrossRef\]](#)
3. Hirzel, A.H.; Le Lay, G.; Helfer, V.; Randin, C.F.; Guisan, A. Evaluating the ability of habitat suitability models to predict species presences. *Ecol. Model.* **2006**, *199*, 142–152. [\[CrossRef\]](#)
4. Phillips, S.J.; Anderson, R.P.; Dudík, M.; Schapire, R.E.; Blair, M.E. Opening the black box: An open-source release of Maxent. *Ecography* **2017**, *40*, 887–893. [\[CrossRef\]](#)
5. Yan, H.; Feng, L.; Zhao, Y.; Wu, D.; Zhu, C. Prediction of the spatial distribution of *Alternanthera philoxeroides* in China based on ArcGIS and MaxEnt. *Glob. Ecol. Conserv.* **2020**, *21*, e00856. [\[CrossRef\]](#)
6. Rondinini, C.; Stuart, S.; Boitani, L. Habitat Suitability Models and the Shortfall in Conservation Planning for African Vertebrates. *Conserv. Biol.* **2005**, *19*, 1488–1497. [\[CrossRef\]](#)
7. Tikkanen, O.-P.; Heinonen, T.; Kouki, J.; Matero, J. Habitat suitability models of saproxylic red-listed boreal forest species in long-term matrix management: Cost-effective measures for multi-species conservation. *Biol. Conserv.* **2007**, *140*, 359–372. [\[CrossRef\]](#)
8. Remya, K.; Ramachandran, A.; Jayakumar, S. Predicting the current and future suitable habitat distribution of *Myristica dactyloides* Gaertn. using MaxEnt model in the Eastern Ghats, India. *Ecol. Eng.* **2015**, *82*, 184–188. [\[CrossRef\]](#)
9. Millar, C.S.; Blouin-Demers, G. Habitat suitability modelling for species at risk is sensitive to algorithm and scale: A case study of Blanding’s turtle, *Emydoidea blandingii*, in Ontario, Canada. *J. Nat. Conserv.* **2012**, *20*, 18–29. [\[CrossRef\]](#)
10. Latif, Q.S.; Saab, V.A.; Dudley, J.G.; Markus, A.; Mellen-McLean, K. Development and evaluation of habitat suitability models for nesting white-headed woodpecker (*Dryobates albolarvatus*) in burned forest. *PLoS ONE* **2020**, *15*, e0233043. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Tittensor, D.P.; Baco, A.R.; Brewin, P.E.; Clark, M.R.; Consalvey, M.; Hall-Spencer, J.; Rowden, A.; Schlacher, T.; Stocks, K.I.; Rogers, A.D. Predicting global habitat suitability for stony corals on seamounts. *J. Biogeogr.* **2009**, *36*, 1111–1128. [\[CrossRef\]](#)
12. Sharma, S.; Arunachalam, K.; Bhavsar, D.; Kala, R. Modeling habitat suitability of *Perilla frutescens* with MaxEnt in Uttarakhand—A conservation approach. *J. Appl. Res. Med. Aromat. Plants* **2018**, *10*, 99–105. [\[CrossRef\]](#)
13. Ahmed, S.E.; McInerney, G.; O’Hara, K.; Harper, R.; Salido, L.; Emmott, S.; Joppa, L.N. Scientists and software—surveying the species distribution modelling community. *Divers. Distrib.* **2015**, *21*, 258–267. [\[CrossRef\]](#)
14. Elith, J.; Graham, C.H.; Anderson, R.P.; Dudík, M.; Ferrier, S.; Guisan, A.; Hijmans, R.J.; Huettmann, F.; Leathwick, J.R.; Lehmann, A.; et al. Novel methods improve prediction of species’ distributions from occurrence data. *Ecography* **2006**, *29*, 129–151. [\[CrossRef\]](#)
15. Hernandez, P.A.; Graham, C.H.; Master, L.L.; Albert, D.L. The effect of sample size and species characteristics on performance of different species distribution modeling methods. *Ecography* **2006**, *29*, 773–785. [\[CrossRef\]](#)
16. Kadmon, R.; Farber, O.; Danin, A. A Systematic Analysis of Factors Affecting the Performance of Climatic Envelope Models. *Ecol. Appl.* **2003**, *13*, 853–867. [\[CrossRef\]](#)
17. Skidmore, A.K.; Gauld, A.; Walker, P. Classification of kangaroo habitat distribution using three GIS models. *Int. J. Geogr. Inf. Syst.* **1996**, *10*, 441–454. [\[CrossRef\]](#)
18. Stockwell, D.R.; Peterson, A.T. Effects of sample size on accuracy of species distribution models. *Ecol. Model.* **2002**, *148*, 1–13. [\[CrossRef\]](#)
19. Wisz, M.S.; Hijmans, R.J.; Peterson, A.T.; Graham, C.H.; Guisan, A.; NCEAS Predicting Species Distributions Working Group. Effects of sample size on the performance of species distribution models. *Divers. Distrib.* **2008**, *14*, 763–773. [\[CrossRef\]](#)
20. Chapman, A.D.; Grafton, O. *Guide to Best Practices for Generalising Sensitive/Primary Species Occurrence-Data, Version 1.0*; Global Biodiversity Information Facility: Copenhagen, Denmark, 2008; Volume 27. [\[CrossRef\]](#)
21. Graham, C.H.; Ferrier, S.; Huettman, F.; Moritz, C.; Peterson, A.T. New developments in museum-based informatics and applications in biodiversity analysis. *Trends Ecol. Evol.* **2004**, *19*, 497–503. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Wiecezorek, J.; Guo, Q.; Hijmans, R. The point-radius method for georeferencing locality descriptions and calculating associated uncertainty. *Int. J. Geogr. Inf. Sci.* **2004**, *18*, 745–767. [\[CrossRef\]](#)

23. Feeley, K.J.; Silman, M.R. Modelling the responses of Andean and Amazonian plant species to climate change: The effects of georeferencing errors and the importance of data filtering. *J. Biogeogr.* **2010**, *37*, 733–740. [\[CrossRef\]](#)
24. Guo, Q.; Liu, Y.; Wiecek, J. Georeferencing locality descriptions and computing associated uncertainty using a probabilistic approach. *Int. J. Geogr. Inf. Sci.* **2008**, *22*, 1067–1090. [\[CrossRef\]](#)
25. Graham, C.H.; Elith, J.; Hijmans, R.J.; Guisan, A.; Peterson, A.T.; Loiselle, B.; The Nceas Predicting Species Distributions Working Group. The influence of spatial errors in species occurrence data used in distribution models. *J. Appl. Ecol.* **2007**, *45*, 239–247. [\[CrossRef\]](#)
26. Dickinson, J.L.; Shirk, J.; Bonter, D.N.; Bonney, R.; Crain, R.L.; Martin, J.; Phillips, T.B.; Purcell, K. The current state of citizen science as a tool for ecological research and public engagement. *Front. Ecol. Environ.* **2012**, *10*, 291–297. [\[CrossRef\]](#)
27. Elith, J.; Leathwick, J.R. Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. *Annu. Rev. Ecol. Evol. Syst.* **2009**, *40*, 677–697. [\[CrossRef\]](#)
28. Franklin, J. *Mapping Species Distributions: Spatial Inference and Prediction*; Cambridge University Press: Cambridge, UK, 2010.
29. Pocock, M.J.O.; Tweddle, J.C.; Savage, J.; Robinson, L.; Roy, H.E. The diversity and evolution of ecological and environmental citizen science. *PLoS ONE* **2017**, *12*, e0172579. [\[CrossRef\]](#) [\[PubMed\]](#)
30. Tulloch, A.I.; Possingham, H.P.; Joseph, L.N.; Szabo, J.; Martin, T.G. Realising the full potential of citizen science monitoring programs. *Biol. Conserv.* **2013**, *165*, 128–138. [\[CrossRef\]](#)
31. Singh, P.; Saran, S. Maximum Entropy Modeling Using Citizen Science: Use Case on Jacobin Cuckoo as an Indicator of Indian Monsoon. *ISPRS Ann. Photogramm. Remote. Sens. Spat. Inf. Sci.* **2020**, *5*, 23–30. [\[CrossRef\]](#)
32. Whitelaw, G.; Vaughan, H.; Craig, B.; Atkinson, D. Establishing the Canadian Community Monitoring Network. *Environ. Monit. Assess.* **2003**, *88*, 409–418. [\[CrossRef\]](#)
33. Cooper, C.B.; Dickinson, J.; Phillips, T.; Bonney, R. Citizen Science as a Tool for Conservation in Residential Ecosystems. *Ecol. Soc.* **2007**, *12*, 11. [\[CrossRef\]](#)
34. Howe, J. The rise of crowdsourcing. *Wired Mag.* **2006**, *14*, 1–4.
35. Irwin, A. Constructing the Scientific Citizen: Science and Democracy in the Biosciences. *Reconfiguring Nature* **2017**, *10*, 281–310. [\[CrossRef\]](#)
36. Burke, J.A.; Estrin, D.; Hansen, M.; Parker, A.; Ramanathan, N.; Reddy, S.; Srivastava, M.B. Participatory Sensing. UCLA: Center for Embedded Network Sensing. 2006. Available online: <https://escholarship.org/uc/item/19h777qd> (accessed on 28 May 2021).
37. Haklay, M. Citizen Science and Volunteered Geographic Information: Overview and Typology of Participation. In *Crowdsourcing Geographic Knowledge*; Springer Science and Business Media LLC: Dordrecht, The Netherlands, 2013; pp. 105–122.
38. Wiggins, A.; Crowston, K. From Conservation to Crowdsourcing: A Typology of Citizen Science. In *Proceedings of the 44th Hawaii International Conference on System Sciences*; Institute of Electrical and Electronics Engineers (IEEE): Piscataway, NJ, USA, 2011; pp. 1–10.
39. Wilderman, C.C. SHERMANS CREEK: Portrait of a watershed. In *Technical Status Report*; Dickinson College: Carlisle, UK, 2004.
40. Brown, P.; Morello-Frosch, R.; Zavestoski, S. *Contested Illnesses: Citizens, Science, and Health Social Movements*; University of California Press: Berkeley, CA, USA, 2011.
41. Schade, S.; Tsinaraki, C.; Roglia, E. Scientific data from and for the citizen. *First Monday* **2017**, *22*. [\[CrossRef\]](#)
42. Campbell, J.; Bowser, A.; Fraisl, D.; Meloche, M. Citizen science and data integration for understanding Marine Litter. In *Data for Good Exchange*; IASA: New York, NY, USA, 2019.
43. Hsu, Y.C.; Cross, J.; Dille, P.; Tasota, M.; Dias, B.; Sargent, R.; Nourbakhsh, I. Smell Pittsburgh: Engaging Community Citizen Science for Air Quality. *ACM Trans. Interact. Intell. Syst.* **2020**, *10*, 1–49. [\[CrossRef\]](#)
44. Kocaman, S.; Gokceoglu, C. A CitSci app for landslide data collection. *Landslides* **2018**, *16*, 611–615. [\[CrossRef\]](#)
45. Kocaman, S.; Gokceoglu, C. On the Use of CitSci and Vgi in Natural Hazard Assessment. *ISPRS Int. Arch. Photogramm. Remote. Sens. Spat. Inf. Sci.* **2018**, *XLII-5*, 69–73. [\[CrossRef\]](#)
46. Woodall, G.M.; Hoover, M.D.; Williams, R.; Benedict, K.; Harper, M.; Soo, J.-C.; Jarabek, A.M.; Stewart, M.J.; Brown, J.S.; Hulla, J.E.; et al. Interpreting Mobile and Handheld Air Sensor Readings in Relation to Air Quality Standards and Health Effect Reference Values: Tackling the Challenges. *Atmosphere* **2017**, *8*, 182. [\[CrossRef\]](#)
47. Can, R.; Kocaman, S.; Gokceoglu, C. Development of a CitSci and artificial intelligence supported GIS platform for landslide data collection. *ISPRS Int. Arch. Photogramm. Remote. Sens. Spat. Inf. Sci.* **2020**, *XLIII-B5-2*, 43–50. [\[CrossRef\]](#)
48. Can, R.; Kocaman, S.; Gokceoglu, C. A Convolutional Neural Network Architecture for Auto-Detection of Landslide Photographs to Assess Citizen Science and Volunteered Geographic Information Data Quality. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 300. [\[CrossRef\]](#)
49. Yalçın, I.; Kocaman, S.; Gokceoglu, C. A CitSci Approach for Rapid Earthquake Intensity Mapping: A Case Study from Istanbul (Turkey). *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 266. [\[CrossRef\]](#)
50. Kelemen-Finan, J.; Scheuch, M.; Winter, S. Contributions from citizen science to science education: An examination of a biodiversity citizen science project with schools in Central Europe. *Int. J. Sci. Educ.* **2018**, *40*, 2078–2098. [\[CrossRef\]](#)
51. Kobori, H.; Dickinson, J.L.; Washitani, I.; Sakurai, R.; Amano, T.; Komatsu, N.; Kitamura, W.; Takagawa, S.; Koyama, K.; Ogawara, T.; et al. Citizen science: A new approach to advance ecology, education, and conservation. *Ecol. Res.* **2016**, *31*, 1–19. [\[CrossRef\]](#)
52. Bonney, R.; Cooper, C.B.; Dickinson, J.; Kelling, S.; Phillips, T.; Rosenberg, K.V.; Shirk, J. Citizen Science: A Developing Tool for Expanding Science Knowledge and Scientific Literacy. *Bioscience* **2009**, *59*, 977–984. [\[CrossRef\]](#)

53. Koomen, M.H.; Rodriguez, E.; Hoffman, A.; Petersen, C.; Oberhauser, K. Authentic science with citizen science and student-driven science fair projects. *Sci. Educ.* **2018**, *102*, 593–644. [\[CrossRef\]](#)
54. Bloom, E.H.; Crowder, D.W. Promoting Data Collection in Pollinator Citizen Science Projects. *Citiz. Sci. Theory Pr.* **2020**, *5*, 5. [\[CrossRef\]](#)
55. Brzeski, K.E.; Gunther, M.S.; Black, J.M. Evaluating river otter demography using noninvasive genetic methods. *J. Wildl. Manag.* **2013**, *77*, 1523–1531. [\[CrossRef\]](#)
56. Kocaman, S.; Gokceoglu, C. CitSci as a New Approach for Landslide Researches. In *Proceedings of the Lecture Notes*; Springer: Cham, Switzerland, 2019; pp. 161–183.
57. Clery, D. Galaxy Zoo Volunteers Share Pain and Glory of Research. *Science* **2011**, *333*, 173–175. [\[CrossRef\]](#) [\[PubMed\]](#)
58. Reed, J.; Raddick, M.J.; Lardner, A.; Carney, K. An Exploratory Factor Analysis of Motivations for Participating in Zooniverse, a Collection of Virtual Citizen Science Projects. In *Proceedings of the 2013, 46th Hawaii International Conference on System Sciences*, Wailea, Maui, HI, USA, 7–10 January 2013; pp. 610–619.
59. Follett, R.; Strezov, V. An Analysis of Citizen Science Based Research: Usage and Publication Patterns. *PLoS ONE* **2015**, *10*, e0143687. [\[CrossRef\]](#) [\[PubMed\]](#)
60. Parrish, J.K.; Burgess, H.; Weltzin, J.F.; Fortson, L.; Wiggins, A.; Simmons, B. Exposing the Science in Citizen Science: Fitness to Purpose and Intentional Design. *Integr. Comp. Biol.* **2018**, *58*, 150–160. [\[CrossRef\]](#)
61. Broeder, L.D.; Devilee, J.; Van Oers, H.; Schuit, J.; Wagemakers, A. Citizen Science for public health. *Health Promot. Int.* **2016**, *33*, 505–514. [\[CrossRef\]](#)
62. Donnelly, A.; Crowe, O.; Regan, E.; Begley, S.; Caffarra, A. The role of citizen science in monitoring biodiversity in Ireland. *Int. J. Biometeorol.* **2013**, *58*, 1237–1249. [\[CrossRef\]](#)
63. Damoulas, T.; Henry, S.; Farnsworth, A.; Lanzone, M.; Gomes, C. Bayesian Classification of Flight Calls with a Novel Dynamic Time Warping Kernel. In *Proceedings of the 2010 Ninth International Conference on Machine Learning and Applications*; Institute of Electrical and Electronics Engineers (IEEE): Piscataway, NJ, USA, 2010; pp. 424–429.
64. Stoeckle, M. Taxonomy, DNA, and the Bar Code of Life. *Bioscience* **2003**, *53*, 796–797. [\[CrossRef\]](#)
65. Turner, W.; Spector, S.; Gardiner, N.; Fladeland, M.; Sterling, E.; Steininger, M. Remote sensing for biodiversity science and conservation. *Trends Ecol. Evol.* **2003**, *18*, 306–314. [\[CrossRef\]](#)
66. Hemmi, A.; Graham, I. Hacker science versus closed science: Building environmental monitoring infrastructure. *Inf. Commun. Soc.* **2013**, *17*, 830–842. [\[CrossRef\]](#)
67. Sullivan, P.J.; Acheson, J.; Angermeier, P.L.; Faast, T.; Flemma, J.; Jones, C.M.; Knudsen, E.E.; Minello, T.J.; Secor, D.H.; Wunderlich, R.; et al. Defining and implementing best available science for fisheries and environmental science, policy, and management. *Fisheries* **2006**, *31*, 460.
68. Singh, P.; Saran, S.; Kumar, D.; Padalia, H.; Srivastava, A.; Kumar, A.S. Species Mapping Using Citizen Science Approach Through IBIN Portal: Use Case in Foothills of Himalaya. *J. Indian Soc. Remote. Sens.* **2018**, *46*, 1725–1737. [\[CrossRef\]](#)
69. Novacek, M.J. Engaging the public in biodiversity issues. *Proc. Natl. Acad. Sci. USA* **2008**, *105*, 11571–11578. [\[CrossRef\]](#)
70. Silvertown, J.; Cook, L.; Cameron, R.; Dodd, M.; McConway, K.; Worthington, J.; Skelton, P.; Anton, C.; Bossdorf, O.; Baur, B.; et al. Citizen Science Reveals Unexpected Continental-Scale Evolutionary Change in a Model Organism. *PLoS ONE* **2011**, *6*, e18927. [\[CrossRef\]](#) [\[PubMed\]](#)
71. Conrad, C.C.; Hilchey, K.G. A review of citizen science and community-based environmental monitoring: Issues and opportunities. *Environ. Monit. Assess.* **2010**, *176*, 273–291. [\[CrossRef\]](#) [\[PubMed\]](#)
72. Freeman, S.N.; Noble, D.G.; Newson, S.E.; Baillie, S.R. Modelling population changes using data from different surveys: The Common Birds Census and the Breeding Bird Survey. *Bird Study* **2007**, *54*, 61–72. [\[CrossRef\]](#)
73. Michener, W.K.; Jones, M.B. Ecoinformatics: Supporting ecology as a data-intensive science. *Trends Ecol. Evol.* **2012**, *27*, 85–93. [\[CrossRef\]](#)
74. Yu, J.; Kelling, S.; Gerbracht, J.; Wong, W.-K. Automated data verification in a large-scale citizen science project: A case study. In *Proceedings of the 2012 IEEE 8th International Conference on E-Science*; Institute of Electrical and Electronics Engineers (IEEE): Piscataway, NJ, USA, 2012; pp. 1–8.
75. McClintock, B.T.; Bailey, L.L.; Pollock, K.H.; Simons, T.R. Unmodeled observation error induces bias when inferring patterns and dynamics of species occurrence via aural detections. *Ecology* **2010**, *91*, 2446–2454. [\[CrossRef\]](#)
76. Boakes, E.H.; McGowan, P.J.K.; Fuller, R.; Chang-Qing, D.; Clark, N.E.; O'Connor, K.; Mace, G. Distorted Views of Biodiversity: Spatial and Temporal Bias in Species Occurrence Data. *PLoS Biol.* **2010**, *8*, e1000385. [\[CrossRef\]](#) [\[PubMed\]](#)
77. Edwards, J.L.; Lane, M.A.; Nielsen, E.S. Interoperability of Biodiversity Databases: Biodiversity Information on Every Desktop. *Science* **2000**, *289*, 2312–2314. [\[CrossRef\]](#)
78. Wheeler, Q.D. What if GBIF? *Bioscience* **2004**, *54*, 718. [\[CrossRef\]](#)
79. Telenius, A. Biodiversity information goes public: GBIF at your service. *Nord. J. Bot.* **2011**, *29*, 378–381. [\[CrossRef\]](#)
80. Suarez, A.V.; Tsutsui, N.D. The value of museum collections for research and society. *BioScience* **2004**, *54*, 66–74. [\[CrossRef\]](#)
81. Ponder, W.F.; Carter, G.A.; Flemons, P.; Chapman, R.R. Evaluation of Museum Collection Data for Use in Biodiversity Assessment. *Conserv. Biol.* **2001**, *15*, 648–657. [\[CrossRef\]](#)
82. Pennisi, E. Taxonomic Revival. *Science* **2000**, *289*, 2306–2308. [\[CrossRef\]](#) [\[PubMed\]](#)

83. Shaffer, H.; Fisher, R.N.; Davidson, C. The role of natural history collections in documenting species declines. *Trends Ecol. Evol.* **1998**, *13*, 27–30. [CrossRef]
84. Lozier, J.D.; Aniello, P.; Hickerson, M.J. Predicting the distribution of Sasquatch in western North America: Anything goes with ecological niche modelling. *J. Biogeogr.* **2009**, *36*, 1623–1627. [CrossRef]
85. Thorn, J.S.; Nijman, V.; Smith, D.; Nekaris, K.A.I. Ecological niche modelling as a technique for assessing threats and setting conservation priorities for Asian slow lorises (Primates: Nycticebus). *Divers. Distrib.* **2009**, *15*, 289–298. [CrossRef]
86. Herrando-Moraira, S.; Vitales, D.; Nualart, N.; Gómez-Bellver, C.; Ibáñez, N.; Massó, S.; Cachón-Ferrero, P.; González-Gutiérrez, P.A.; Guillot, D.; Herrera, I.; et al. Global distribution patterns and niche modelling of the invasive *Kalanchoe × houghtonii* (Crassulaceae). *Sci. Rep.* **2020**, *10*, 1–18. [CrossRef] [PubMed]
87. Préau, C.; Nadeau, I.; Sellier, Y.; Isselin-Nondedeu, F.; Bertrand, R.; Collas, M.; Capinha, C.; Grandjean, F. Niche modelling to guide conservation actions in France for the endangered crayfish *Austropotamobius pallipes* in relation to the invasive *Pacifastacus leniusculus*. *Freshw. Biol.* **2019**, *65*, 304–315. [CrossRef]
88. Alhajer, B.H.; Fourcade, Y. High correlation between species-level environmental data estimates extracted from IUCN expert range maps and from GBIF occurrence data. *J. Biogeogr.* **2019**, *46*, 1329–1341. [CrossRef]
89. Sung, S.; Kwon, Y.-S.; Lee, D.K.; Cho, Y. Predicting the Potential Distribution of an Invasive Species, *Solenopsis invicta* Buren (Hymenoptera: Formicidae), under Climate Change using Species Distribution Models. *Entomol. Res.* **2018**, *48*, 505–513. [CrossRef]
90. Huettmann, F.; Artukhin, Y.; Gilg, O.; Humphries, G. Predictions of 27 Arctic pelagic seabird distributions using public environmental variables, assessed with colony data: A first digital IPY and GBIF open access synthesis platform. *Mar. Biodivers.* **2011**, *41*, 141–179. [CrossRef]
91. Gomes, V.H.F.; Mayle, F.E.; Gosling, W.D.; Vieira, I.C.G.; Salomão, R.P.; Ter Steege, H. Modelling the distribution of Amazonian tree species in response to long-term climate change during the Mid-Late Holocene. *J. Biogeogr.* **2020**, *47*, 1530–1540. [CrossRef]
92. Hastings, R.; Rutterford, L.A.; Freer, J.J.; Collins, R.A.; Simpson, S.D.; Genner, M.J. Climate Change Drives Poleward Increases and Equatorward Declines in Marine Species. *Curr. Biol.* **2020**, *30*, 1572–1577.e2. [CrossRef] [PubMed]
93. Siqueira, S.D.F.; Higuchi, P.; Da Silva, A.C. Contemporary and Future Potential Geographic Distribution of *Cedrela fissilis* Vell. under Climate Change Scenarios. *Revista Árvore* **2019**, *43*, 43. [CrossRef]
94. Bender, I.M.A.; Kissling, W.D.; Böhning-Gaese, K.; Hensen, I.; Kühn, I.; Nowak, L.; Töpfer, T.; Wiegand, T.; Dehling, D.M.; Schleuning, M. Projected impacts of climate change on functional diversity of frugivorous birds along a tropical elevational gradient. *Sci. Rep.* **2019**, *9*, 1–12. [CrossRef]
95. Ikeda, D.H.; Max, T.L.; Allan, G.J.; Lau, M.K.; Shuster, S.M.; Whitham, T.G. Genetically informed ecological niche models improve climate change predictions. *Glob. Chang. Biol.* **2017**, *23*, 164–176. [CrossRef] [PubMed]
96. Sharma, R.K.; Goyal, A.K.; Sharma, M. Ecology and Evolution of Nest Parasitism in Indian Cuckoo. *Nat. Environ. Pollut. Technol.* **2015**, *14*, 847–853.
97. GBIF.org. GBIF Occurrence. Available online: <https://doi.org/10.15468/dl.gd9tk3> (accessed on 23 April 2021).
98. Southwest Monsoon Season. Available online: <http://www.imdchennai.gov.in/swweb.htm> (accessed on 31 October 2020).
99. A Study of the Northeast Monsoon Rainfall of Tamilnad. Available online: https://metnet.imd.gov.in/mausamdocs/1413_F.pdf (accessed on 31 October 2020).
100. Fick, S.E.; Hijmans, R.J. WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. *Int. J. Climatol.* **2017**, *37*, 4302–4315. [CrossRef]
101. Global Climate and Weather Data. Available online: <https://www.worldclim.org/data/index.html> (accessed on 31 October 2020).
102. Séférian, R.; Nabat, P.; Michou, M.; Saint-Martin, D.; Voldoire, A.; Colin, J.; Decharme, B.; Delire, C.; Berthet, S.; Chevallier, M.; et al. Evaluation of CNRM Earth System Model, CNRM-ESM2-1: Role of Earth System Processes in Present-Day and Future Climate. *J. Adv. Model. Earth Syst.* **2019**, *11*, 4182–4227. [CrossRef]
103. Eyring, V.; Bony, S.; Meehl, G.A.; Senior, C.A.; Stevens, B.; Stouffer, R.J.; Taylor, K.E. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.* **2016**, *9*, 1937–1958. [CrossRef]
104. Dormann, C.F.; Elith, J.; Bacher, S.; Buchmann, C.; Carl, G.; Carré, G.; Marquéz, J.R.G.; Gruber, B.; Lafourcade, B.; Leitão, P.J.; et al. Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography* **2013**, *36*, 27–46. [CrossRef]
105. Naimi, B. Usdm: Uncertainty Analysis for Species Distribution Models. R Package ver. 1.1–18. 2017. Available online: <https://cran.r-project.org/web/packages/usdm/index.html> (accessed on 12 January 2021).
106. Zuur, A.F.; Ieno, E.N.; Elphick, C.S. A protocol for data exploration to avoid common statistical problems: Data exploration. *Methods Ecol. Evol.* **2010**, *1*, 3–14. [CrossRef]
107. Phillips, S.J. A brief tutorial on Maxent. *AT&T Res.* **2005**, *190*, 231–259.
108. Qin, A.; Liu, B.; Guo, Q.; Bussmann, R.W.; Ma, F.; Jian, Z.; Xu, G.; Pei, S. Maxent modeling for predicting impacts of climate change on the potential distribution of *Thuja sutchuenensis* Franch., an extremely endangered conifer from southwestern China. *Glob. Ecol. Conserv.* **2017**, *10*, 139–146. [CrossRef]
109. Dingliang, X.; Zhanqing, H. The principle of maximum entropy and its applications in ecology. *Biodivers. Sci.* **2011**, *19*, 295–302. [CrossRef]

-
110. Yang, X.; Kushwaha, S.; Saran, S.; Xu, J.; Roy, P. Maxent modeling for predicting the potential distribution of medicinal plant, *Justicia adhatoda* L. in Lesser Himalayan foothills. *Ecol. Eng.* **2013**, *51*, 83–87. [[CrossRef](#)]
 111. He, J.; Kolovos, A. Bayesian maximum entropy approach and its applications: A review. *Stoch. Environ. Res. Risk Assess.* **2018**, *32*, 859–877. [[CrossRef](#)]
 112. Kleidon, A.; Malhi, Y.; Cox, P. Maximum entropy production in environmental and ecological systems. *Philos. Trans. R. Soc. B Biol. Sci.* **2010**, *365*, 1297–1302. [[CrossRef](#)]
 113. Fourcade, Y.; Engler, J.O.; Rödder, D.; Secondi, J. Mapping Species Distributions with MAXENT Using a Geographically Biased Sample of Presence Data: A Performance Assessment of Methods for Correcting Sampling Bias. *PLoS ONE* **2014**, *9*, e97122. [[CrossRef](#)]
 114. Pearson, R.G.; Raxworthy, C.J.; Nakamura, M.; Peterson, A.T. ORIGINAL ARTICLE: Predicting species distributions from small numbers of occurrence records: A test case using cryptic geckos in Madagascar. *J. Biogeogr.* **2006**, *34*, 102–117. [[CrossRef](#)]
 115. Kumar, S.; Stohlgren, T.J. Maxent modeling for predicting suitable habitat for threatened and endangered tree *Canacomyrica monticola* in New Caledonia. *J. Ecol. Nat. Environ.* **2009**, *1*, 094–098. [[CrossRef](#)]
 116. Fielding, A.H.; Bell, J.F. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environ. Conserv.* **1997**, *24*, 38–49. [[CrossRef](#)]
 117. Swets, J.A. Measuring the accuracy of diagnostic systems. *Science* **1988**, *240*, 1285–1293. [[CrossRef](#)]
 118. Guhathakurta, P.; Rajeevan, M.; Sikka, D.R.; Tyagi, A. Observed changes in southwest monsoon rainfall over India during 1901–2011. *Int. J. Climatol.* **2015**, *35*, 1881–1898. [[CrossRef](#)]
 119. Cheaib, A.; Badeau, V.; Boé, J.; Chuine, I.; Delire, C.; Dufrêne, E.; François, C.; Gritti, E.S.; Legay, M.; Pagé, C.; et al. Climate change impacts on tree ranges: Model intercomparison facilitates understanding and quantification of uncertainty. *Ecol. Lett.* **2012**, *15*, 533–544. [[CrossRef](#)]