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Research article

Understanding the Spatial Distribution and Environmental Drivers of Kingfishers (Alcedinidae) Through the Species Distribution Modeling Approach

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Abstract

Accurate prediction of species distribution is crucial for biodiversity conservation, particularly amid widespread habitat loss. As one of the largest islands and heavily developed landmasses in the Indonesian archipelago, Java is facing rapid habitat deterioration due to environmental changes. While most studies have historically focused on the protection species within protected areas, species distribution outside protected areas remain largely understudied. Consequently, metrics of citizen science are necessary to quantify the contemporary requirements of species, and to predict their potential distributions. We therefore developed habitat suitability models for nine species of the kingfishers (family Alcedinidae) distributed broadly across Java. Each model evaluates species occurrence data derived from citizen science platforms. Species distribution models of each species were constructed using bioclimatic, physiographic, and hydrologic variables through the random forest machine learning model. The models showed moderate to high predictive performance, with AUC-ROC values ranging from 0.75–0.93 and cross-validated AUC values ranging from 0.74 to 0.92, indicating reliable discrimination ability across species. Annual rainfall, elevation, vegetation, and proximity to water bodies are key factors influencing the distribution of kingfishers. The study highlights that potential habitats for all the studied species are located across Java, extending beyond protected forest areas to most other types of land uses. Conservation efforts should focus on preserving critical habitat features and implementing landscape-level management strategies, particularly for endemic and rare species.

Keywords: habitat suitability model; alcedinidae; human-altered habitat; spatial thinning; wildlife conservation.

1. Introduction

The unprecedented decline in global biodiversity is largely driven by rapid environmental changes such as deforestation, rapid urbanisation and increasing anthropogenic pressures (Kong *et al.,* 2021; Meena & Jha, 2023). These changes alter the structure and function of natural ecosystems, and are often caused by human activities (Gao *et al.,* 2021; Peña *et al.,* 2023). Southeast Asia, a global biodiversity hotspot, is experiencing environmental pressures from land-use change, deforestation and climate change, threatening habitats and species diversity (Liu *et al.,* 2025; Namkhan *et al.,* 2022). In the context of ongoing land use transformation, understanding of species distribution is a critical priority in landscape planning and conservation biodiversity (Barik *et al.,* 2022; Martín *et al.,* 2021). However, conservation efforts in developing countries such as Indonesia face challenges due to limited biodiversity data (Shmelev, 2025). Spatial ecology plays a fundamental role in addressing this challenge by examining how species are distributed across landscapes and how these patterns are influenced by environmental gradients and ecological processes (Stenbacka *et al.,* 2025). Species distribution models (SDMs) are essential for assessing species ecological requirements and predicting suitable habitats (Yao *et al.,* 2025) by linking species occurrences with environmental conditions (Anselmetto *et al.,* 2025). Machine learning approaches can be used to develop SDMs, potentially strengthening and supporting conservation efforts by improving the accuracy of predictive models (Branco *et al.,* 2023). The distribution and persistence of wildlife species are influenced by various environmental conditions (Kindlmann *et al.,* 2025). Each species limits its potential distribution based on the resources available for foraging and success in breeding across spatiotemporal scales (Binley *et al.,* 2023; Cubley *et al.,* 2020; Stenbacka *et al.,* 2025). The area occupied by a population varies depending on resources and environmental conditions (Crego *et al.,* 2025), with habitat selection in animals driven by species-specific behaviours that reflect their ecological requirements and adaptation strategies (Beumer *et al.,* 2023; Mirante *et al.,* 2024). Each species including birds selects specific habitat features based on biotic and abiotic factors which govern their use or otherwise (Kindlmann *et al.,* 2025; Stenbacka *et al.,* 2025).

The presence of wildlife such as birds can reflect environmental conditions (Sinha *et al.,* 2019). Each species has a functional role within the community and influences ecosystem functions (Takola & Schielzeth, 2022). Birds, including kingfishers, are suitable indicator species due to their sensitivity to environmental changes. Their ecological role also makes them valuable for inclusion in monitoring schemes as indicators of environmental damage (Maznikova *et al.,* 2024; Shifa *et al.,* 2023). Species within the kingfishers are able to utilise riparian ecosystems as their habitat (Lane et al., 2013) and respond to small changes in their microenvironment (Barik *et al.,* 2022; Shifa *et al.,* 2023). Java Island, home to 56.1% of Indonesia's population (Central Bureau of Statistics, 2024), faces intense anthropogenic pressure due to its high population density and annual growth rate of 1.25%. Land conversion primarily affects lowland regions, where agriculture and urban expansion have significantly altered natural landscapes, while highland areas are increasingly dominated by plantation crops (Setiawan & Kunihiko, 2020). Anthropogenic pressure on the island has led to a decline in ecological functions such as water reservoirs, flood barriers, landslide protection, soil fertility, clean air provision, and biodiversity (Dsikowitzky *et al.,* 2019; Huylenbroeck *et al.,* 2021; Wiwoho *et al.,* 2023). Waste from factory processing and agricultural activities pollutes rivers posing a threat to species that live or feed in these areas (Kustamar & Wulandari, 2020; Risjani *et al.,* 2020), including those within the Alcedinidae family. Despite environmental degradation, Java plays a crucial role as a habitat for a diverse range of species belonging to this family. Among all the species found on the island of Java, which one is listed on the 2024 IUCN Red List of Threatened Species, namely Alcedo euryzona. This species is protected under the Minister of Environment and Forestry Regulation No. P.106/MENLHK/SETJEN/KUM.1/12/2018. Three kingfisher species are migratory birds: Alcedo atthis, Todiramphus sanctus, and Halcyon pileate. The island's diverse land cover types offer a range of resources that support different needs of avian communities. At a spatial scale, generalist bird species select different land cover types based on the availability of environmental resources (Cady *et al.,* 2021). Kingfisher species have been observed using various resources in modified riparian ecosystems, including settlements, parks, gardens, and agricultural lands (Marcellia *et al.,* 2023).

Studies on the application of SDM are still largely concentrated in temperate regions (Fadda *et al.,* 2026; Vasconcelos *et al.,* 2024). In Asia, SDMs applications are increasing (Tümer *et al.,* 2026), but their representation is relatively limited in tropical ecosystems, particularly in Southeast Asia. Numerous approaches are available for SDM, including generalized linear models, MaxEnt, ANN and other machine learning techniques. This study uses the random forest (RF) model a machine learning algorithm widely used in ecological modeling which has been shown to outperform various other predictive methods (Breiman, 2001; Rongcheng *et al.,* 2025). This is particularly relevant in the context of understanding species ecology on the island of Java, where environmental heterogeneity require modeling approaches such as RF which are capable of capturing complex and nonlinear species-environment relationships (Tümer e*t al.,* 2026).

For bird taxa, particularly kingfisher species, most research focuses on species-specific ecology or habitat use at the local scale (Kesler & Haig, 2007b; Naher *et al.,* 2021; Taufiqurrahman *et al.,* 2020; Yaghmour *et al.,* 2025) but without linkage to area management units. Meanwhile, at the scale of island landscapes dominated by human activity, information on factors influencing the distribution and habitat use of kingfisher species remains limited. Many such species are common, adaptable, and widespread. Therefore, they are often perceived as having less immediate, high-profile conservation value than that of endangered species (Imron *et al.,* 2023; Paga *et al.,* 2022; Syartinilia *et al.,* 2024). Consequently, spatial understanding of how environmental gradients influence kingfishers habitat suitability in the tropics remains underdeveloped. This study aims to determine the suitable habitats of kingfisher species on the island of Java, with a particular focus on understanding their distribution across the island's heterogeneous landscapes. The study contributes not only by expanding geographic coverage, but also by demonstrating the application of machine learning-based SDM in the tropical landscapes of developing countries with limited biodiversity data. It provides new insights into species–environment relationships in understudied tropical regions and highlights the potential of machine learning approaches to model the distribution of kingfisher species on Java Island. This spatial information is relevant for landscape-level management within multifunctional landscapes rather than being confined to forest area.

2. Methods

2.1. Study Area

The study encompassed the whole island of Java which is located on the southern part of the Indonesian archipelago (Figure 1). The island spans 132,792 km², extending from 5°52′S, 105°04′E in the northwest to 8°47′S, 114°36′E in the southeast. Administratively, it is divided

into six provinces : Banten, DKI Jakarta, West Java, Central Java, Yogyakarta, and East Java. Java has a tropical climate characterised by consistently warm temperatures and high humidity throughout the year, with seasonal variations in rainfall, with most regions receivinge between 2,000 and 4,000 mm of annual precipitation. The wet season typically occurs from November to March, bringing substantial rainfall to much of the island, while the eastern parts of Java tend to remain relatively dry from May to September (Sosilawati *et al.,* 2017). Almost all lowlands are used for agricultural and settlements, while the highlands are dominated by an increasing number of plantation crops (Setiawan & Kunihiko, 2020). The human population continues to grow, along with the expansion of residential areas into non-urban areas (Pravitasari *et al.,* 2024). However, Java still aprovides suitable habitat for six threatened species based on data from the Indonesia citizen science project (Squires *et al.,* 2021).

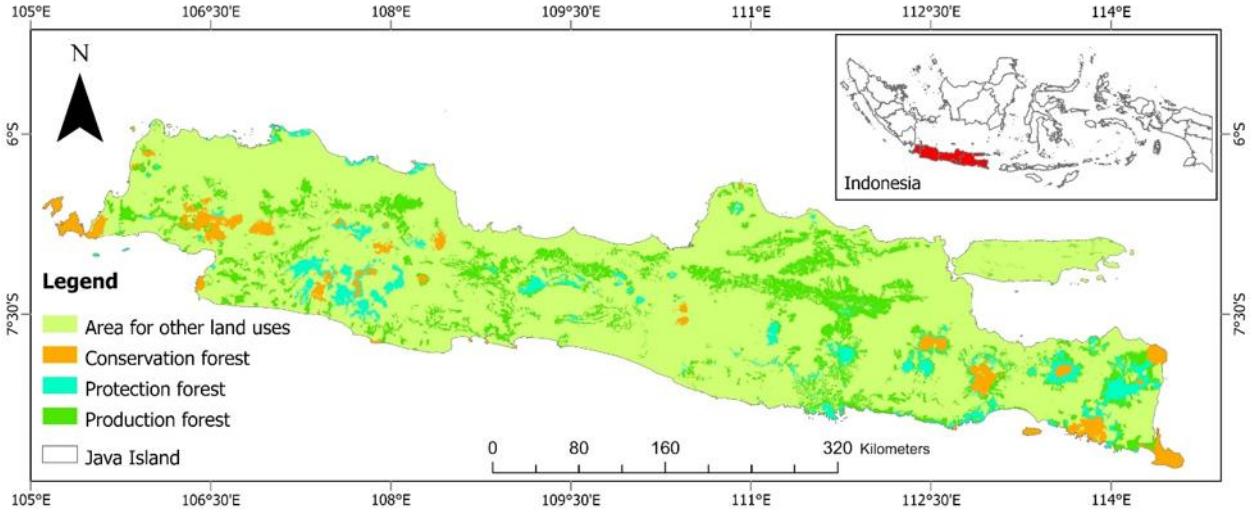

Figure 1. Map of the Study Area Illustrating the Spatial Distribution of Forest Function Across Java Island.

2.2. Data Acquisition

Data were collected for 13 kingfisher species (the blue-eared kingfisher (Alcedo meninting), the Javan blue-banded kingfisher (Alcedo euryzona), the cerulean kingfisher (Alcedo coerulescens), the rufous-backed kingfisher (Ceyx rufidorsa), the banded kingfisher (Lacedo pulchela), the Javan kingfisher (Halcyon cyanoventris), the collared kingfisher (Todirhampus chloris), the white-throated kingfisher (Halcyon smyrnensis), the sacred kingfisher (Todiramphus sanctus), the ruddy kingfisher (Halcyon coromanda), the common kingfisher (Alcedo atthis), the stork-billed kingfisher (Pelargopsis capensis) and the black-capped kingfisher (Halcyon pileate)) from the period 2016 to 2023. We combined data from multiple citizen science (CS) platforms, thus obtaining a more balanced and comprehensive perspective (Silva *et al.,* 2023). The CS data expanded survey coverage into remote regions with limited road access, thereby reducing spatial bias (Squires *et al.,* 2021). Data were obtained from the Burungnesia CS project (https://birdpacker.org/burungnesia-kupunesia/); eBird (https://ebird.org/, accessed on 13 March 2024); and the Global Biodiversity Information Facility (GBIF; https://www.gbif.org/, accessed on 04 October 2023). These CS platforms follow standardised protocols for data recording, including the use of complete checklists (Callaghan *et al.,* 2021; Kelling *et al.,* 2019) with data subsequently verified by a team of local experts (Sullivan *et al.,* 2009).

Data filtering began by downloading occurrence data based on human observation or protocol type (traveling, stationary and incidental) (Johnston *et al.,* 2021; Kelling *et al.,* 2019). Occurrence records for kingfisher species were checked for duplicate entries, which were subsequently removed (Chowdhury *et al.,* 2023; Galván *et al.,* 2022) by using the "Delete Duplicate" feature in ArcGIS Pro 3.2. Spatial filtering was then applied in order to retain only one presence point per species within its estimated home range (Lajeunesse & Fourcade, 2023). To reflect biological realism, we considered known variations in home range size among Alcedinidae subfamilies. For example, species in the Halcyoninae subfamily are generally associated with larger home ranges than those in the Alcedininae family, largely due to differences in body size and behavior (Musseau *et al.,* 2021). Accordingly, we used one occurrence per grid cell of 7.29 km² for Halcyoninae (Kesler & Haig, 2007a, 2007b) and 5.74 km² for Alcedinidae (Musseau *et al.,* 2021). We applied a spatial rarefaction filter using home range estimates for Alcedininae as a baseline (Lajeunesse & Fourcade, 2023).

Table 1. Description and Sources of Environmental Variables for the Development of a Habitat Suitability Model for Kingfishers on the Island of Java.

Variable	Description	Source
NDVI	Vegetation density characterises the condition of vegetation cover (Barik *et al.,* 2022)	Landsat 8 satellite imagery available at https://earthexplorer.usgs.gov
Temperature	Temperature (Kesler & Haig, 2004, 2005)	Average temperature (oC) available at https://www.worldclim.org/data/worldclim21.html
Elevation	Altitude above mean sea level (m) (Kesler & Haig, 2007a)	30-Meter SRTM Tile Downloader available at https://dwtkns.com/srtm30m/
Vertical stratification of vegetation (palsar HH and HV; radar VV and VH)	Vegetation strata increases at polarisation values and decreases drastically on land surfaces and open waters (Vilches *et al.,* 2012)	Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar (ALOS/PALSAR) band L generating HH and HV polarisations (Dabrowska-Zielinska *et al.,* 2014) and optical sensor SENTINEL-1 band C generating VV and VH radar polarisations (Wajs, 2018) available at https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S1_GRD
Dist_water	Distance from water bodies (m) (Barik *et al.,* 2022)	Sub Region Java available at https://download.geofabrik.de/asia/indonesia.html
Built_up	Built-up areas (m^2) (Barik *et al.,* 2022; Naher *et al.,* 2021)	GHS-BUILT-S available at https://ghsl.jrc.ec.europa.eu/download.php?ds=bu
Precipitation	Average rainfall per year (mm) (Sultana & Sarker, 2016)	Annual precipitation available at https://www.worldclim.org/data/worldclim21.html

Thirteen kingfisher species have been recorded on Java, of which nine were retained for modeling after filtering: the blue-eared kingfisher (N = 715), the Javan blue-banded kingfisher (N = 38), the cerulean kingfisher (N = 1103), the rufous-backed kingfisher (N = 144), the banded kingfisher (N = 116), the Javan kingfisher (N = 2946), the collared kingfisher (N = 3671), the white-throated kingfisher (N = 33), and the sacred kingfisher (N = 197). The black-capped kingfisher was excluded due to the availability of only one presence point following filtering, which was insufficient for model training and validation. The ruddy kingfisher, the common kingfisher, and the stork-billed kingfisher were also excluded due to the caution needed when interpreting results from small samples (N < 30) (Breiner *et al.,* 2015; Cao *et al.,* 2024).

2.3. Environmental Predictors

To understand the distribution patterns of various kingfisher species in relation to geographic and environmental factors, we selected key environmental variables based on their ecological relevance and common use in habitat assessments (Fang *et al.,* 2025). Those considered for the study included vegetation density, temperature, elevation, vegetation strata, distance to water bodies, proximity to built-up areas, and annual rainfall (Table 1). These data were reprojected and all environment variables were standardised to the same coordinate system (WGS 1984 UTM Zone 49S) with a spatial resolution of 100 x 100 m, and saved in GeoTIFF file format, as required by the random forest model, in order to facilitate interpretation of the model outputs. Prior to model development, multicollinearity among the selected variables was analysed using Pearson's correlation analysis. A dendrogram derived from hierarchical clustering of correlation distances was used to visualize the structure of the relationship between predictors and to identify clusters of highly-correlated variables. In cases where two or more variables were highly correlated cluster ($|r| > 0.70$), we retained the variable that was more ecologically meaningful (Achour & Kalboussi, 2020) in relation to the known habitat preferences and requirements of kingfisher species.

2.4. Species Distribution Model

We built habitat suitability models using a random forest (RF) algorithm implemented in the randomForest package in R version 4.1.1 (2021-08-10). RF is relatively robust to multicollinearity and overfitting due to its ensemble structure (Breiman, 2001; Fink *et al.,* 2023) particularly in relation to spatial citizen science data (Imron *et al.,* 2025). The models were built with a collection of decision trees to obtain accurate and stable predictive information (Breiman, 2001; Sun *et al.,* 2024). Model robustness was further assessed using repeated cross-validation (Ramampiandra *et al.,* 2023) and multiple evaluation metrics (Figure 2).

Absence data were approximated through pseudo-absence generation, simulating non-detection areas within the environmental space of the study region (Broussin *et al.,* 2024). The RF model, applied to both presence and pseudo-absence samples, produced reliable predictions, thereby maximising the value of the data collected through citizen science initiatives (Bird *et al.,* 2014; O'Neill *et al.,* 2023). The number of pseudo-absence sample data for each kingfisher species was

the same as the presence sample points (Bracho-Estévanez *et al.,* 2024; Broussin *et al.,* 2024; Valavi *et al.,* 2021). The approach taken restricts the estimated environmental niche of a species because the model becomes dominated by absence data (Broussin *et al.,* 2024). Pseudo-absence points were randomly generated outside the buffer area using the 'Generate Random Points' tool in ArcGIS Pro. The buffer area was an average dispersal distance of 849 meters (as the radius of the circle), reflecting the typical movement range of kingfisher, which aggressively defend their territories during the breeding season (Kesler & Haig, 2007b). All background locations were considered to represent the possibility of not finding the species at a particular location and were treated as pseudo-absence data (Sillero *et al.,* 2021; Zhang *et al.,* 2019).

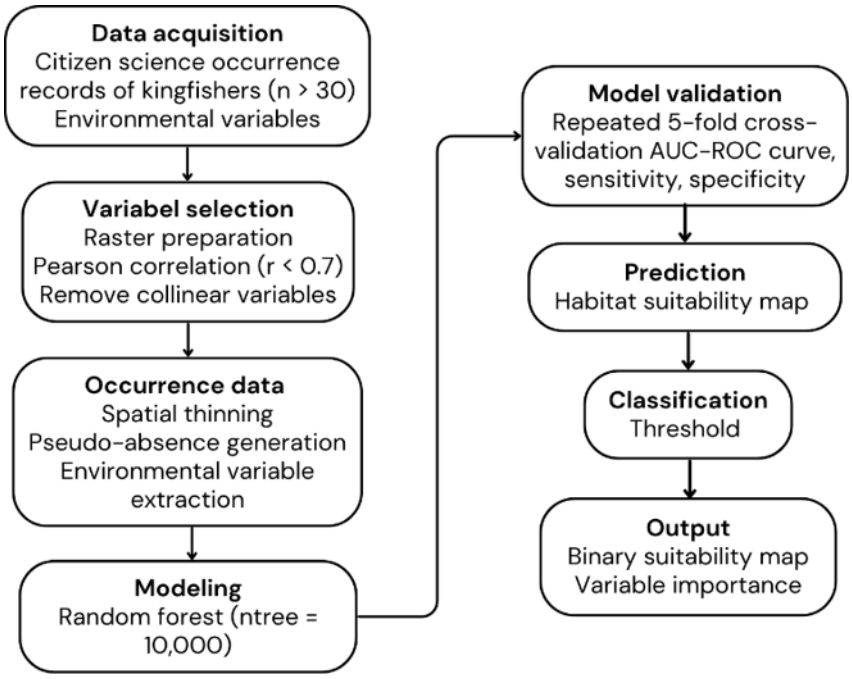

Figure 2. Research Flowchart.

Model performance was evaluated using repeated 5-fold cross-validation implemented through the caret R-package. Such cross-validation is essential for obtaining an estimate of predictive performance and to detect potential overfitting, ensuring that the RF model captures ecologically meaningful relationships rather than noise in the data (Ramampiandra *et al.,* 2023). The discrimination ability of the model was quantified using the area under the curve (AUC). Cross-validation AUC values were reported as mean standard deviation (SD) to reflect model stability across folds. The RF model (ntree = 10,000) was trained on the full dataset to produce continuous habitat suitability prediction. A higher number of trees is beneficial in reducing model variance and ensuring reliable estimation of variable importance (Breiman, 2001). RF performance has been shown to be relatively robust to parameter settings (Sillero *et al.,* 2021). The number of predictor variables considered at each node split (mtry) followed the default RF classification setting, corresponding to the square root of the total number of predictor variables (Albertini *et al.,* 2024) in the randomForest package. Binary presence-absence maps were derived using a data-driven threshold based on receiver operating characteristic (ROC) (Brownscombe *et al.,* 2021). Sensitivity and specificity (TPR + TNR) were calculated for possible thresholds derived from RF predictions. Data-based thresholds, determined by maximising the sum of TPR and TNR, provide objective criteria for converting continuous habitat suitability predictions into biner presence-absence maps (Sahragard *et al.,* 2018).

2.5. Distribution of Kingfishers Across the Heterogeneous Landscapes of Java Island

Spatial distribution data were used to develop a predictive habitat suitability model for the selected kinfisher species. This model was then overlaid with forest function data from Java Island. The 2023 forest function designation map from the Ministry of Environment and Forestry (KLHK) of the Republic of Indonesia was used in the analysis. Indonesia classifies its land into forest areas and area for other land uses (APL). Predicted habitat suitability values at field occurrence locations for kingfisher species were extracted from the habitat suitability maps using the extract values to points tool in ArcGIS. These values were summarised using boxplots to evaluate the correspondence between model predictions and species occurrence records.

3. Results and Discussion

3.1.1. Suitable Areas for Kingfisher Species on the Island of Java

Prior to model development, multicollinearity diagnostics were conducted on ten independent environmental variables. The dendrogram of the Pearson correlation analysis indicated high multicollinearity for several variables, including elevation, temperature, radar VH and radar VV (Figure 3). Specifically, elevation and temperature suggested strong interdependence. This result is consistent with established ecological theory, in which temperature gradients are closely linked to elevation changes, particularly in mountainous regions (Loewen *et al.,* 2023). Given this relationship, and to minimize collinearity, elevation was retained in the model as a proxy variable.

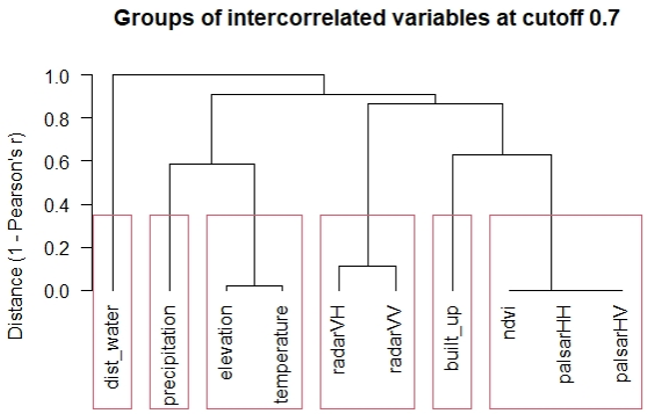

Figure 3. Spatial Similarity Between Distribution Model Treatments Evaluated Using the Pearson Correlation and Illustrated as a Dendrogram.

Additionally, PALSAR HV, PALSAR HH and NDVI (Normalized Difference Vegetation Index) were found to be perfectly collinear. To address this issue, only NDVI was retained for further analysis, given its strong ecological relevance as a proxy for vegetation density. Consequently, six independent variables were selected for inclusion in the random forest (RF) model and further evaluated using a variable importance analysis (varImp). The variables were built-up land (built_up), elevation (elevation), vegetation density (NDVI), distance to the nearest water body (dist_water), rainfall (precipitation), and vegetation structural complexity (radar VH). All models were developed using the six independent predictor variables. The RF analysis resulted in differing proportions of predicted suitable habitats across the nine species.

Table 2. Relative Importance (%) of Environmental Variables and Performance Metrics of the RF Habitat Suitability Models for Kingfisher Species on the Island of Java.

Species	varImp						AUC-ROV curve	Mean CV-AUC	Sensitivity	Specificity	Threshold	Area (Ha)
	NDVI	elevation	dist water	built up	radarVH	precipitation						
T.sanctus	16.25	35.71	11.78	5.14	12.97	17.82	0.87	0.89 ± 0.05	0.82	0.82	0.57	1,842,201
T.chloris	17.38	18.24	15.58	11.55	17	19.74	0.75	0.74 ± 0.01	0.68	0.67	0.5	4,310,325
H.smyrnensis	16.6	20.77	25.38	11.51	12.75	11.45	0.82	0.82 ± 0.10	0.68	0.78	0.61	2,877,309
H.cyanoventris	16.52	18.93	15.52	11.59	16.36	20.56	0.75	0.75 ± 0.01	0.69	0.68	0.5	4,334,525
L.pulchela	16.78	23.9	10.57	3.44	12.22	32.61	0.86	0.75 ± 0.01	0.78	0.77	0.54	2,345,102
C.rufidorsa	22.31	14.66	14.77	5.21	13.78	28.89	0.88	0.87 ± 0.05	0.78	0.82	0.6	1,842,654
A.euryzona	13.13	20.31	13.71	1.58	10.6	39.31	0.88	0.88 ± 0.04	0.81	0.86	0.63	998,128.40
A.meninting	14.8	15.84	23.04	13.14	14.8	18.17	0.83	0.89 ± 0.08	0.76	0.74	0.47	3,532,079
A.coerulescens	16.61	37.01	12.5	5.47	11.21	17.05	0.93	0.93 ± 0.01	0.86	0.86	0.57	1,831,206

The model achieved AUC-ROC values exceeding 0.70 for all nine species, indicating strong predictive capacity (AUC range = 0.75–0.93; mean = 0.83; SD = 0.06). Repeated 5-fold cross-validation results were consistent across species, ranging from 0.74 ± 0.01 to 0.93 ± 0.01, suggesting stable model performance. Sensitivity values ranged from 0.68 to 0.86, while specificity ranged from 0.67 to 0.86. The optimal classifications thresholds derived from the ROC analysis varied slightly among species, ranging from 0.47 to 0.63. These findings demonstrate that the habitat suitability models performed well overall, although model accuracy varied depending on the level of presence data available for each species.

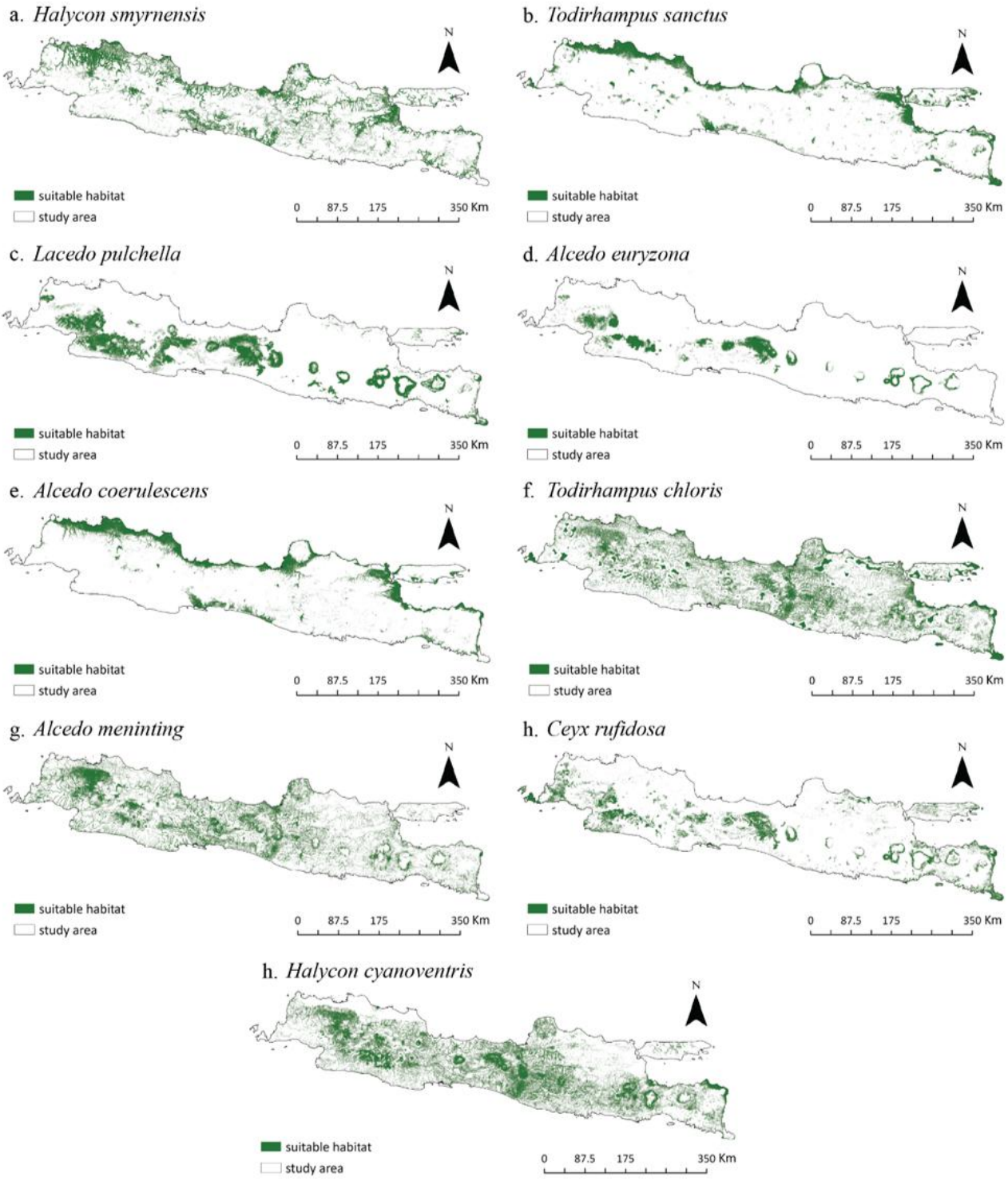

Figure 4. Comparison Map of Habitat Suitability for the Nine Kingfisher Species on Java Island: (a) White-Throated Kingfisher (Halcyon smyrnensis); (b) Sacred Kingfisher (Todiramphus sanctus); (c) Banded Kingfisher (Lacedo pulchella); (d) Javan Blue-Banded Kingfisher (Alcedo euryzona); (e) Cerulean Kingfisher (Alcedo coerulescens); (f) Collared Kingfisher (Todiramphus chloris); (g) Blue-Eared Kingfisher (Alcedo meninting); (h) Rufous-Backed Kingfisher (Ceyx rufidorsa); (i) Javan Kingfisher (Halcyon cyanoventris).

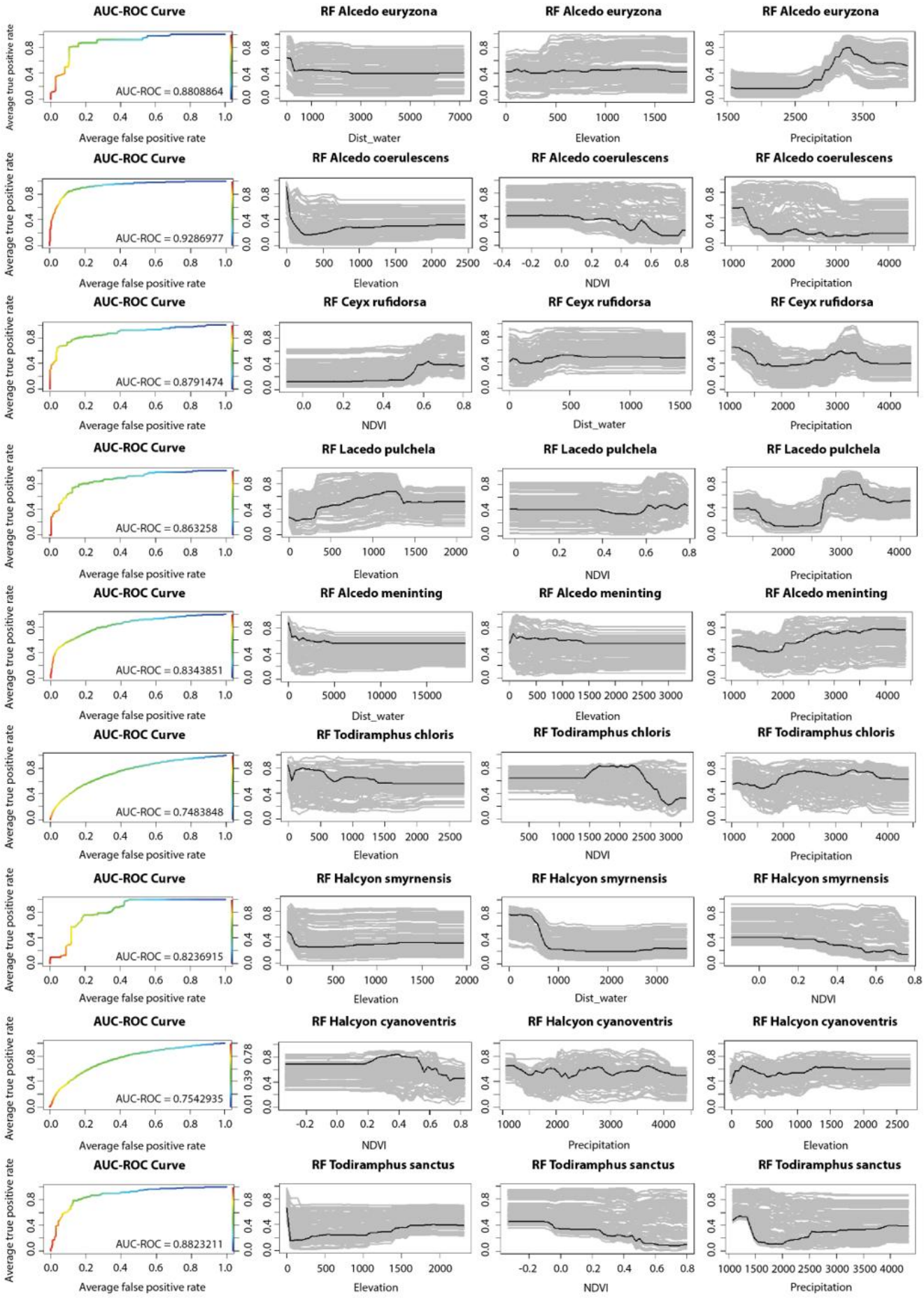

Figure 5. Area Under the ROC Curve (AUC) and the Response Curve of Kingfisher Species to Environmental Variables.

Based on the varImp values, three key variables were identified, with elevation and precipitation emerging as the main factors influencing the distribution of most kingfisher species in Java (Table 2). However, for the white-throated kingfisher, rufous-backed kingfisher, Javan blue-banded kingfisher and blue-eared kingfisher, the variable dist_water influenced the presence of suitable habitat.

To explore the functional relationships between the independent variables and species presence probabilities, the itsdm package in R was employed to generate response curves (Figure 5). These visualizations revealed species-specific variation in how predictor variables influenced the likelihood of occurrence. For example, increasing elevation was generally associated with a decline in the probability of occurrence for several species, namely the cerulean kingfisher, sacred kingfisher, white-throated kingfisher, and banded kingfisher. The probability of the presence of the cerulean kingfisher and sacred kingfisher declined when precipitation exceeded > 1750 mm.

In contrast, elevation showed a weak and non-linear relationship with the presence of the Javan blue-banded kingfisher, as indicated by a relatively flat response curve centered around a probability of ~0.4. This suggests either limited variation in the elevation data for this species or the existence of complex interactions with other environmental variables. For the Javan blue-banded kingfisher, the probability of occurrence increased notably with proximity to water bodies (within 0–300 meters) and with higher precipitation levels (ranging from 2,575 to 3,250 mm), highlighting the species' preference for moist, riparian habitats. Increased precipitation (> 1750 mm) also increased the presence probability of the blue-eared kingfisher and collared kingfisher.

3.1.2. Distribution of Kingfisher Species Across the Heterogeneous Landscapes of Java Island

The distribution of suitable habitat varies based on forest area function and kingfisher species on Java. For all species, the majority of these suitable habitats were located within areas designated for other land uses (Figure 6). This indicates that, in addition to forest status, environmental variables contribute to habitat suitability. These areas are not only important habitats for resident species, but also for migratory ones, including the sacred kingfisher, which is widely distributed across the island. As shown in (Figure 4), distribution is concentrated along the island's periphery and river channels.

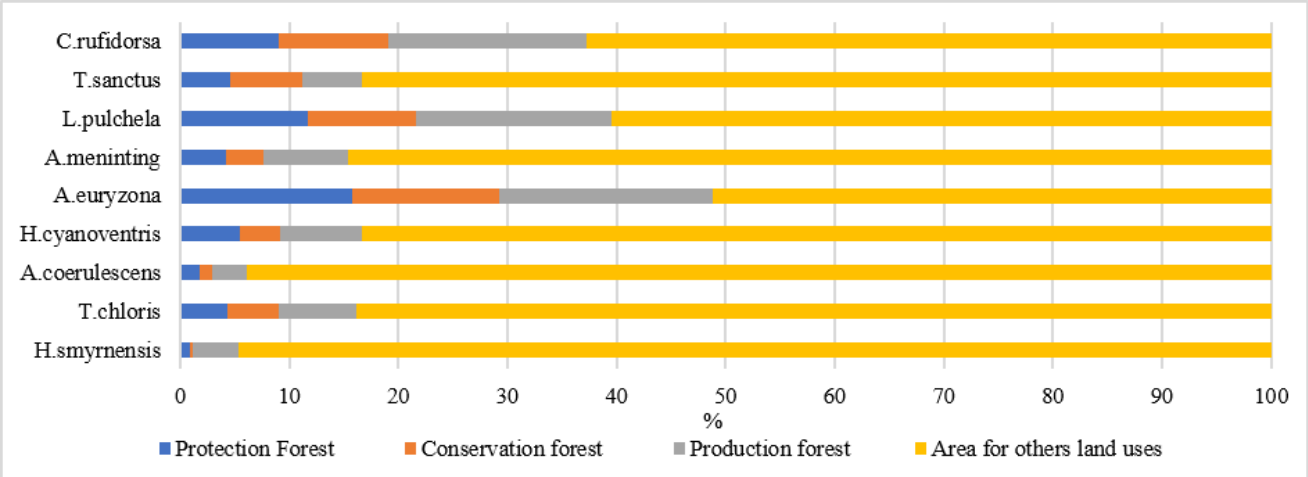

Figure 6. Bar Chart of the Proportion of Kingfisher Habitats in Each Forest Function on Java.

The collared kingfisher and Javan kingfisher demonstrate the most extensive spatial distributions among resident species, reflecting their ecological adaptability and capacity to occupy a wide range of land-use types. In contrast, the Javan blue-banded kingfisher exhibits the smallest predicted suitable habitat area, totaling 998,128.4 hectares (Table 2), but shows the highest proportion of suitable habitats in forest areas (48.78%). The distribution of the Javan blue-banded kingfisher is fragmented, occurring primarily in isolated patches associated with mountainous and valley regions that include more extensive natural landscapes or designated protected forest areas, in contrast to the broader and more anthropogenically influenced distributions observed for other kingfisher species (Figure 5).

The habitat suitability model was validated based on habitat suitability values extracted from occurrence locations (indicated by citizen science data) of each kingfisher species on the island of Java. The boxplot shows that the habitat suitability values for the occurrence for all species have

a median value > 0.80 (Figure 7). This indicates that the majority of occurrence records recorded by citizens are located within areas predicted by the model as highly suitable habitats. Although there were several outlier occurrence locations with low suitability values, these represent only a small proportion of the data, where environmental conditions are not fully represented by the dominance of predictor variables.

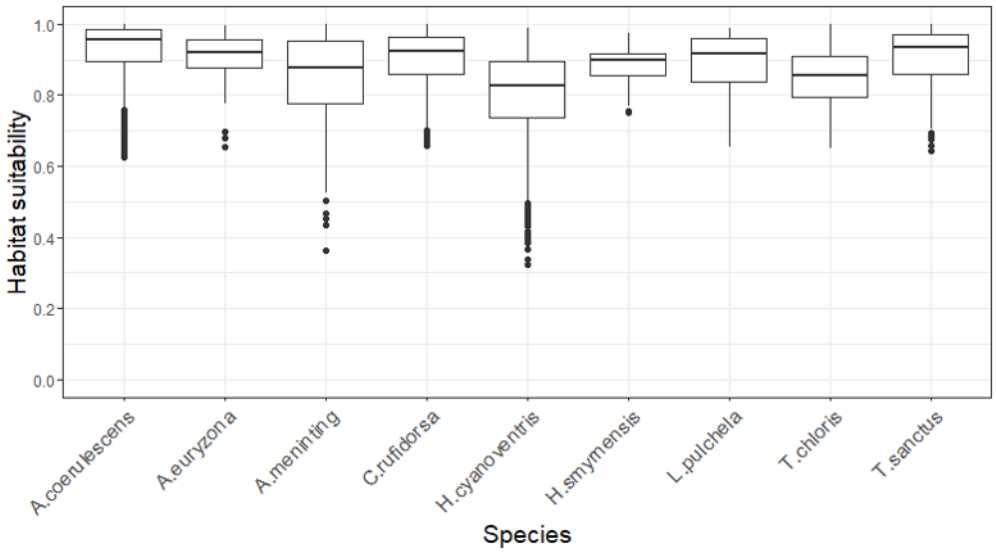

Figure 7. Boxplot of the Distribution of Habitat Suitability Values Extracted From the Occurrence of King-Fisher Species on Java Based on Citizen Science Data.

The distribution of habitat suitability values for all species varies in terms of habitat use (Figure 6) and ecological requirements (Figure 5). In the boxplot, the Javan kingfisher species shows the greatest variability, with outliers ranging from approximatelty 0.33 to 0.50 and with the lowest median suitability value (~0.82), indicating a broader habitat tolerance than the other species. Conversely, the sacred kingfisher, cerulean kingfisher and rufous-backed kingfisher species have high median habitat suitability values (> 0.90), indicating strong agreement in model predictions and occurrences. The Javan blue-banded kingfisher, the species with the smallest habitat suitability area yet the highest percentage within forested areas, exhibits a high median habitat suitability value (~0.92) with relatively small variation. Similar variation in habitat suitability is also observed in the white-throated kingfisher, with outlier values that are not particularly low (~0.75). The overall variation in the model effectively captures the environmental conditions associated with species occurrences in the field.

3.2. Discussion

The ongoing global biodiversity crisis requires rapid assessment of knowledge gaps and the setting of conservation priorities based on large-scale biodiversity data. While earlier studies on kingfisher relied heavily on direct field observations and telemetry methods (Kesler, 2012), our approach reveals broader spatial patterns using accessible data sources. In the study, we modeled the potential distribution of nine kingfisher species across Java Island and examined the relationship between their occurrence and key environmental variables. The findings demonstrate that species distribution models using varied citizen science platform data—analysed with the RF algorithm can provide reliable performance; avoid overfitting in spatial prediction (Valavi *et al.,* 2022); and prevent over-confidence in predictive abilities (Akselrud, 2024). Consequently, model performance was contingent upon repeated cross-validation and several evaluation metrics. The combination of machine learning techniques and massive datasets in citizen science projects is a useful approach to identifying spatial distribution (Martín *et al.,* 2021). The consistency between model outputs and established ecological knowledge for each species reflects species-environment relationships and validates the robustness of the modelling approach (Mahmoud *et al.,* 2024). This allows the model to uncover patterns that reflect the ecological responses of species to environmental gradients. The potential distribution map produced the by RF model therefore provided more accurate and informative results (Zhao *et al.,* 2022). Although natural colonisation of a species takes considerable time, the target species may not always be present or detected (Frakes & Knight, 2021).

The predictive models showed relatively good accuracy for all species, with distinct associations with specific habitat features. Notably, despite Java being the most densely populated island in

Indonesia, with extensive non-forest areas, built-up areas did not significantly influence the distribution of any kingfisher species (Table 2). Instead, most species were associated with human-impacted, non-forest habitats (Figure 6), underscoring their generalist tendencies (Ariyanto *et al.,* 2024). However, environmental variables such as elevation and precipitation emerged as primary factors shaping habitat suitability for nearly all species. Furthermore, proximity to water bodies (dist_water) was particularly important for the white-throated kingfisher, rufous-backed kingfisher, Javan blue-banded kingfisher, and blue-eared kingfisher, suggesting species-specific habitat preferences within the group. Citizen science observers often recorded kingfisher in human-modified landscapes, such as rice fields in Java, which are commonly located near water sources. Around 75% of Indonesia's irrigated rice fields use surface or groundwater, while the rest rely on natural sources such as rain, tidal rivers, seawater or seepage (Tirtalistyani *et al.,* 2022). Kingfisher species are also commonly found in urban areas that maintain or create wetlands and water bodies (Xie *et al.,* 2022). These water features play an important role in supporting bird presence, even in degraded habitats (Paga *et al.,* 2022). Hence, we cannot exclude the possibility that some models may not have performed optimally because unsampled combinations of environmental predictors were not taken into account (e.g., interspecific interactions, key specific resources or local disturbance). Future research which compares their distribution across different landscapes, such as watersheds with varying human population densities, could provide deeper insights into their home range and habitat preferences on a finer scale. Caution in interpreting habitat suitability on the local scale is necessary to ensure the results remain valid in representing the actual occurrence or absence.

Rainfall plays a critical role in shaping the distribution patterns of many kingfisher species on Java, as indicated by the predictive habitat models. Being a large and topographically varied island, Java experiences greater rainfall variability than smaller islands, which contributes to diverse microhabitats across the landscape (De Ruyck & Koper, 2024). However, ongoing climate change is expected to significantly alter rainfall regimes and temperature patterns, which may disrupt the ecological conditions that currently support kingfisher populations (Liang *et al.,* 2021; McPherson *et al.,* 2025). These changes could lead to shifts in species distributions, making some areas that are presently suitable become less hospitable in the future. This is particularly concerning given that the majority of suitable habitats identified for kingfisher species are located in non-forest, human-modified landscapes, which are also under pressure from land-use change and development. As such, understanding the interplay between climate variability—especially rainfall—and species ecology is essential for long-term conservation planning. Future research should integrate climate projections and rainfall variability to improve predictive models and assess potential habitat shifts, thereby helping to anticipate the impacts of climate change on kingfisher species across the Island.

The presence probability of endemic, migratory and protected kingfisher species in Java is strongly influenced by vegetation density, as indicated by the NDVI. For example, the banded kingfisher is typically associated with protected hill forests with dense vegetation and intersected by rivers, highlighting its preference for intact forest ecosystems (Hazwani *et al.,* 2023). Vegetation near water bodies is ecologically important as it provides perching sites used by kingfishers to detect and capture prey (Naher & Sarker, 2014). Similarly, species such as the cerulean kingfisher and sacred kingfisher show higher distribution probabilities along the northern coastal regions of Java (Figure 4), where large mangrove areas exist. However, these habitats are under increasing threat due to human activities such as fish pond development and aquaculture expansion (Hanifa *et al.,* 2024).

Despite variations in vegetation cover, many kingfisher e species continue to associate closely with wetland environments. For instance, the collared kingfisher is commonly found near rivers, even in areas with abundance of vegetation (Biswas & Deuti, 2025), while the cerulean kingfisher inhabits open coastal zones with sparse vegetation (Van Balen, 1998). The lowland riverbanks of the island are often exposed and heavily influenced by human disturbance (Prihestiwi *et al.,* 2023), yet remain vital for feeding and breeding. Rivers provide not only food sources, such as fish, for the collared kingfisher (Biswas & Deuti, 2025), but also nesting sites, including steep soil banks used by the Javan kingfisher for burrow construction (Taufiqurrahman *et al.,* 2020). Additionally, the blue-eared kingfisher is known to stay along riverbanks during the non-breeding season, suggesting riparian dependence (Palkar, 2016). These findings emphasise that vegetation density—especially in riparian zones—has a stronger influence on kingfisher habitat suitability in Java than vegetation structure or forest cover alone, underlining the importance of conserving water-associated landscapes even in modified environments. We utilised the Ministry of Environment and Forestry's forest area function classification in this analysis by including water bodies covering 0.001% of the total area of Java Island. The modeling results indicate that water bodies constitute

a very small percentage (0 - 0.01 %) of the suitable habitat area for each kingfisher species. Given the very small proportion of water bodies at the geographic scale on the island, they were retained in the analysis but combined with APL to facilitate categorization based on forest area function. Kingfisher species have strong ecological associations with water areas and tree cover (Barik *et al.,* 2022; Shifa *et al.,* 2023). Therefore, further research on finer scales is needed to understand the mechanisms driving kingfisher habitat selection at the microsite scale, particularly with regard to water body characteristics and riparian vegetation. Riparian ecosystems are widely surrounded by landscapes that have been modified by human activities such as intensive agriculture and artificial water infrastructure to support agriculture (Petit *et al.,* 2023), as is the case on Java.

The predicted habitat distribution of kingfisher species provides important information to support conservation planning at local scales by identifying suitable habitats based on key environmental variables in managed and unmanaged areas. Many of these habitats are located outside designated conservation zones, underscoring the need to expand protection measures to non-conservation areas across Java. This is particularly critical for rare species such as the Javan blue-banded kingfisher, which require connectivity between suitable and fragmented habitats to maintain viable populations. Therefore, preventing land-use conversion and establishing ecological corridors to connect habitat patches should be prioritised to facilitate species movement and reduce isolation (Ariyanto *et al.,* 2024; Imron *et al.,* 2023). Although there is limited evidence of hunting pressure on kingfisher species, threats from land conversion and declining environmental quality—particularly water pollution—pose more significant risks to their survival (Barik *et al.,* 2022; Shifa *et al.,* 2023). Further investigation of the potential roles of markets in their distribution might provide clearer conservation intervention (Imron *et al.,* 2025). Active community involvement through citizen science initiatives on the island of Java also plays a crucial role not only in expanding species occurrence data (Winnasis *et al.,* 2018), but also in enabling long-term monitoring of population trends and distributions, especially for endemic, migratory, and protected species (Squires *et al.,* 2021).

4. Conclusion

The application of the RF machine learning algorithm utilising citizen science data effectively characterised the spatial distribution of suitable habitats for nine kingfisher species across Java Island. The model demonstrated strong predictive performance for all species, highlighting its utility in large-scale ecological modeling. The landscape of the island is predominantly composed of anthropogenic land cover or areas for other land uses (APL), which were identified as suitable habitats for several kingfisher species. Future research should consider the application of occupancy modeling in areas identified as suitable habitats to generate more robust inferences regarding species–habitat relationships and to better understand the mechanisms underlying habitat selection among kingfisher species.

The influence of land cover types and associated environmental variables, indicated in (Table 2), produced species-specific responses in habitat suitability. The findings highlight the diverse ecological requirements and tolerances of kingfisher species in both forested and non-forested environments. In particular, vegetation characteristics were shown to significantly affect the probability of species presence, reflecting the importance of both biotic and abiotic resource availability in habitat selection. The study results provide valuable insights for government agencies and conservation practitioners in designing strategies to protect high-suitability habitats located outside formal conservation areas. Priority actions should include the restoration of human-dominated landscapes and the protection of natural features, such as riparian corridors, to enhance ecological connectivity. Such efforts are essential to support the movement, dispersal, and long-term persistence of kingfishers and other bird species in Java's fragmented and human-dominated landscapes. Future research should incorporate occupancy modeling in identifying suitable areas to strengthen inferences on species–habitat relationships on finer scale and to better understand the ecological mechanisms driving habitat selection.

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Conceptualization: Aryanti, N. A., Imron, M. A.; **methodology**: Aryanti, N. A., Tafrichan, M.; **investigation**: Author N.A.A , Author M.T; **writing—original draft preparation**: Aryanti, N. A. ; **writing—review and editing**: Aryanti, N. A.., Imron, M. A., Retnaningtyas, R. W., Pudyatmoko, S., ; **visualization**: Aryanti, N. A., Tafrichan, M., Imron, M. A. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

All authors declare that they have no conflicts of interest.

Data availability

Data is available upon Request.

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References

Achour, H., & Kalboussi, M. (2020). Modelling and mapping the current and future potential habitats of the Algero-Tunisian endemic newt Pleurodeles nebulosus under climate change. *European Journal of Wildlife Research*, 66(4), 1–12. doi: 10.1007/s10344-020-01386-x

Akselrud, C. I. A. (2024). Random forest regression models in ecology: Accounting for messy biological data and producing predictions with uncertainty. *Fisheries Research*, 280, 107161. doi: 10.1016/j.fishres.2024.107161

Albertini, C., Gioia, A., Iacobellis, V., Petropoulos, G., & Manfreda, S. (2024). Remote Sensing Applications : Society and Environment Assessing multi-source random forest classification and robustness of predictor variables in flooded areas mapping. *Remote Sensing Applications: Society and Environment*, *35*(August 2024), 101239. doi: 10.1016/j.rsase.2024.101239

Anselmetto, N., Garbarino, M., Weldy, M. J., Bell, D. M., Daly, C., Epps, C. W., Ferrari, N., Kim, H., LaManna, J. A., Lesmeister, D. B., Penaluna, B. E., Schulze, M., Sutton, M., Tosa, M. I., & Betts, M. G. (2025). Leveraging long-term data to improve biodiversity monitoring with species distribution models. *Journal of Applied Ecology*, 62(11), 2914–2929. doi: 10.1111/1365-2664.70177

Ariyanto, A. C., Wang, T., Skidmore, A. K., Ario, A., Imron, M. A., & Wahyudi, H. A. (2024). Ensemble species distribution models reveal Javan leopard's preference for areas with high prey species diversity. *Global Ecology and Conservation*, 56, e03335. doi: 10.1016/j.gecco.2024.e03335

Barik, S., Kumar, G., & Mazumdar, S. (2022). Conservation prioritization through combined approach of umbrella species selection, occupancy estimation, habitat suitability and connectivity analysis of kingfisher : A study from an internationally important wetland complex (Ramsar site) in India. *Ecological Informatics*, 72, 101833. doi: 10.1016/j.ecoinf.2022.101833

Beumer, L. T., Schmidt, N. M., Pohle, J., Signer, J., Chimienti, M., Desforges, J.-P., Hansen, L. H., Pedersen, S. H., Rudd, D. A., Stelvig, M., van Beest, F. M., Hansen, L. H., Pedersen, S. H., Rudd, D. A., Stelvig, M., & Beest, F. M. Van. (2023). Accounting for behaviour in fine- - scale habitat selection : A case study highlighting methodological intricacies. *Journal of Animal Ecology*, 92(10), 1937–1953. doi: 10.1111/1365-2656.13984

Binley, A., Bennett, J., Schuster, R., Rodewald, A., Sorte, F., Fink, D., Zuckerberg, B., & Wilson, S. (2023). Species traits drive responses of forest birds to agriculturally- modified habitats throughout the annual cycle. *Ecograph*, 2023(9), 1–12. doi: 10.1111/ecog.06457

Bird, T. J., Bates, A. E., Lefcheck, J. S., Hill, N. A., Thomson, R. J., Edgar, G. J., Stuart-smith, R. D., Wotherspoon, S., Krkosek, M., Stuart-smith, J. F., Pecl, G. T., Barrett, N., & Frusher, S. (2014). Statistical solutions for error and bias in global citizen science datasets. *Biological Conservation*, 173, 144–154. doi: 10.1016/j.biocon.2013.07.037

Biswas, D., & Deuti, K. (2025). Breeding ecology, feeding of nestlings and nestling development of the Collared Kingfisher (*Todiramphus chloris*) in the Indian Sundarbans. *Rivista Italiana Di Ornitologia*, 95(1), 29–38. doi: 10.4081/rio.2025.863

Bracho-Estévanez, C. A., Arenas-Castro, S., González-Varo, J. P., & González-Moreno, P. (2024). Spatially explicit metrics improve the evaluation of species distribution models facing sampling biases. *Ecological Informatics*, 84, 102916. doi: 10.1016/j.ecoinf.2024.102916

Branco, V. V., Correia, L., & Cardoso, P. (2023). The use of machine learning in species threats and conservation analysis. *Biological Conservation*, 283, 110091. doi: 10.1016/j.biocon.2023.110091

Breiman, L. (2001). Random Forests. *Machine Learning*, 45, 5–32.

Breiner, F. T., Guisan, A., Bergamini, A., & Nobis, M. P. (2015). Overcoming limitations of modelling rare species by using ensembles of small models. *Methods in Ecology and Evolution*, 6(10), 1210–1218. doi: 10.1111/2041-210X.12403

Broussin, J., Mouchet, M., & Goberville, E. (2024). Generating pseudo-absences in the ecological space improves the performance of species distribution models. *Ecological Modelling*, 498, 110865. doi: 10.1016/j.ecolmodel.2024.110865

Brownscombe, J. W., Midwood, J. D., & Cooke, S. J. (2021). Modeling fish habitat : model tuning, fit metrics, and applications. *Aquatic Sciences*, 83(44), 1–14. doi: 10.1007/s00027-021-00797-5

Cady, S. M., Davis, C. A., Fuhlendorf, S. D., Scholtz, R., Uden, D. R., & Twidwell, D. (2021). Generalist bird exhibits site-dependent resource selection. *Ecology and Evolution*, 11(18), 12714–12727. doi: 10.1002/ece3.8016

Callaghan, C. T., Poore, A. G. B., Hofmann, M., Roberts, C. J., & Pereira, H. M. (2021). Large - bodied birds are over - represented in unstructured citizen science data. *Scientific Reports*, 11(19073), 1–11. doi: 10.1038/s41598-021-98584-7

Cao, Y., Chen, R. C., & Katz, A. J. (2024). Why is a small sample size not enough? *Oncologist*, 29(9), 761–763. doi: 10.1093/oncolo/oyae162

Central Bureau of Statistics. (2024). STATISTIK INDONESIA 2024. In *BPS-Statistics Indonesia* (Vol. 52). Retrieved From https://www.bps.go.id/publication/2020/04/29/e9011b3155d45d70823c141f/statistik-indonesia-2020.html

Chowdhury, S., Fuller, R. A., Ahmed, S., Alam, S., Callaghan, C. T., Das, P., Correia, R. A., Di Marco, M., Di Minin, E., Jarić, I., Labi, M. M., Ladle, R. J., Rokonuzzaman, M., Roll, U., Sbragaglia, V., Siddika, A., & Bonn, A. (2023). Using social media records to inform conservation planning. *Conservation Biology*, 38(1), 1–11. doi: 10.1111/cobi.14161

Crego, R. D., Brown, M. B., Stabach, J. A., Fennessy, J., Fennessy, S., Monterroso, P., Vyver, D. van De, & Marneweck, C. (2025). Validating habitat suitability assessments with post-translocation animal movement data. *Restoration Ecology*, e70243, 1–10. doi: 10.1111/rec.70243

Cubley, E. S., Bateman, H. L., Riddle, S. B., Holmquist-Johnson, C., & Merritt, D. M. (2020). Predicting Bird Guilds Using Vegetation Composition and Structure on a Wild and Scenic River in Arizona. *Wetlands*, 40(6), 1829–1842. doi: 10.1007/s13157-020-01371-9

Dabrowska-Zielinska, K., Budzynska, M., Tomaszewska, M., Bartold, M., Gatkowska, M., Malek, I., Turlej, K., & Napiorkowska, M. (2014). Monitoring Wetlands Ecosystems Using ALOS PALSAR (L-Band, HV) Supplemented by Optical Data: A Case Study of Biebrza Wetlands in Northeast Poland. *Remote Sens.*, 6, 1605–1633. doi: 10.3390/rs6021605

De Ruyck, C. C., & Koper, N. (2024). Seasonal movements of small-island birds along habitat and elevation gradients highlights the conservation value of small-scale agroforests. *Agriculture, Ecosystems and Environment*, 375, 109195. doi: 10.1016/j.agee.2024.109195

Dsikowitzky, L., Damar, A., Ferse, S. C. A., Irianto, H. E., Jennerjahn, T. C., Lukas, M. C., Nordhaus, I., Pohlmann, T., Schwarzbauer, J., Sugama, K., & Sumiono, B. (2019). Java Island , Indonesia. In C. Sheppard (Ed.), *World Seas: An Environmental Evaluation (Second Edition)*, 459–490. Academic Press. doi: 10.1016/B978-0-08-100853-9.00029-4

Fadda, L. A., Lasa-Covarrubias, R., Osorio-Olvera, L., Murúa, M. G., & Lira-Noriega, A. (2026). Applications of ecological niche and species distribution models in agricultural, livestock, and forestry systems: A comprehensive review. *Agricultural Systems*, 231. doi: 10.1016/j.agsy.2025.104542

Fang, T., Jin, J., Chen, C., Zhang, L., Li, Y., & Li, C. (2025). Prediction of suitable habitat for tundra swans in the Nanji wetland Nature Reserve of Poyang Lake under different water level conditions. *Ecological Indicators*, *170*(December 2024), 113030. doi: 10.1016/j.ecolind.2024.113030

Fink, D., Johnston, A., Strimas-Mackey, M., Auer, T., Hochachka, W. M., Ligocki, S., Jaromczyk, L. O., Robinson, O., Wood, C., Kelling, S., & Rodewald, A. D. (2023). A Double machine learning trend model for citizen science data. *Methods in Ecology and Evolution*, 14(9), 2435–2448. doi: 10.1111/2041-210X.14186

Frakes, R. A., & Knight, M. L. (2021). Location and extent of unoccupied panther (*Puma concolor coryi*) habitat in Florida : Opportunities for recovery. *Global Ecology and Conservation*, 26, e01516. doi: 10.1016/j.gecco.2021.e01516

Galván, S., Barrientos, R., & Varela, S. (2022). No Bird Database is Perfect : Citizen Science and Professional Datasets Contain Different and Complementary Biodiversity Information. *Ardeola*, 69(1), 97–114. doi: 10.13157/arla.69.1.2022.ra6

Gao, B., Gong, P., Zhang, W., Yang, J., & Si, Y. (2021). Multiscale effects of habitat and surrounding matrices on waterbird diversity in the Yangtze River Floodplain. *Landscape Ecology*, 36(1), 179–190. doi: 10.1007/s10980-020-01131-4

Hanifa, S. N., Rachman, H. A., & Hidayah, Z. (2024). Temporal Analysis of Mangrove Canopy Cover of High Resolution Satellite Imagery on the West Coast of Bangkalan Regency , Madura East Java. *Jurnal Kelautan Tropis*, 27(3), 579–594. doi: 10.14710/jkt.v27i3.24273

Hazwani, N., Azman, M., Md Fauzi, N., Munian, K., Mahyudin, N., Azahar, M., Baharudin, M., Appanan, M., Beri, A., & Tahir, R. (2023). Small vertebrates in CFS ecological corridor (D- PL1 : Lojing - Sungai Brok - Sungai Betis Forest Reserves) Kelantan. *BIO Web of Conferences*, 73, 1–9. doi: 10.1051/bioconf/20237301010

Huylenbroeck, L., Latte, N., Lejeune, P., Georges, B., Claessens, H., & Michez, A. (2021). What Factors Shape Spatial Distribution of Biomass in Riparian Forests ? Insights from a LiDAR Survey over a Large Area. *Forests*, 12(3), 371. doi: 10.3390/f12030371

Imron, M. A., Glass, D. M., Tafrichan, M., Crego, R. D., Stabach, J. A., & Leimgruber, P. (2023). Beyond protected areas: The importance of mixed-use landscapes for the conservation of Sumatran elephants (*Elephas maximus sumatranus*). *Ecology and Evolution*, 13(10), 1–13. doi: 10.1002/ece3.10560

Imron, M. A., Tafrichan, M., Nijman, V., Nekaris, K. A. I., Campera, M., Nugroho, F. E., Winasis, S., Retnaningtyas, R., Gale, G. A., & Chutipong, W. (2025). Quantifying market prevalence, abundance, and suitable habitats of bulbuls in Java, Indonesia. *Biological Conservation*, 304, 111035. doi: 10.1016/j.biocon.2025.111035

Johnston, A., Hochachka, W. M., Strimas-Mackey, M. E., Gutierrez, V. R., Robinson, O. J., Miller, E. T., Auer, T., Kelling, S. T., & Fink, D. (2021). Analytical guidelines to increase the value of community science data: An example using eBird data to estimate species distributions. *Diversity and Distributions*, 27(7), 1265–1277. doi: 10.1111/ddi.13271

Kelling, S., Johnston, A., Bonn, A., Fink, D., Ruiz-gutierrez, V., Bonney, R., Fernandez, M., Hochachka, W. M., Julliard, R., Kraemer, R., & Guralnick, R. (2019). Using Semistructured Surveys to Improve Citizen Science Data for Monitoring Biodiversity. *BioScience*, 69(3), 170–179. doi: 10.1093/biosci/biz010

Kesler, D. C. (2012). Foraging Habitat Distributions Affect Territory Size and Shape in the Tuamotu Kingfisher. *International Journal of Zoology*, 2012, 632969. doi: 10.1155/2012/632969

Kesler, D. C., & Haig, S. M. (2004). Thermal Characteristics of wild and Captive Micronesian Kingfisher Nesting Habitats. *Zoo Biology*, 23, 301–308.

Kesler, D. C., & Haig, S. M. (2005). Microclimate and nest-site selection in Micronesian Kingfishers. *Pacific Science*, 59(4), 499–508. doi: 10.1353/psc.2005.0045

Kesler, D. C., & Haig, S. M. (2007a). Multiscale Habitat Use and Selection in Cooperatively Breeding Micronesian Kingfishers. *The Journal of Wildlife Management*, 71(3), 765–772. doi: 10.2193/2006-011

Kesler, D. C., & Haig, S. M. (2007b). Territoriality , Prospecting , and Dispersal In Cooperatively Breeding Micronesian Kingfishers (*Todiramphus cinnamominus reichenbachii*). *The Auk*, 124(2), 381–395. doi: 10.1642/0004-8038

Kindlmann, P., Tsiftsis, S., Buchbauerová, L., Traxmandlová, I., & Štípková, Z. (2025). How Will Environmental Conditions Affect Species Distribution and Survival in the Coming Decades — A Review. *Diversity*, 17(793), 1–32. doi: 10.3390/ d17110793

Kong, X., Zhou, Z., & Jiao, L. (2021). Hotspots of land-use change in global biodiversity hotspots. *Resources, Conservation & Recycling*, 174, 105770. doi: 10.1016/j.resconrec.2021.105770

Kustamar, & Wulandari, L. K. (2020). The pollution index and carrying capacity of the upstream Brantas river. *International Journal of GEOMATE*, 19(73), 26–32. doi: 10.21660/2020.73.55874

Lajeunesse, A., & Fourcade, Y. (2023). Temporal analysis of GBIF data reveals the restructuring of communities following climate change. *Journal of Animal Ecology*, *92*(2), 391–402. doi: 10.1111/1365-2656.13854

Lane, O. P., Arendt, W. J., Tórrez, M. A., & Castellón, J. C. G. (2013). Pilot Assessment of Mercury Exposure in Selected Biota from the Lowlands of Nicaragua. *Mesoamericana*, 17(1), 19–28.

Liang, J., Peng, Y., Zhu, Z., Li, X., Xing, W., Li, X., Yan, M., & Yuan, Y. (2021). Impacts of changing climate on the distribution of migratory birds in China : Habitat change and population centroid shift. *Ecological Indicators*, 127, 107729. doi: 10.1016/j.ecolind.2021.107729

Liu, J., Hu, Y., Feng, Z., & Xiao, C. (2025). A Review of Land Use and Land Cover in Mainland Southeast Asia over Three Decades (1990 – 2023). *Land*, 14(4), 828. doi: 10.3390/land14040828

Loewen, C. J. G., Jackson, D. A., & Gilbert, B. (2023). Biodiversity patterns diverge along geographic temperature gradients. *Global Change Biology*, 29(3), 603–617. doi: 10.1111/gcb.16457

Mahmoud, A. R., Farahat, E. A., Hassan, L. M., & Halmy, M. W. A. (2024). Towards optimizing conservation planning: A performance evaluation of modeling techniques for predicting Mediterranean native species distribution. *Journal for Nature Conservation*, 82, 126733. doi: 10.1016/j.jnc.2024.126733

Marcellia, Mardiastuti, A., & Mulyani, Y. A. (2023). Bird community to be developed for birdwatching in Buperta Cibubur Urban Forest, Jakarta. *IOP Conference Series: Earth and Environmental Science*, 1220, 012016. doi: 10.1088/1755-1315/1220/1/012016

Martín, B., González–arias, J., & Vicente–vírseda, J. A. (2021). Machine learning as a successful approach for predicting complex spatio–temporal patterns in animal species abundance. *Animal Biodiversity and Conservation*, 44(2), 289–301. doi: 10.32800/abc.2021.44.0289

Maznikova, V. N., Ormerod, S. J., & Gómez-Serrano, M. Á. (2024). Birds as bioindicators of river pollution and beyond: specific and general lessons from an apex predator. *Ecological Indicators*, 158, 111366. doi: 10.1016/j.ecolind.2023.111366

McPherson, R. A., Alger, K. E., & Hofmeister, E. (2025). Climate-related drivers of migratory bird health in the south-central USA. *Biological Reviews*, 100, 1272–1293. doi: 10.1111/brv.70000

Meena, P., & Jha, V. (2023). Environmental Change, Changing Biodiversity, and Infections–Lessons for Kidney Health Community. *Kidney International Reports*, 8(9), 1714–1729. doi: 10.1016/j.ekir.2023.07.002

Mirante, D., Ancillotto, L., Zampetti, A., Coiro, G., Pisa, G., Santocchi, C., Giuliani, M., Santini, L., & Santini, L. (2024). Fine-tuning coexistence : Wildlife ' s short-term responses to dynamic human disturbance patterns. *Global Ecology and Conservation*, 54, e03053. doi: 10.1016/j.gecco.2024.e03053

Musseau, R., Bastianelli, M., Bely, C., Rousselle, C., & Dehorter, O. (2021). Using miniaturized GPS archival tags to assess home range features of a small plunge - diving bird : the European Kingfisher (*Alcedo atthis*). *Avian Research*, 12(30), 1–10. doi: 10.1186/s40657-021-00267-4

Naher, H., & Sarker, N. J. (2014). Food And Feeding Habits Of White-Throated Kingfisher (*Halcyon smyrnensis*) In Bangladesh. *Bangladesh J. Zool.*, 42(2), 237–249. doi: 10.3329/bjz.v42i2.23366

Naher, H., Sarker, N. J., & Khan, S. I. (2021). Threats And Conservation Issues Of Common Kingfisher (Alcedo atthis, Linnaeus, 1758) And White- Throated Kingfisher (*Halcyon smyrnensis*, Linnaeus, 1758) In Some Rural And Urban Areas Of Bangladesh. *Journal of Life and Earth Sciences*, 6(1), 1–16.

Namkhan, M., Sukumal, N., & Savini, T. (2022). Impact of climate change on Southeast Asian natural habitats , with focus on protected areas. *Global Ecology and Conservation*, 39, e02293. doi: 10.1016/j.gecco.2022.e02293

O'Neill, D., Häkkinen, H., Neumann, J., Shaffrey, L., Cheffings, C., Norris, K., & Pettorelli, N. (2023). Investigating the potential of social media and citizen science data to track changes in species' distributions. *Ecology and Evolution*, 13(5), 108136. doi: 10.1002/ece3.10063

Paga, B., Pudyatmoko, S., Wijayanti, L. R., Yuda, P., & Sulaksono, N. (2022). The habitat suitability of Timor friarbird *Philemon inornatus* in Western Timor Island, Indonesia. *Biodiversitas*, 23(2), 703–713. doi: 10.13057/biodiv/d230215

Palkar, S. B. (2016). Breeding biology of Blue-eared Kingfisher Alcedo meninting. *Indian Birds*, 11(4), 85–90.

Peña, R., Schleuning, M., Miñarro, M., & García, D. (2023). Variable relationships between trait diversity and avian ecological functions in agroecosystems. *Functional Ecology*, 37(1), 87–98. doi: 10.1111/1365-2435.14102

Peris, S. J., & Rodriguez, R. (1996). Some factors related to distribution by breeding Kingfisher (*Alcedo atthis* L.). *Polish Journal of Ecology*, 44(1–2), 31–38. doi: 10.13140/RG.2.1.4950.0568

Petit, M., Celis, C., Weideman, C., Gouin, N., & Bertin, A. (2023). Agriculture , Ecosystems and Environment Effects of land cover and habitat condition on the bird community along a gradient of agricultural development within an arid watershed of Chile. *Agriculture, Ecosystems and Environment*, 356, 108635. doi: 10.1016/j.agee.2023.108635

Pravitasari, A. E., Indraprahasta, G. S., Rustiadi, E., Rosandi, V. B., Stanny, Y. A., Wulandari, S., Priatama, R. A., & Murtadho, A. (2024). Dynamics and Predictions of Urban Expansion in Java , Indonesia : Continuity and Change in Mega-Urbanization. *ISPRS Int. J. Geo-Inf*, 13(103), 1–18. doi: 10.3390/ijgi13030102

Prihestiwi, R. C., Handayani, W., & Sarasadi, A. (2023). Land Use and Surface Runoff Change in Babon Watershed Semarang Greater Area. *IOP Conference Series: Earth and Environmental Science*, 1264, 012020. doi: 10.1088/1755-1315/1264/1/012020

Ramampiandra, E. C., Scheidegger, A., Wydler, J., & Schuwirth, N. (2023). A comparison of machine learning and statistical species distribution models : Quantifying overfitting supports model interpretation. *Ecological Modelling*, 481, 110353. doi: 10.1016/j.ecolmodel.2023.110353

Risjani, Y., Loppion, G., Couteau, J., Yunianta, Y., Widowati, I., Hermawati, A., & Minier, C. (2020). Genotoxicity in the rivers from the Brantas catchment (East Java, Indonesia): occurrence in sediments and effects in Oreochromis niloticus (Linnæus 1758). *Environmental Science and Pollution Research*, 27(17), 21905–21913. doi: 10.1007/s11356-020-08575-w

Rongcheng, R., Yi, H., Jialing, M., Ying, Y., Fanning, L., Xiya, W., Xinyuan, S., Caigang, L., Yingen, D., Qinghai, H., Jinxiang, Y., & Jianglong, Q. (2025). The species distribution model based on the random forest algorithm reveals the distribution patterns of Neophocaena asiaeorientalis. *Scientific Reports*, 15, 10037. doi: 10.1038/s41598-025-92508-5

Sahragard, H. P., Ajorlo, M., & Karami, P. (2018). Modeling habitat suitability of range plant species using random forest method in arid mountainous rangelands. *J. Mt. Sci.*, 15(10), 2159–2171. doi: 10.1007/s11629-018-4898-1

Setiawan, Y., & Kunihiko, Y. (2020). Spatial modeling on land use change in regional scale of Java Island based-on biophysical characteristics. *Journal of Natural Resources and Environmental Management*, 10(3), 511–523. doi: 10.29244/jpsl.10.3.511-523

Shifa, C. T., Dayananda, S. K., Yanjie, X., Rubeena, K. A., Bin Muzaffar, S., Nefla, A., Jobiraj, T., Thejass, P., Reshi, O. R., & Aarif, K. M. (2023). Long-term anthropogenic stressors cause declines in kingfisher assemblages in wetlands in southwestern India. *Ecological Indicators*, 155, 111062. doi: 10.1016/j.ecolind.2023.111062

Shmelev, S. E. (2025). Biodiversity Offset Schemes for Indonesia : Pro et Contra. *Sustainability*, 17(14), 6283. doi: 10.3390/su17146283

Sillero, N., Arenas-Castro, S., Enriquez-Urzelai, U., Vale, C. G., Sousa-Guedes, D., Martínez-Freiría, F., Real, R., & Barbosa, A. M. (2021). Want to model a species niche? A step-by-step guideline on correlative ecological niche modelling. *Ecological Modelling*, 456. doi: 10.1016/j.ecolmodel.2021.109671

Silva, S. Da, Matsushita, R., & Esquierro, L. (2023). The Granular Size Concept in Avian Ecology : A Critical Analysis of eBird Data Bias Using the Bird Rank Abundance Distribution. *Birds*, 4, 330–336. doi: 10.3390/birds4040028

Sinha, A., Chatterjee, N., Ormerod, S. J., Singh, B., & Krishnamurthy, R. (2019). River birds as potential indicators of local- and catchment-scale influences on Himalayan river ecosystems. *Ecosystems and People*, 15(1), 90–101. doi: 10.1080/26395916.2019.1591508

Sosilawati, Handayani, A., Wahyudi, A., Mahendra, Z., Massudi, W., Listiani, A., & Rizkianto, A. (2017). Sinkronisasi Program dan Pembiayaan Pembangunan Jangka Pendek 2018-2020 Keterpaduan Pengembangan Kawasan dengan Infrastruktur PUPR Pulau Jawa. In *Ministry of Public Works and Housing (PUPR)*. Retrieved From https://bpiw.pu.go.id/uploads/publication/attachment/Buku_1Jawa.pdf

Squires, T. M., Yuda, P., Akbar, P. G., Collar, N. J., Devenish, C., Taufiqurrahman, I., Wibowo, W. K., Winarni, N. L., Yanuar, A., & Marsden, S. J. (2021). Citizen science rapidly delivers extensive distribution data for birds in a key tropical biodiversity area. *Global Ecology and Conservation*, 28(e01680), 1–11. doi: 10.1016/j.gecco.2021.e01680

Stenbacka, D. G., Bastianelli, M. L., Singh, N. J., Heurich, M., Ericsson, G., & Neumann, W. (2025). Influence of landscape composition and structure on habitat selection of a large herbivore in managed forests along a latitudinal gradient. *Forest Ecology and Management*, 597, 123167. doi: 10.1016/j.foreco.2025.123167

Sullivan, B. L., Wood, C. L., Iliff, M. J., Bonney, R. E., Fink, D., & Kelling, S. (2009). eBird: A citizen-based bird observation network in the biological sciences. *Biological Conservation*, 142(10), 2282–2292. doi: 10.1016/j.biocon.2009.05.006

Sultana, M., & Sarker, N. J. (2016). Patterns of daily activities frequencies of Common Kingfisher (*Alcedo atthis*) in Nikunja-1 , Dhaka. *International Journal of Fauna and Biological Studies*, 3(5), 23–28.

Sun, Z., Wang, G., Li, P., Wang, H., Zhang, M., & Liang, X. (2024). An improved random forest based on the classification accuracy and correlation measurement of decision trees. *Expert Systems with Applications*, 237, 121549. doi: 10.1016/j.eswa.2023.121549

Syartinilia, S., Condro, A. A., & Tsuyuki, S. (2024). Geography and Sustainability Projected impacts of climate change and anthropogenic effects on habitat distribution of endangered Javan Hawk-Eagle in Indonesia. *Geography and Sustainability*, 5(2), 241–250. doi: 10.1016/j.geosus.2024.01.009

Takola, E., & Schielzeth, H. (2022). Hutchinson's ecological niche for individuals. *Biology and Philosophy*, 37(4), 1–22. doi: 10.1007/s10539-022-09849-y

Taufiqurrahman, I., Suparno, K., Kiryono, Dwiwardhana, I. S., Fauzy, N. H., & Nurhidayat, A. (2020). The ecology of nestlings of Javan Kingfisher *Halcyon cyanoventris* observed in Jatimulyo village , Yogyakarta province , Java , Indonesia. *BirdingASIA*, 33, 58–64.

Tirtalistyani, R., Murtiningrum, M., & Kanwar, R. S. (2022). Indonesia Rice Irrigation System : Time for Innovation. *Sustainability*, 14(19), 12477. doi: 10.3390/su141912477

Tümer, Y. Ö., Caglayan, İ., Yeşil, A., & Iverson, L. (2026). Two decades of species distribution modeling : A systematic review of methods and applications. *Ecological Modelling*, 513, 111441. doi: 10.1016/j.ecolmodel.2025.111441

Valavi, R., Elith, J., Lahoz-Monfort, J. J., & Guillera-Arroita, G. (2021). Modelling species presence-only data with random forests. *Ecography*, 44(12), 1731–1742. doi: 10.1111/ecog.05615

Valavi, R., Elith, J., Lahoz-Monfort, J. J., & Guillera-Arroita, G. (2022). Flexible species distribution modelling methods perform well on spatially separated testing data. *Global Ecology and Biogeography*, 32(3), 369–383. doi: 10.1111/geb.13639

Van Balen, S. (Bas). (1998). Hovering Cerulean Kingfishers *Alcedo coerulescens*. Forktail, 13, 1998.

Vasconcelos, R. N., Cantillo-Pérez, T., Rocha, W. J. S. F., Aguiar, W. M., Mendes, D. T., de Santana, C. O., de Santana, M. M. M., de Jesus, T. B., & Oliveira, R. P. O. (2024). Advances and Challenges in Species Ecological Niche Modeling : A Mixed Review. *Earth*, 5(4), 963–989. doi: 10.3390/earth5040050

Vilches, A., Miranda, R., Arizaga, J., & Galicia, D. (2012). Short Note Habitat selection by breeding Common Kingfishers (*Alcedo atthis* L .) in rivers from Northern Iberia. *Ann. Limnol. - Int. J. Lim.*, 48(3), 289–294. doi: 10.1051/limn/2012020

Wajs, J. (2018). First experience with Remote Sensing methods and selected sensors in the monitoring of mining areas – a case study of the Belchatow open cast mine. *XVIIth Conference of PhD Students and Young Scientists*, 29, 1–9. doi: 10.1051/e3sconf/20182900023

Winnasis, S., Hakim, L., & Imron, M. A. (2018). The Utilization of Burungnesia to Detect Citizen Scientist Participation Preference in Birding Sites Observation in Java Island. *Journal of Indonesian Tourism and Development Studies*, 6(1), 49–54. doi: 10.21776/ub.jitode.2018.006.01.07

Wiwoho, B. S., Phinn, S., & McIntyre, N. (2023). Characterizing Watersheds to Support Land-use Planning in Indonesia: A Case Study of Brantas Tropical Watershed. *Ecohydrology and Hydrobiology*, 23(4), 635–649. doi: 10.1016/j.ecohyd.2023.06.001

Xie, S., Marzluff, J. M., Su, Y., Wang, Y., Meng, N., Wu, T., Gong, C., Lu, F., Xian, C., Zhang, Y., & Ouyang, Z. (2022). Science of the Total Environment The role of urban waterbodies in maintaining bird species diversity within built area of Beijing. *Science of the Total Environment*, 806, 150430. doi: 10.1016/j.scitotenv.2021.150430

Yaghmour, F., Whittington-Jones, B., & Al Naqbi, H. (2025). Diet of the Arabian collared kingfisher (Todiramphus chloris kalbaensis): Insights from trail cameras and regurgitation pellets. *Food Webs*, 42, e00391. doi: 10.1016/j.fooweb.2025.e00391

Yao, W., Wang, Z., Fan, Y., Liu, D., Ding, Z., Zhou, Y., Hu, S., Zhang, W., & Ou, J. (2025). Prediction of Potential Habitat Distributions and Climate Change Impacts on the Rare Species *Woonyoungia septentrionalis* (Magnoliaceae) in China Based on MaxEnt. *Plants*, 14(1), 86. doi: 10.3390/plants14010086

Zhang, L., Huettmann, F., Zhang, X., Liu, S., Sun, P., Yu, Z., & Mi, C. (2019). The use of classification and regression algorithms using the random forests method with presence-only data to model species' distribution. *MethodsX*, 6, 2281–2292. doi: 10.1016/j.mex.2019.09.035

Zhao, Z., Xiao, N., Shen, M., & Li, J. (2022). Comparison between optimized MaxEnt and random forest modeling in predicting potential distribution: A case study with *Quasipaa boulengeri* in China Ziyi. *Science of the Total Environment*, 842, 156867. doi: 10.1016/j.scitotenv.2022.156867