Bioclimatic Drivers of Amur Falcon Habitat Dynamics Using Advanced Machine Learning Models

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Abstract

The Amur Falcon (*Falco amurensis*) is a migratory raptor known for its long-distance journeys from eastern Russia and northern China to southern Africa, passing through various stopovers, including northeastern India and Southeast Asia. The Amur Falcon's migration spans diverse habitats and climatic zones, offering insights into its dynamics. However, climate change, habitat loss, and bio-climatic variability increasingly threaten its breeding and stopover sites. To date, no comprehensive study has analyzed how bio-climatic factors influence migration patterns across such a broad range. This study explores the bio-climatic factors influencing the falcon's migration and habitat suitability using remote sensing, GIS, and machine learning models—Maximum Entropy (MaxEnt) and Random Forest (RF). It evaluates 56 bio-climatic variables, such as temperature, precipitation, solar radiation, wind speed & water vapour pressure. Species occurrence data from citizen science is used to train and validate models. RF showed higher accuracy (AUC=0.98) than MaxEnt (AUC=0.96) and identified 6.69% of global land as moderately to highly suitable for the falcon, compared to MaxEnt's 2.07%. The analysis also revealed potential habitats outside the bird's natural migration route, including parts of North America, South America, and Oceania. Key factors affecting habitat suitability included mean temperature, precipitation, and solar radiation. This research emphasizes the importance of bio-climatic data in understanding species distribution and migration patterns, offering valuable insights for conservation planning and avian ecology.

1. Introduction

The Amur Falcon (*Falco amurensis*) is a small migratory raptor recognized for its extensive transcontinental, transequatorial, long-distance migration that spans from breeding grounds in eastern Russia and northern China to wintering areas in southern Africa (Meyburg et. al., 2017). Covering nearly 22,000 kilometers, this species undertakes one of the longest migratory journeys in the avian world, traversing diverse ecological and climatic regions. This long-distance flight includes moving south through China, skirting the eastern edge of the Himalayas to reach north-east India and Bangladesh, where they settle temporarily to fatten before embarking on the latter stage of the migration through the Indian subcontinent and across the Indian Ocean to the equatorial Africa (Clement & Holman, 2001; Bildstein, 2006). The wide geographic range and the complex migration pattern of the Amur Falcon underscore its ecological significance and adaptability to varying environmental conditions (Orta et. al., 2020; Symes&Woodborne, 2010).

Despite the bird's resilience and a stable population count with the least concern category in the IUCN Red List (IUCN, 2011), the Amur Falcon faces numerous environmental challenges that threaten them along their arduous journey during the annual migration.Climate change, habitat loss, hunting practices, and the variability of bio-climatic conditions increasingly impact the falcon's breeding, migration, and wintering habitats (Aiyadurai& Banerjee, 2020; O'Mahony, 2016). The ongoing degradation of ecosystems and unpredictable weather patterns due to climate change can severely disrupt its migratory routes and the availability of essential stopover sites, posing a serious threat to the species (Wyatt, 2008).

Over the years, conservation efforts, such as the protection of the species under international wildlife laws like the Convention on International Trade in Endangered Species (CITES) and the Convention on the Conservation of Migratory Species (CMS), have provided some safeguards (Wijnstekers, 2003; Martin, 2007). Moreover, community-driven conservation projects in Nagaland, India, where large numbers of Amur Falcons stop during migration, have successfully reduced hunting and poaching activities since 2012 (Kudalkar and Verissimo, 2024). The hunting of Amur falcons has effectively been banned by Indian wildlife authorities. Furthermore, community development and awareness initiatives were headed by the Nagaland Wildlife & Biodiversity Conservation Trust (NWBCT), and a shift toward eco-tourism has been adopted in recent years (Aiyadurai& Banerjee, 2020). However, despite the bird's ecological importance and conservation efforts, there remains a gap in research analyzing the influence of bio-climatic factors on its migration and habitat suitability across its vast migratory range.

Migratory birds like the Amur Falcon are highly sensitive to factors such as temperature, precipitation, wind patterns, food availability (primarily large insect swarms like locusts and dragonflies), and environmental changes which play a critical role in shaping the falcon's migratory dynamics (Bildstein, 2006; Symes&Woodborne, 2010). These bio-climatic drivers determine not only the timing of migration but also the choice of breeding and stopover habitats (Negro et. al., 2022). Nevertheless, to date, there has been no comprehensive analysis of the impact of these bio-climatic factors on the falcon's migration patterns across its entire range. Understanding how these environmental variables shape habitat preferences is crucial for conservation planning, particularly in light of the growing threats from climate change and habitat destruction.

This study addresses the critical research gap by employing advanced remote sensing technologies, Geographic Information Systems (GIS), and machine learning models—Maximum Entropy (MaxEnt) and Random Forest (RF)—to assess the bio-climatic drivers of habitat suitability for the Amur Falcon. MaxEnt focuses on specific environmental factors with conservative estimates, while RF captures complex interactions among variables, offering a more dynamic perspective on habitat suitability (Breiman, 2001; Catani et. al., 2013; Kim et. al., 2019). These models offer powerful tools for predicting species distribution and identifying suitable habitats based on environmental variables (Williams et. al., 2009; Zhao et. al., 2022).

The research provides a comprehensive analysis of the bio-climatic factors influencing the Amur Falcon's habitat and migration routes, offering valuable insights for conservation efforts. By using advanced machine learning models, the study emphasizes how these tools can enhance our understanding of migratory species' ecological needs, supporting more targeted strategies to mitigate climate change and habitat loss impacts. The findings contribute significantly to avian ecology, demonstrating the role of data-driven approaches in addressing the challenges migratory species face in our changing world.

2. Study Area

Amur Falcon's migration spans diverse regions from breeding grounds in eastern Russia (43°N-52°N, 131°E-135°E) and northern China (42°N-49°N, 120°E-127°E) to wintering sites in southern Africa (10°S-35°S, 15°E-30°E)(Meyburg et. al., 2017) (Figure 1). The breeding areas have a temperate climate with cold winters and warm summers. The migration corridor traverses central Asia, north-eastern India, Myanmar, and Thailand. These regions vary from grasslands and temperate forests to tropical zones. The wintering grounds in southern Africa are characterized by a warm climate, with summer rainfall. This extensive route highlights a range of bio-climatic zones critical for the falcon's migration(Orta et. al., 2020; Symes&Woodborne, 2010).

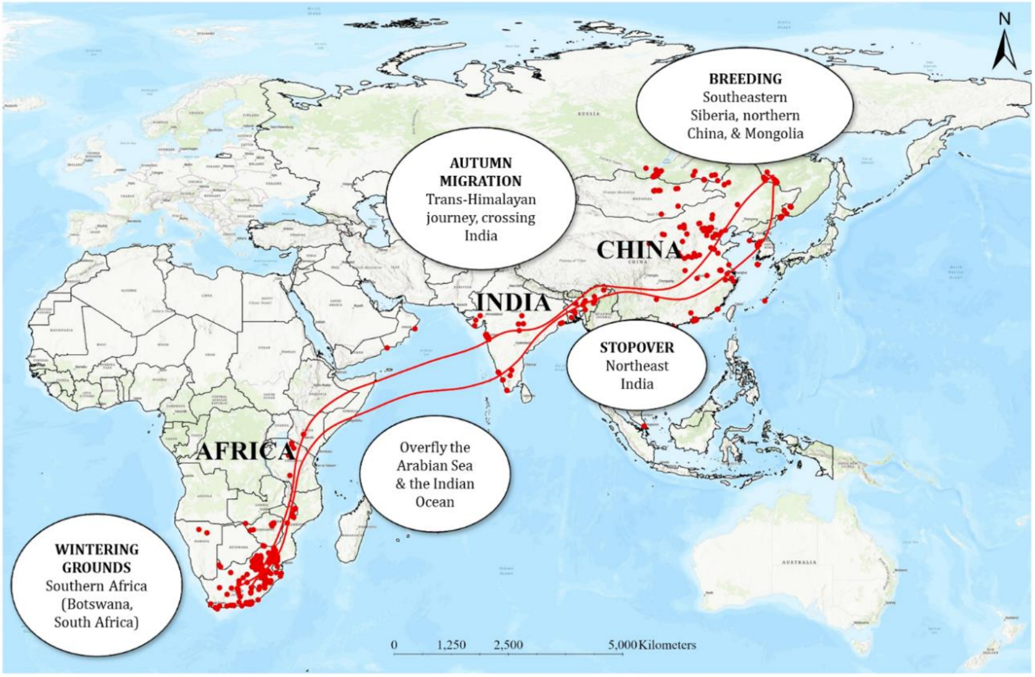

Figure 1. Study area map

3. Material & Method

3.1 Dataset used

In this study, 56 bio-climatic variables (30 Arc Second) including temperature, precipitation, solar radiation, wind speed & water vapour pressure, are acquired from the WorldClim database to identify suitable habitats for Amur Falcon (Fick &Hijmans, 2017). Species occurrence data for the period of 2022-2024is sourced from iNaturalist, a citizen science database (Nugent, 2018) (Table 1).

Table 1. Detail of 56 bio-climatic variables

Variable	Description
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (×100)
BIO4	Temperature Seasonality (standard deviation ×100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

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Srad	Solar radiation (kJ m-2 day-1) (12 months)
Wind	Wind speed (m s-1) (12 months)
Vapr	Water vapor pressure (kPa) (12 months)

3.2 Methodology

3.2.1 Data Preprocessing: Species occurrence data, sourced from the citizen science platform, were meticulously filtered to include only research-grade records. To prepare the data for modeling, 70% of the species occurrence data was randomly selected for model training, while the remaining 30% was reserved for validation. The bio-climatic variables were processed by removing any missing values, outliers, and irrelevant data, ensuring precise predictions during modeling.

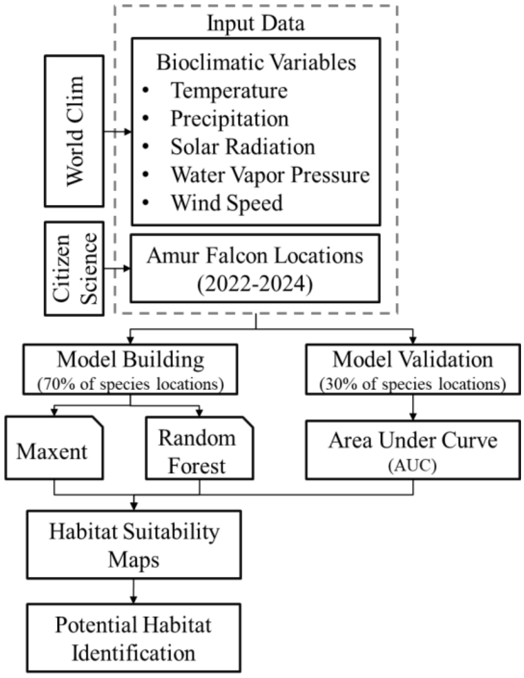

Figure 2. Methodology flowchart for the study

3.2.2 Modeling Habitat Suitability: This study uses two advanced machine learning models—Maximum Entropy (MaxEnt) and Random Forest (RF)—to model habitat suitability for the Amur Falcon based on bio-climatic variables.

(a) Maximum Entropy Model: MaxEntis a widely used model for species distribution modeling based on the maximum entropy principle. It predicts habitat suitability based on the environmental variables present at species occurrence locations (Kim et al., 2019). The model operates by estimating the probability distribution of maximum entropy, subject to the constraint that the expected value of each environmental variable matches its empirical average. This ensures that the model is as uniform as possible given the constraints, leading to conservative estimates of habitat suitability (Phillips 2005; 2006). In this study, MaxEnt identifies suitable habitats for the Amur Falcon by correlating the species' occurrence with bio-climatic factors.

(b) Random Forest:RF is a classification and regression model that builds an ensemble of decision trees to predict the response variable, in this case, the suitability of habitats based on bio-climatic variables (Breiman, 2001). RF is particularly effective at capturing complex interactions between variables and provides robust predictions even with noisy or missing data. In this study, RF was used to analyze the influence of bio-climatic variables on the habitat dynamics of the Amur Falcon. The model works by aggregating the predictions of multiple decision trees, each trained on a different subset of the data, to produce a more accurate and reliable prediction (Catani et al., 2013).

3.2.3Model Evaluation: Validating the model is an essential process to ensure that the predictions generated are reliable and applicable for future research. In this study, 30% of the Amur Falcon location data,those not used during model training, were set aside for testing and validation. The Receiver Operating Characteristic (ROC) curve, which plots the true positive rate against the false positive rate, was used to assess model performance. The Area Under the Curve (AUC) serves as a quantitative measure of a model's effectiveness, with values ranging from 0 to 1. Higher AUC values indicate stronger model performance, while an AUC of 0.5 suggests the model is no better than random predictions. Generally, models with AUC values exceeding 0.7 are considered to produce fair to good predictions (Kim et al., 2019). Both MaxEnt and RF were assessed using AUC scores to determine their accuracy in predicting suitable habitats for the Amur Falcon, with values closer to 1 indicating higher precision in habitat identification.

4. Results & Discussion

4.1 Global Habitat Suitability for Amur Falcon

The global distribution of suitable habitats for the Amur Falcon, as identified by the MaxEnt and RF models, reveals varying extents of potential areas where the species can thrive.

4.1.1 Suitable Areas along the Amur Falcon's Flight Path: The Amur Falcon follows a well-documented migration route that spans vast distances between its breeding grounds in northeastern Asia and its wintering grounds in southern Africa(Meyburg et. al., 2017). Both the MaxEnt and RF models confirmed the suitability of key regions within the Amur Falcon's well-established migratory corridor.Northeastern India, specifically regions like Nagaland and Assam, emerges as a critical stopover area for the falcons as they migrate through Southeast Asia (Kaur et al., 2024). Southern China and parts of Myanmar are also identified as suitable areas within this migration corridor, reflecting the importance of these regions for the falcons as they journey toward Africa (Figure 3).

Once the species reaches Africa, the models confirm large areas in southern Africa, particularly in South Africa, Botswana, and Namibia, as ideal wintering grounds. These regions offer optimal conditions for the Amur Falcon during the non-breeding season, with the RF model extending the range slightly further than MaxEnt's more focused predictions. Overall, these areas correspond to well-known, frequently used migration paths that are essential for the species' survival.

4.1.2 Potential area identified by both models: In addition to the known migratory route, both models predict additional potential habitats that extend beyond the Amur Falcon's typical flight path.

The RF model identifies a broader range of suitable habitats extending into regions beyond the traditional migratory route, such as parts of North and South America, as well as southwestern Australia (Figure 4b). However, MaxEnt, with its conservative estimates, limited suitable habitat identification to the species' more traditional range, primarily focusing on central

Asia, northeastern India, and parts of southern Africa (Figure 4a). This suggests that MaxEnt is more sensitive to established bio-climatic conditions that are critical to the species' known behaviors, whereas RF's broader identification may highlight regions with less immediately apparent suitability factors.

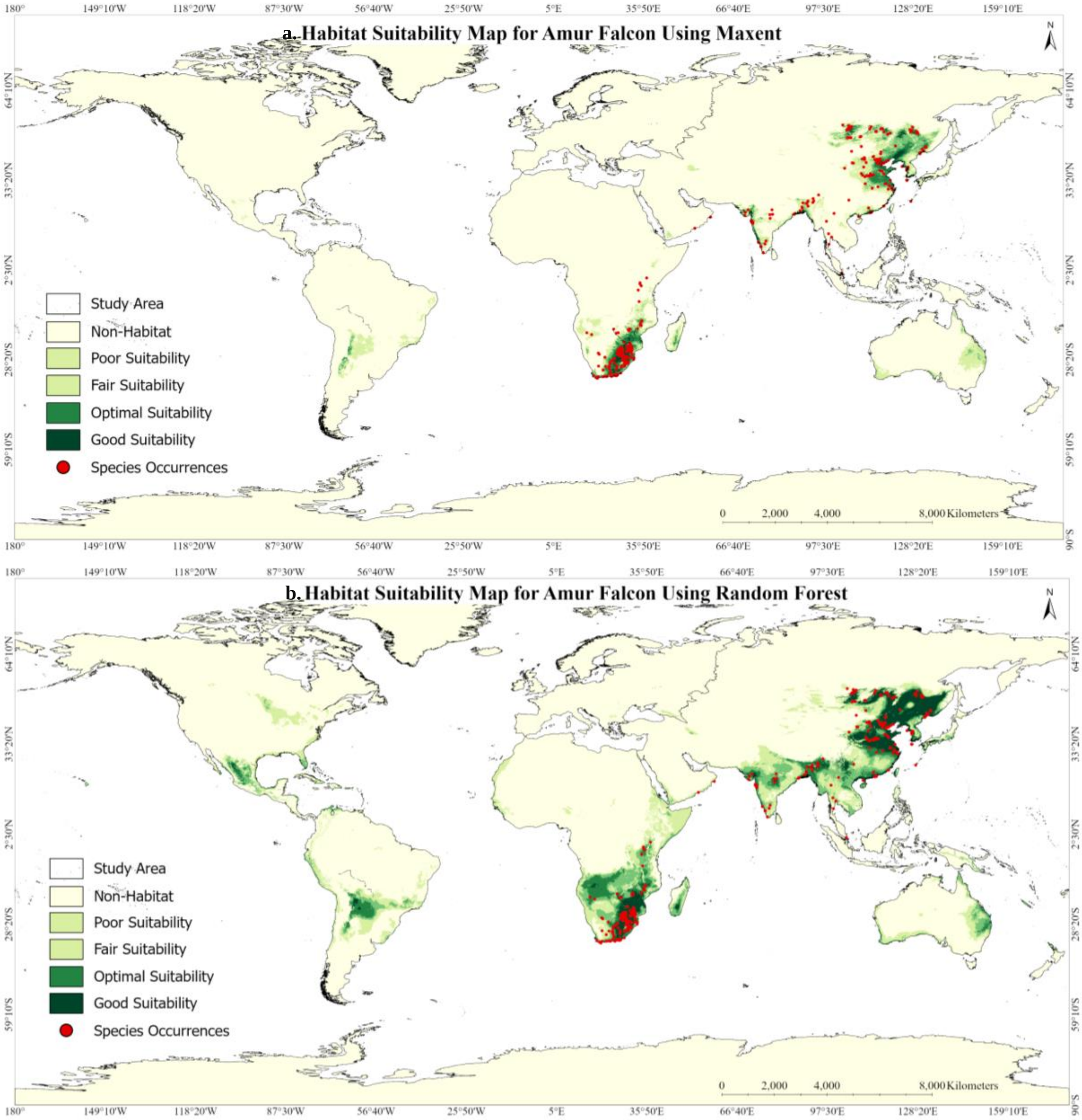

Figure 3. Habitat Suitability Map for Amur Falcon, (a) MaxEnt, (b) Random Forest

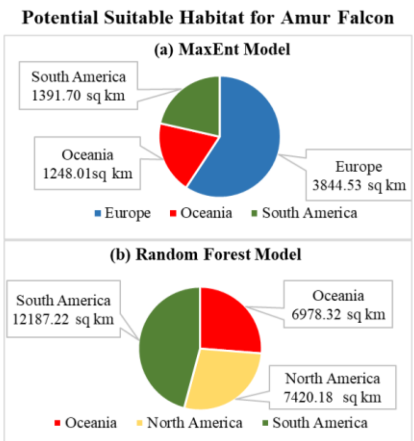

Figure 4. Potential Suitability Habitat for Amur Falcon, (a) MaxEnt, (b) Random Forest

Despite the identification of these potential habitats, the Amur Falcon is unlikely to utilize these regions, possibly due to various natural barriers. For example, northern Australia, while showing suitable conditions, is separated from Asia by the Wallace Line—an ecological boundary that has historically limited the exchange of species between Asia and Australia (Van Oosterzee, 1997). This line has resulted in distinct faunal regions between the two continents. Additionally, the vast oceanic barriers between Asia and America pose significant challenges to the species' long-distance flight capabilities, making these regions inaccessible. Similarly, the small suitable pockets identified in Europe are too distant from the falcon's migratory path and separated by vast stretches of unsuitable terrain, further preventing their utilization by the species. Thus, while both models identify potential areas for habitation, these regions remain unused, which could be due to natural barriers and geographical constraints, however further research is required.

4.2 Comparison and Validation of the Models

The RF model predicted that approximately 6.69% of the global land area is moderately to highly suitable for the Amur Falcon, covering a broad range of regions across different continents. In contrast, the MaxEnt model provided a more conservative estimate, highlighting only 2.07% of the global land area as suitable for the species (Figure 5).

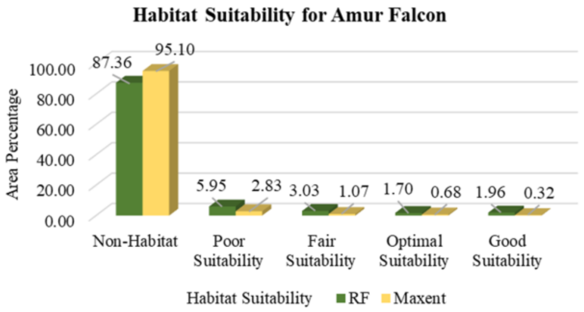

Figure 5. Area percentage of suitable habitat for Amur Falcon based on MaxEnt and Random Forest models

The performance of both models, assessed using AUC scores, demonstrated that both MaxEnt and RF provide highly accurate predictions of habitat suitability for the Amur Falcon. RF achieved an AUC score of 0.98, slightly outperforming MaxEnt, which had an AUC score of 0.96 (Figure 6). The high accuracy of both models underscores their effectiveness in ecological research, particularly in modeling habitat dynamics under varied bio-climatic conditions.

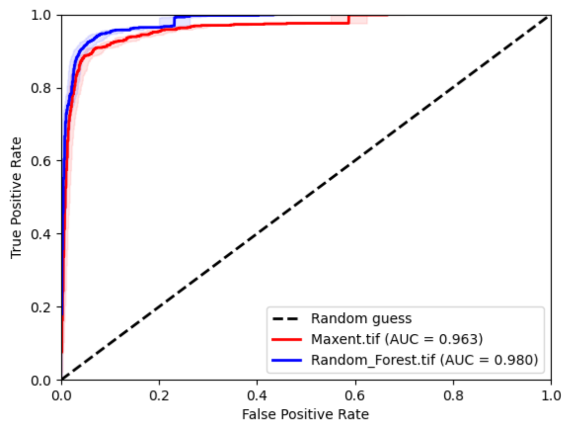

Figure 6. Receiver Operating Characteristics (ROC) curves (AUC)

The higher accuracy of RF can be attributed to its ability to handle complex, non-linear relationships between variables and its ensemble learning method, which constructs multiple decision trees to increase prediction reliability(Breiman, 2001). Conversely, MaxEnt's focus on presence-only data makes it highly specialized for predicting the most suitable environments based on specific ecological and bio-climatic variables(Kim et al., 2019). Despite these methodological differences, both models have provided valuable insights into the falcon's potential habitat distribution.

4.3 Country-wise analysis of suitable habitat

The results of the habitat suitability analysis indicate significant variation across countries within the Amur Falcon's migratory route. The highest concentrations of suitable habitats were found in Russia, northern China, and northeastern India, consistent with the species' known breeding and stopover sites(Clement & Holman, 2001; Bildstein, 2006).The Random Forest model, demonstrating higher accuracy in predicting suitable habitats for the Amur Falcon, reveals significant country-wise variations in habitat availability. The analysis indicates that China has the largest percentage of suitable habitat, contributing around 30% of the total area deemed suitable for the falcon. This is followed by India, with approximately 10%, making these two countries critical to the Amur Falcon's breeding and migration paths (Figure 7).

South Africa, another key location along the falcon's migration route, ranks third with about 8% of the total suitable habitat. Countries such as Russia, Angola, Mozambique, and Zambia follow, each contributing between 3-5% of the suitable area. These nations are also essential for the species, particularly as stopover sites during migration(Meyburg et. al., 2017).Several African countries, such as Botswana, Zimbabwe, Namibia, and Madagascar, contribute smaller but notable percentages of suitable habitat (Figure 7). These areas serve as critical wintering grounds, offering necessary conditions for the falcon during the non-breeding season(Meyburg et. al., 2017).

Further, countries like Myanmar, Mongolia, and Tanzania, each contribute a small but significant portion of the habitat, reflective of the wide-ranging distribution of potential areas across continents. In contrast, several countries show minimal but still relevant habitat availability for the species, including Vietnam, Bangladesh, and several Southeast Asian nations like Laos, Japan, and North Korea. These regions contribute less than 1% of the suitable area, emphasizing that although the falcon's habitat is concentrated in certain regions, its potential range is quite broad.

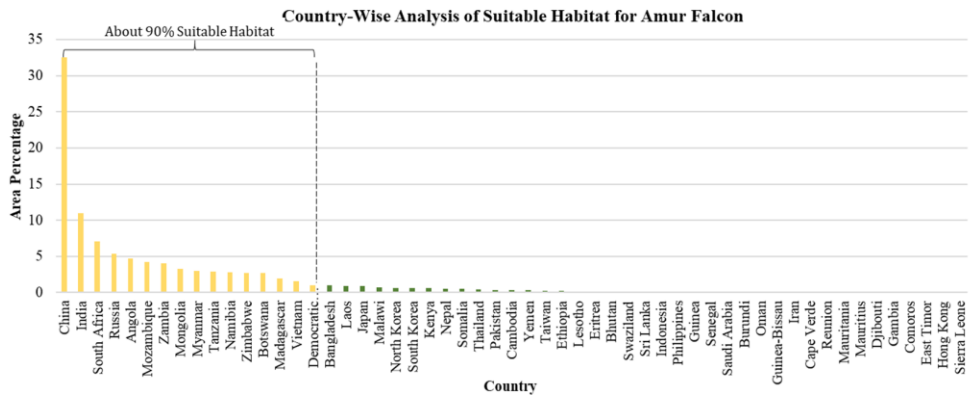

Figure 7. Country-wise analysis of suitable habitat for Amur Falcon

While this distribution highlights vast suitable areas for the Amur Falcon, it also shows that about 90% of the species' suitable habitat is concentrated in just a handful of countries, making these regions vital for the conservation and protection of the species during migration and other life stages.

5. Conclusion

The results of this study provide valuable insights into the conservation of the Amur Falcon, particularly in the context of climate change and habitat loss. By identifying key bio-climatic drivers of habitat suitability, this research supports the development of targeted conservation strategies aimed at preserving critical habitats along the species' migration route. Conservation efforts should focus on maintaining and restoring suitable habitats in key regions, such as northeastern India, China, and southern Africa while addressing the environmental threats posed by climate change and human activities. Moreover, the findings underscore the need for international cooperation in the conservation of migratory species like the Amur Falcon. Given the species' transcontinental migration, conservation efforts must involve multiple countries and stakeholders to ensure its long-term survival.

This study also highlights the effectiveness of machine learning models, such as MaxEnt and Random Forest, in predicting species distribution and assessing habitat suitability. By leveraging bio-climatic data and advanced modeling techniques, researchers can gain a deeper understanding of the environmental factors that influence migratory species like the Amur Falcon. This approach not only enhances habitat conservation efforts but also advances the field of avian ecology by providing robust tools for species distribution modeling. In conclusion, while both MaxEnt and Random Forest models offer valuable insights into bio-climatic drivers of habitat suitability, the integration of these models with field-based research and conservation initiatives will be crucial in developing effective strategies to protect the Amur Falcon and other migratory species in a rapidly changing environment.

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