Turkish Journal of Zoology

Volume 48 | Number 4 Article 4

7-10-2024

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Turkish Journal of Zoology

http://journals.tubitak.gov.tr/zoology/

Research Article

Turk J Zool
(2024) 48: 220-232
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doi:10.55730/1300-0179.3178

Modeling habitat suitability and current distribution of the Maghreb magpie (*Pica mauritanica*)

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Received: 01.03.2024 • **Accepted/Published Online:** 03.06.2024 • **Final Version:** 10.07.2024

Abstract: The Maghreb magpie (*Pica mauritanica*) is an endemic bird to North Africa, encompassing Algeria, Morocco, and Tunisia. Unfortunately, its population is facing a significant decline primarily attributed to habitat loss and fragmentation resulting from urbanization and agricultural practices. Due to the lack of large-scale studies on habitat requirements of *Pica mauritanica*, investigating the habitat preferences of this species and understanding the potential threats remain crucial for effective conservation strategies. We performed species distribution model (SDM), incorporating both occurrence records and predictor variables, to investigate the potentially suitable habitat and the factors influencing the distribution of the Maghreb magpie (*Pica mauritanica*) in North Africa. Among the environmental predictors examined, the enhanced vegetation index (EVI), elevation, and human settlement have been identified as key factors influencing habitat suitability. Specifically, EVI and human settlements positively contribute to suitability, while precipitation and temperature exert negative effects. The SDM results were consistent with our field observations, indicating that *Pica mauritanica* tends to avoid urban settlements or densely forested regions, thus preferring village farm areas, especially during the breeding period. The model forecasts high habitat suitability for Pica mauritanica along the eastern coastal regions of Tunisia, the western coastal areas and the High Atlas Mountain range of Morocco, as well as the Hautes Plaines region in Algeria, with a fragmented patch pattern. To ensure the sustainable survival of *Pica mauritanica*, we endorse the preservation of traditional farming practices, where farmland birds are mainly impacted by agricultural intensification and land use changes. Further extensive studies are needed to determine population size and explore habitat requirements at a micro-scale to guide conservation priorities.

Key words: *Pica mauritanica*, remote sensing, nesting habitat, GIS, SDM, Algeria

1. Introduction

Pica mauritanica, commonly known as the Maghreb Magpie, is a distinctive corvid species endemic to North Africa. Originally considered as a subspecies of the Eurasian magpie (*Pica pica*), subsequent studies have revealed distinct differences in the North African population compared to other global populations (Kryukov et al., 2017). Consequently, this species has been reevaluated and recognized as a separate species (Del Hoyo et al., 2018). Furthermore, Isenmann et al. (2005) have identified *Pica mauritanica* as abundant in Algeria, Morocco, and Tunisia. However, the population of *Pica mauritanica* is currently facing challenges due to the fragmentation and destruction of its natural habitats caused by many factors such as wildfires, clearing, deforestation, intensification of modern agriculture, and urban expansion. Therefore, the species' nesting range has become increasingly restricted, leading to a small spatial distribution across the mentioned North African countries with isolated populations, some of which contain threatened breeding pairs at risk of extinction (Isenmann and Thévenot, 2020; Nefla et al., 2021). Despite these critical circumstances, limited research has been conducted on *Pica mauritanica*. Apart from Nefla's et al.'s (2021) study, which primarily explores the breeding biology of this species in Tunisia, there exists a lack of information regarding the habitat characterization

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and suitability of the species across the defined scale of its distribution. Therefore, mapping the habitat of *Pica mauritanica* becomes vital for a comprehensive understanding of the current distribution of this species for developing effective conservation strategies throughout North Africa (Guisan et al., 2013). Species range maps, such as those from BirdLife International and the IUCN, are essential for identifying and conserving key areas and species. However, these traditional maps often lack regular updates, leading to outdated data, and they typically do not incorporate environmental factors that influence species distributions (Li et al., 2019). Additionally, these maps typically depict broad and generalized regions where species occur, without the detailed resolution needed to capture specific habitat preferences or microhabitat requirements (Peterson et al., 2018). To address these limitations, conservation efforts can benefit from the use of more advanced techniques such as species distribution models (SDMs). In ecology, species distribution models (SDMs), also known as ecological niche models (ENMs), are tools that use occurrence data and environmental variables to predict and map the species' potential distribution, thereby assessing the likelihood of its presence or absence in a specified geographical area (Guisan and Zimmermann, 2000).

In the recent years, SDMs find extensive application across diverse domains such as conservation biology, biodiversity assessment, climate change modeling, and invasive species management (Araújo and Peterson, 2012). Additionally, the use of SDMs in avian biology has provided valuable insights into the distribution and abundance of bird species, as well as the ecological and environmental factors that influence these patterns (Stiels and Schidelko, 2018). Consequently, combining expert-based range maps with results from species distribution models offers an unbiased and comprehensive understanding of species' geographic distributions across habitats, providing more rigorous estimates tightly linked to environmental variables (Engler et al., 2017).

Using this modeling framework, this study aims (1) to predict and map the current distribution of *Pica mauritanica*, thus depicting it potentially suitable areas, (2) to identify factors driving it potential distribution, and (3) to determine the environmental niche requirements of this species in the Maghreb region. Ultimately, this approach will provide insight into identifying high-priority conservation areas and defining conservation implications.

2. Materials and methods

2.1. Study area

The Maghreb region (encompassing Algeria, Morocco, and Tunisia) covers an area of approximately 3,254,000 km^2. This region is characterized by a Mediterranean climate, where the precipitation varies between 78 and 390 mm. Moreover, temperature varies between an annual mean of 13.7 °C in Atlas Mountains and 23.1 °C in the Sahara. Our research was carried out across an area of 974,536 km^2. The altitude ranged between –61 and 3697 m. The Algerian sites from which we found signs of the species were located at 11 stations in the extreme west (Beni Boussaid - Tlemcen Province), in the east of the country (Tazoult - Batna Province), in the north (Bordj Zemoura - Bordj Bou Arreridj Province) and towards the south of the country (Senalba - Djelfa Province) (Figure 1 and Table 1).

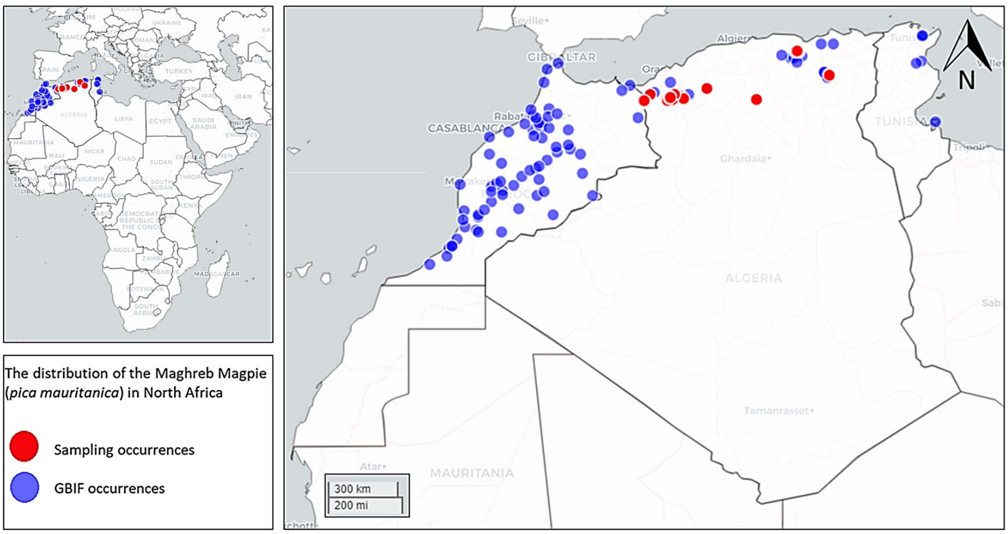

Figure 1. The distribution of *Pica mauritanica* throughout North Africa.

Table 1. Location and characteristics of nesting sites of the *Pica mauritanica.* Data recorded in 2022.

Region	**Province**	**Date of record**	**Nesting area**	**Habitat type**	**GPS coordinates**	**Municipality**	**Number of nests**	**Altitude (m)**
Eastern part of Algeria	Batna	March 2022	Tazoult	Category 2	35°28’43.3236”N 6°17’9.726”E	Tazoult	_	1275
	Bordj Bou Arreridj	March 2022	Bordj Zemoura	Category 1	36°18’12.8736”N 4°54’43.0956”E	Bordj Zemoura	_	1400
Western part of Algeria	Tiaret	22/05/2022	Ain El Hadid	Category 2	34°58’49.62891”N 0°57’44.22722”E	Ain El Hadid	03	1158
	Saïda	24/05/2022	Hassi Aoun	Category 2	34°42’59.27”N 0°7’14.28”W	Ain El Hadjar	06	1091
		24/05/2022	Lala Setti	Western part (category 2), Eastern part (category 3),	34°37’59.8”N 0°3’8.9”W	Moulay Larbi	07	1094
	Sidi Bel Abbes	26/05/2022	Sidi Chaib	Category 4	34°35’43”N 0°32’29.67156”W	Sidi Chaib	08	1098
		31/05/2022	Oued Sebaa	Category 3	34°34’3.07925”N 0°45’17.01609”W	Oued Sebaa	02	1183
		31/05/2022	Dhaya Ben Attia	Northen part (Category 2), Southern part (Category 3)	34°39’40.64926”N 0°39’18.15387”W	Dhaya	17	1350
	Tlemcen	28/06/2022	Moutas	Category 1	34°45’52.1”N 1°29’19.6”W	Bouhlou	03	1095
		02/07/2022	Al-Asfour	Category 1	34°31’39.5868”N 1°44’25.4112”W	Beni Boussaid	_	1490
Center of Algeria	Djelfa	August 2022	Senalba	Category 3	34°35’58.6”N 3°6’26.9 E	Djelfa	10	1289

2.2. Species distribution model

2.2.1. Occurrence point and environmental data

We compiled a checklist (226 occurrences) of Maghreb magpie by merging georeferenced occurrences data gathered from the public online repositories GBIF (2021) and field surveys carried out from (2000–2019).

Many observers, especially wildlife photographers and ornithologists, have extensively documented the presence and distribution of the Maghreb magpie within Algeria. Based on these efforts, field surveys were carried out, thus visiting 11 nesting sites across the Algerian territory. We recorded the nest or species presence using a GPS in order to georeference its location.

We downloaded 19 bioclimatic variables from the WorldClim 2 database (Hijmans et al., 2005) at a spatial resolution of 30 arc-s (approximately 1 km). Additionally, we obtained elevation raster data, EVI (enhanced vegetation index), slope, and World Settlement Footprint through the Google Earth Engine platform. All predictor's variables were standardized at a spatial resolution of 30 arc-s (approximately 1 km) in order to handle multicollinearity issues (Dormann et al., 2013). We first explored correlations among all predictor variables using the 'chart correlation' function implemented in the R package 'Performance Analytics' and created a dendrogram based on Pearson's distance. We retained a final set of variables that presented a correlation coefficient (r) < 0.75. Afterward, we used the function vifstep from the R package 'usdm' (Naimi et al., 2014), to compute the VIF (variance inflation factor) scores of the predictor variables. We retained variables with a VIF score less than (<5). The seven variables retained were BIO 1, BIO 8, BIO 12, slope, world human settlement, elevation, and EVI.

2.2.2. Premodeling

We processed the predictor layers using a shapefile acquired from Ecoregions[1]. The buffer zone was defined based on Ecoregion characteristics, resulting in the exclusion of deserts and xeric shrublands. This process involved restricting the distribution area to the pertinent geographic extent, ultimately enhancing the accuracy of the model.

A spatial thinning was performed where duplicated records and points within a distance of less than 1 km (falling in the same pixel of the explanatory variables) were removed using the function 'thin_by_dist' implemented in tidysdm package (Leonardi et al., 2023). This process kept only one point per pixel to minimize sampling bias (Boria et al., 2014), thereby reducing the number of occurrences to 138 points. Furthermore, using the function 'sdmData' based on a gRandom method, we randomly generated 200 background points, nearly twice the number of presence points (Cancellario et al., 2022), resulting in a prevalence ratio of approximately 0.41. It has been shown that randomly selected background points, which are equally weighted to the presence points, yield the most reliable distribution models (Barbet-Massin et al., 2012). In addition, the number of background points and the dataset balance impact model performance. Linear algorithms, such as regression techniques (GLM and GAM), are more efficient with a large number of background points with equal weight. In contrast, classification and machine-learning models (RF and BRT) perform better with a moderate number of pseudo-absences, thus improving predictive precision and minimizing bias and variability (Li and Wang, 2013).

2.2.3. Modeling and postprocessing

We used the 'sdm' function implemented in the sdm R package to run species distribution models using three algorithms: generalized linear model (GLM), boosted regression trees (BRT), and random forest (RF), which belong to regression models and machine learning methods. These algorithms were selected for their high performance in accurately capturing species-environment relationships and their complementarity (Barbet-Massin et al., 2012).

Generalized linear models are adapted to binary (presence/absence) or count (abundance or richness) outcome variables (Miller, 2010). However, they may not be suitable for complex, species-environment relationships. On the other hand, random forest and boosted regression trees models are less sensitive to multicollinearity (Dormann et al., 2013), can handle unbalanced datasets, and are capable of managing complex relationships (Crase et al., 2012).

We used default parameterization of SDM, where GLMs were fitted using a binomial family with a logit link function, and RF models were fitted with 500 trees and the number of variables tried at each split set to the square root of the number of predictors. In addition, BRT were adjusted with default settings, including 1000 trees.

Simultaneously, the dataset was divided into 30% for testing and 70% for training. Three replications were performed for both subsampling and bootstrapping methods. Afterward, we created an ensemble model using a weighted averaging procedure overall predictions from several fitted models based on the true skill statistic (TSS). The threshold was set equal to max (sensitivity + specificity) (Naimi and Araújo, 2016), thereby minimizing the mean error rate for both positive and negative observations. This ensemble forecast framework aimed to leverage the strengths of various modeling techniques while minimizing the impact of individual model weaknesses due to prevalence and sampling bias. This approach ultimately improves the overall predictive performance of the ensemble model (Miller, 2010), and maximizes the effectiveness of background points (Barbet-Massin et al., 2012).

2.2.4 Model evaluation

We conducted a thorough assessment of model performance using three primary metrics: true skill statistic (TSS), area under the curve (AUC) derived from the receiver operating characteristic (ROC) curve, and

[1] Ecoregions (2017). Mediterranean Forests, Woodlands & Scrub [online]. Website https://ecoregions.appspot.com/ [accessed 01 March 2024].

kappa statistic. AUC values falling between 0.7 and 1.0 signify strong discriminatory capability, whereas values below 0.5 indicate poorer predictive accuracy (Hanley and McNeil, 1982). TSS values ranging from -–1 to 1 follow a similar pattern: positive values denote performance better than random chance, while negative values indicate less effective performance (Swets, 1988). In addition, kappa statistic, which ranges from –1 to +1, indicates the level of agreement between observations. A value of +1 represents perfect agreement, while values at or below zero indicate agreement no better than random chance (Cohen, 1960).

3. Results

The area under the curve and true skill statistic (TSS) of the models ranged from 0.704 to 0.957 and from 0.339 to 0.797, respectively (Table 2). The ensemble model showed an AUC value of 0.82 ± 0.07 and a TSS of 0.54 ± 0.14. Additionally, the kappa statistic ranged from 0.33 to 0.846, with an average of 0.53 ± 0.15.

The point of occurrence area exhibits distinctive climatic and geographical features that collectively shape its environmental profile. The average annual precipitation amounted to 438.17 mm, with a peak concentration occurring between 300 and 400 mm. In addition, the average annual temperature was recorded at 15.22 °C, while the average temperature of the wettest quarter was 9.74 °C. The average elevation was 951.02 m, with most locations falling within the range of 1000 m to 1600 m. Moreover, the slope had an average value of 3.31, indicating a moderately inclined topography. The enhanced vegetation index exhibited a mean value of 0.2026, with a peak concentration between 0.2 and 0.25. The average human settlement score was 12.61, displaying a distinct concentration peak between 10 and 12 (Figure 2).

EVI and elevation were the most influential variables, together accounting for a contribution of 68%, followed by human settlement, which contributed 10.2%. This highlights their important role in elucidating the factors influencing the current distribution of *Pica mauritanica* (Figure 3).

The suitability index ranges from a minimum of zero to a maximum of 8.9, indicating a congruent distribution in concordance with the known occurrence of the species. Highly suitable areas for the Maghreb magpie are located in the coastal regions of eastern Tunisia and western Morocco, respectively. Additionally, high suitability is also located in the Algerian Hautes Plaines region and the Moroccan High Atlas (Figure 4A). The binary map delineates suitable areas at a threshold greater than 0.6, revealing a total expanse of approximately 64,843 km^2 across the entire study area. Within this scope, Algeria encompasses 34,853 km^2 of suitable terrain, Morocco accounts for 25,440 km^2, and Tunisia comprises 4550 km^2. The distribution of the species is mainly in the form of separated patches (Figure 4B).

Table 2. Model performance metrics of GLM, BRT, and RF models with two replication techniques.

Method	Replication	AUC	TSS	Kappa
GLM	Subsampling	0.704	0.339	0.331
GLM	Subsampling	0.766	0.442	0.433
GLM	Subsampling	0.717	0.339	0.331
GLM	Bootstrap	0.727	0.366	0.355
GLM	Bootstrap	0.714	0.39	0.388
GLM	Bootstrap	0.809	0.629	0.621
BRT	Subsampling	0.787	0.485	0.475
BRT	Subsampling	0.824	0.485	0.475
BRT	Subsampling	0.813	0.485	0.475
BRT	Bootstrap	0.817	0.484	0.472
BRT	Bootstrap	0.858	0.577	0.574
BRT	Bootstrap	0.885	0.615	0.605
RF	Subsampling	0.839	0.588	0.578
RF	Subsampling	0.841	0.528	0.517
RF	Subsampling	0.836	0.545	0.536
RF	Bootstrap	0.918	0.7	0.69
RF	Bootstrap	0.957	0.795	0.846
RF	Bootstrap	0.957	0.797	0.792
Ensemble		Mean ± SD	Mean ± SD	Mean ± SD
		0.82 ± 0.07	0.54 ± 0.14	0.53 ± 0.15

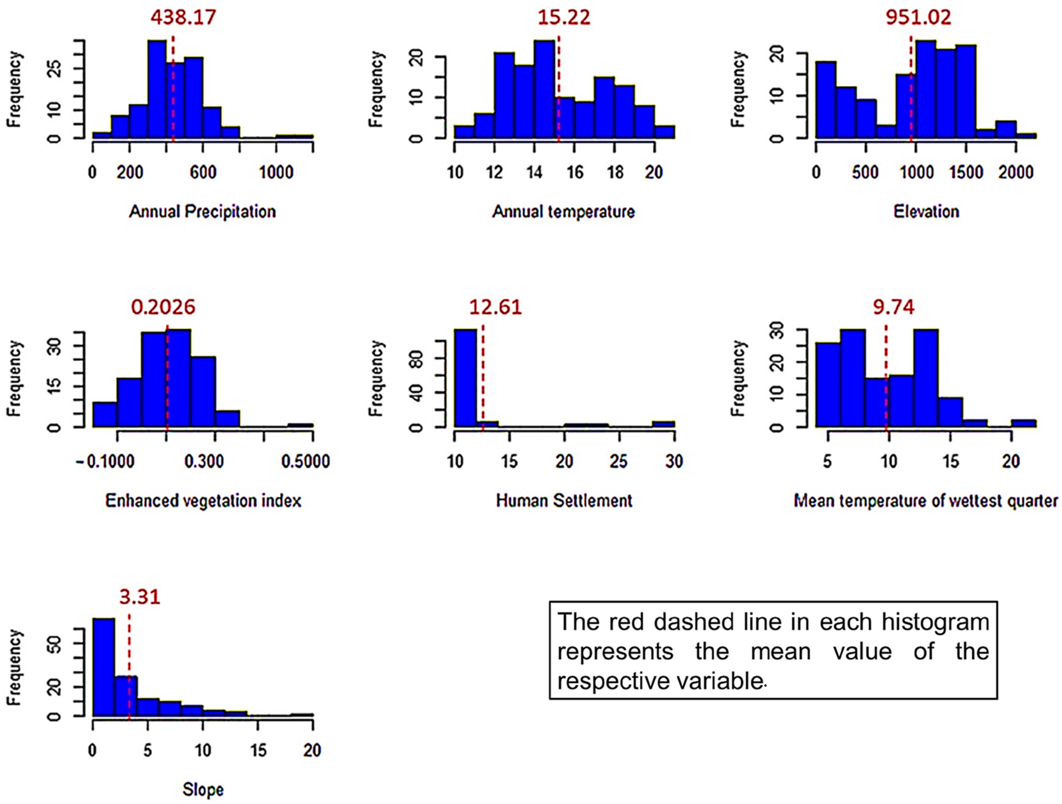

Figure 2. Histograms illustrating descriptive analyses of climatic and environmental characteristics related to the occurrence point of Maghreb Magpies.

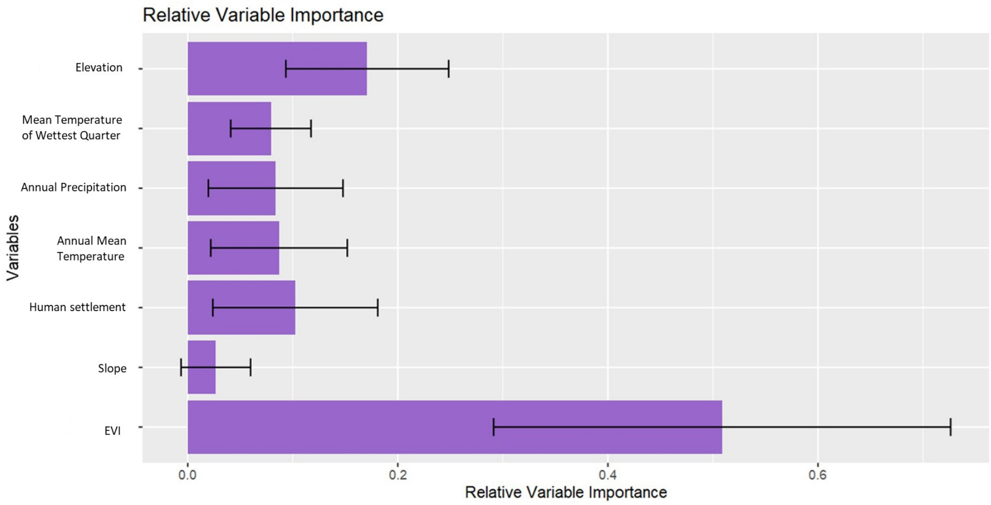

Figure 3. Variable importance (based on correlation metric) of the ensemble model.

The high suitability area is concentrated in a moderate temperature range of 1.3 °C to 12 °C during the wettest quarter (bio8), along with medium vegetation density and an elevation range between 750 and 2300 m. The annual temperature (bio1) ranges from 7 °C to 14 °C. Additionally, the suitable area has an annual precipitation average (bio12) of approximately 900 mm and a moderate level of human settlement (smode) corresponding to Rural grid cell (Figure 5).

There were positive relationships between the habitat suitability of *Pica mauritanica* and various explanatory variables, including EVI, human settlement, and slope.

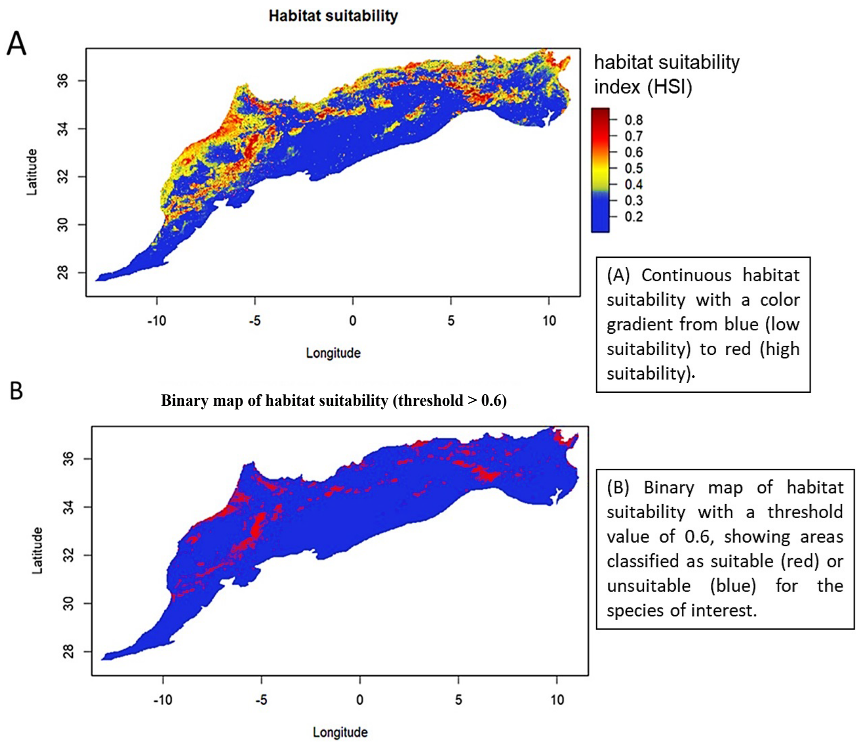

Figure 4. (A) Current distribution of the Maghreb magpie in North Africa, (B) binary map of habitat suitability with a threshold > 0.6.

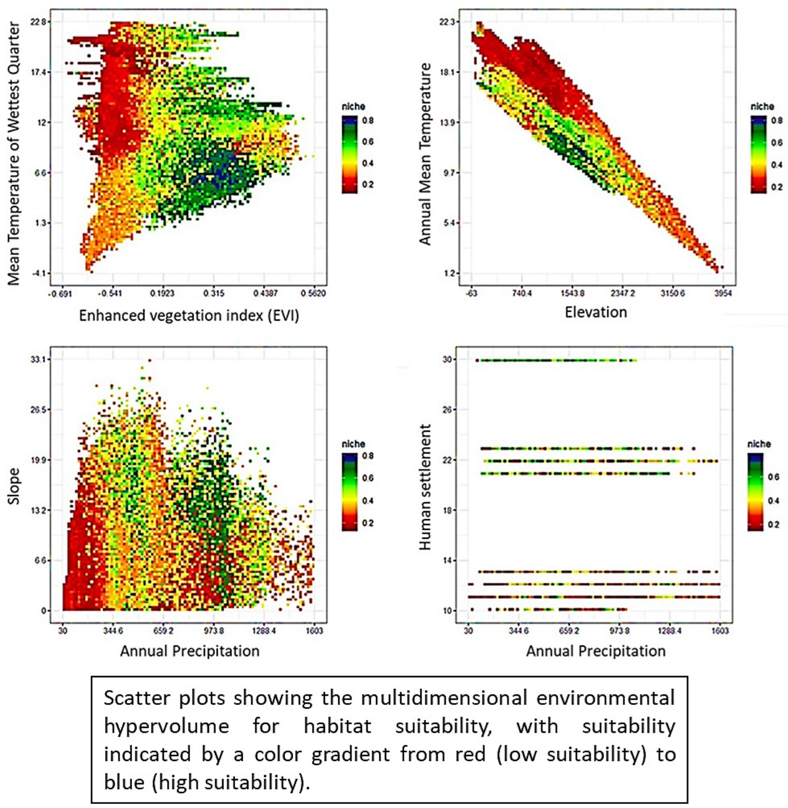

Figure 5. Two-dimensional plots of *Pica mauritanica* niche hypervolume with the most influential variables.

Conversely, annual precipitation (bio12) and mean temperature of the driest quarter (bio8) showed negative relationships with habitat suitability.

Additionally, the probability of habitat suitability exhibited a slight increase within the elevation range of 1000 to 3000 m and a slope under 5% (Figure 6).

4. Discussion

4.1. SDM modeling

The preservation of avian biodiversity is a major concern in the current context. Our study aimed to assess species distribution models to predict high-suitability areas for *Pica mauritanica* in North Africa, using ecological niche modeling methods that have shown a high ability to predict bird distribution in a real-world situation, even in poorly known areas (Peterson et al., 2002). Our study represents the first predictive assessment of the distribution of *Pica mauritanica* in North Africa. The results demonstrate a strong correlation between predictions of high-suitability areas and high values of the area under the curve. Our model was comparable to the study that used SDM's, conducted by Brambilla and Ficetola (2012). However, AUC can be misleading when dealing with imbalanced datasets, and kappa is sensitive to prevalence, unlike TSS (Allouche et al., 2006). Therefore, incorporating this multimetric approach allows for a deeper understanding of how well the model generalizes across different aspects of the data, enhancing the overall reliability of the evaluation process. In addition, several factors such as positional uncertainty (Naimi et al., 2011), spatial autocorrelation, and sampling bias arising from variations in sampling effort (Baker et al., 2022), imperfect detection (Guillera-Arroita et al., 2015) or biases inherent in public occurrence platforms such as GBIF (Beck et al., 2014) present significant hurdles in accurately modeling species distributions and interpreting ecological patterns. Addressing these challenges requires a combination of methodological approaches and data quality control measures.

Strategies for mitigating sampling bias may include spatially explicit sampling designs, incorporating sampling bias correction techniques into modeling workflows (Inman et al., 2021), integrating complementary expert knowledge (Boyd et al., 2023), as well as employing spatial filtering and weighted target-group background (Gutierrez-Velez and Wiese, 2020).

4.2. Suitability habitat distribution

The binary map of habitat suitability showed many isolated areas for *Pica mauritanica* in North Africa. It may be suggested that the Maghreb magpie in North Africa was a metapopulation, distributed in small groups across scattered patches in the area, as formulated in the theory of Opdam (1991). The Maghreb magpie populations are geographically isolated, with more nesting sites on the western side than on the eastern side of Algeria. Because the smallest forest fragments might not have the capacity to support biodiversity to the extent that larger fragments can (Torezan et al., 2020), we can consider that *Pica mauritanica* became more vulnerable as highly adapted patches became smaller and more isolated. Therefore, we can consider the situation of *Pica mauritanica* as the

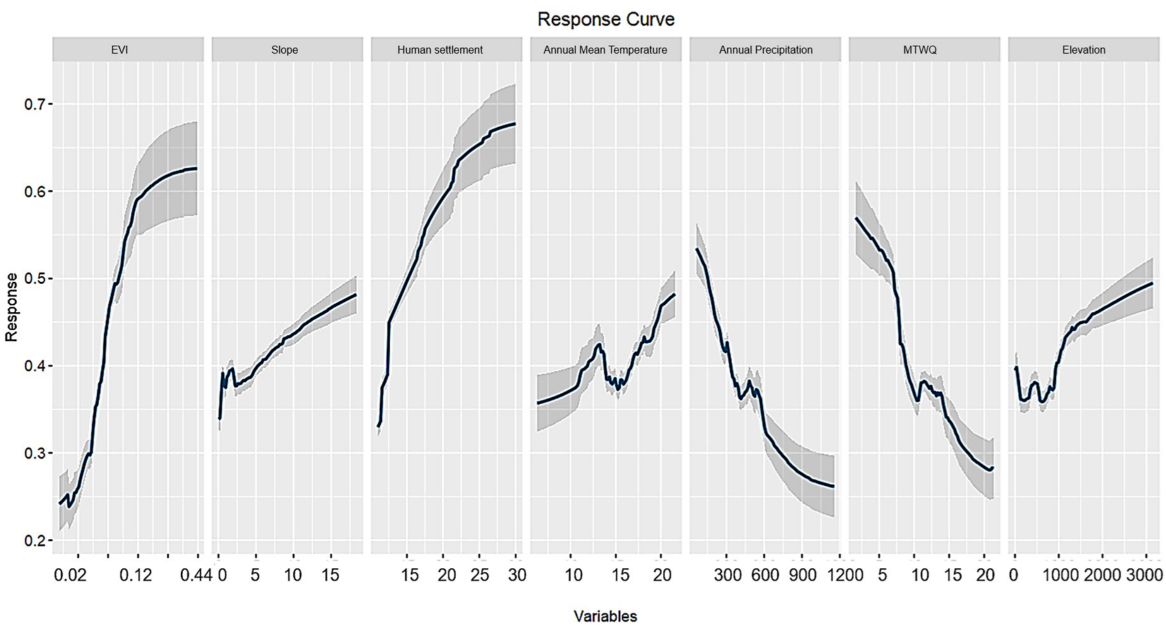

Figure 6. Response curves of the explanatory variables included in the species distribution model (SDM) for *Pica mauritanica*. (MTWQ: mean temperature of wettest quarter).

same as that of the Asir magpie *Pica asirensis*, which faces habitat fragmentation due to multiple factors such as residential development and recreational activities, roads, and other infrastructure (Boland and Burwell, 2020). Moreover, the distribution of *Pica mauritanica* in North Africa is notably fragmented and restricted, with a sole relic population persisting in Tunisia (Nefla et al., 2021) and only a few populations identified on the eastern side of Algeria. Consequently, in the event of additional habitat fragmentation in North Africa, especially in the eastern region, the vulnerability of *Pica mauritanica* populations would be exacerbated.

4.3. Enhanced vegetation index

The analysis of the wavelengths showed a positive correlation between plant biomass and the value of the vegetation index (Galidaki et al., 2017). The EVI presented the highest contribution as a variable in our model. The frequency distribution of EVI ranged between 0.19 and 0.5, deliberately excluding extreme values (both high and low EVI values). Concerning vegetation cover, the Maghreb magpie specifically selects areas that are at least partially surrounded by vegetation. However, it tends to avoid both densely forested regions and unvegetated landscapes. Similar observations were recorded for *Pica pica* by Kamburova (2004) in Bulgaria and in Seoul, South Korea by Kang et al. (2012). These species preferred isolated trees or small groups of trees near open areas in parks and gardens, while avoiding parks with no open areas. Furthermore, Kamburova (2004) noticed that while *Pica pica* was present in urban areas, it demonstrated a preference for nesting and feeding in urban green areas. In Tunisia, the only breeding population of Maghreb magpie was reported to breed near farmland, where nest were mainly built on thorny shrubs *Searsia tripartita* and *Ziziphus lotus*. In Tunisia, the exclusive breeding population of the Maghreb magpie has been documented to breed in close proximity to farmland. Nests are constructed on thorny shrubs, including *Searsia tripartita* and *Ziziphus lotus* (Nefla et al., 2021). Similarly, in Algeria, the breeding population located near agricultural areas in Sidi Chaib constructs nests within the thorny perennial shrub *Lycium shawii*.

4.4. Topographical and climatic parameters

In this study, we found that the average elevation was 951.02 m, with a frequency concentrated between 1000 and 1600 m elevation. Our study results aligned with previous research conducted on Eurasian magpie. For instance, a study in the Pitarque River valley in Spain by Ponz and Gil-Delgado (2004) highlighted that the habitat of *Pica pica* was distributed along an elevation gradient from 970 to 1442 m, which corresponded to a Mediterranean bioclimatic zone. On the other hand, Boland and Burwell (2020) reported that *Pica asirensis* nests were mostly located at elevations above 2150 m with high temperatures. In India, Khan et al. (2022) highlighted that *Pica pica* nesting sites were at an elevation gradient ranging from 2750 m to 3450 m with very low temperatures, which is higher than our values (1000–1600 m in North Africa). In addition, various studies have presented contradictory findings regarding to the altitudinal variations of nesting habitats for different magpie species around the world. In South Korea (Seoul), the nesting sites of magpies were found at a relatively low altitude of 30 m (Kang et al., 2012).

Altitudinal variations in the nesting habitat have been observed in several magpie species, including *Pica. asirensis* in Saudi Arabia, *Pica pica* in India, *Pica sericea* in South Korea, and *Pica mauritanica* in North Africa. These variations may also apply to other populations of *Pica pica* across different regions globally. The differences in altitudinal preferences among these populations could potentially be explained by various climate conditions, particularly temperature levels and precipitation amount, which are influenced by geographical and topomorphological factors, creating what was known as an altitudinal pluvial-thermal gradient (Douguédroit and de Saintignon, 1984). It appears that the negative correlation between annual precipitation and habitat suitability is attributed to variations in spring precipitation, with higher spring rainfall potentially harming nest success during the nestling period (Nefla et al., 2021).

Additionally, our model indicated a suitable slope of less than 20%, which is comparable to the Saudi Arabian endemic species *Pica asirensis*, where it was observed on mountains with slopes less than 30% (Boland and Burwell, 2020). Most of the studied stations were located in semiarid bioclimatic regions. This finding was consistent with the study of Nefla et al. (2021) on the relict population of the Maghreb magpie in Tunisia. Furthermore, the wide geographical distribution of the magpie species, spanning from America to the northwest, includes several isolated populations (Kryukov et al., 2017). Each of these populations is characterized by unique bioclimatic conditions due to their specific geographical locations and local environmental conditions. In summary, the elevation variability in nesting habitats observed among different magpie species and populations can be attributed to a combination of factors, including climatic conditions linked to geographical and topomorphological influences, as well as the diverse ecological adaptations exhibited by these widespread and geographically distinct populations.

4.5. Human settlement

The peak frequency was between 10 and 12, indicating that species occurrences and nesting sites were mainly located near small villages and farms. A similar observation was reported in Spain, where Ponz and Gil-Delgado (2004) studied a population close to bull breeding activity. This finding is also consistent with the study by Nefla et al. (2021) on Maghreb magpies in Tunisia. Although the Tunisian population was found closer to a farm in a rural habitat, the results suggest that even in rural habitats, magpies select nesting sites closest to human activity.

Therefore, to ensure the sustainable survival of farmland bird population, we endorse the preservation of traditional farming practices, where farmland birds are mainly impacted by agricultural intensification and land use changes (Nefla et al., 2021).

Kamburova (2004) have focused on *Pica pica* in urban areas. Furthermore, other studies have reported *Pica pica* nesting on human constructions and electricity pylons (Lu et al., 2008). However, in the eleven stations visited in Algeria, such nesting behaviors were not observed for *Pica mauritanica*. The Maghrebian species was not as much of a generalist species as others magpie species, which could explain its lower adaptation to anthropized environments, where the distribution of *Pica mauritanica* was mainly concentrated in farmland near rural region.

Our methodological approach, based on integrating occurrence, topographic, and climatic data, has refined the precision of our models. The selected variables showed a significant influence on the distribution of bird species in the studied region, especially the enhanced vegetation index; however, it is important to acknowledge the limitations of our study. As cited in Boland and Burwell (2020), the habitat model outlined in this context is recognized for its simplicity, as it draws upon restricted data. Despite its inherent limitations, the model represents a proactive initiative to rapidly assess and map the potential habitat for the Maghreb magpie. SDM model depends on occurrence data and environmental variables, raising questions about the generalization of our results to other geographical contexts. Hence, environmental variables can vary significantly across different regions, leading to inaccuracies when models are applied outside their original context (Peterson and Soberón, 2012). Species may also exhibit local adaptations that are not captured by models trained in different areas (Guisan et al., 2017). Additionally, the quality and completeness of species occurrence data can be inconsistent, with regions lacking comprehensive data resulting in unreliable predictions (Elith et al., 2011).

Climate change and dynamic environmental conditions further complicate predictions, as SDMs often rely on static historical data (Thomas et al., 2004). Model transferability is another challenge, as species-environment relationships can differ across regions, reducing model performance when applied elsewhere (Rödder and Lötters, 2010). Biotic interactions, which are typically not included in SDMs, can vary regionally and affect species distributions (Wisz et al., 2013). Spatial autocorrelation and sampling bias in occurrence data can also lead to overfitting and decreased generalizability (Boria et al., 2014). To address these limitations and enhance the model's applicability to diverse regions, future studies could focus on refining the model by incorporating more influencing variables specific to different habitat scales. Future research could explore the effectiveness of identifying additional influencing variables on bird species at microhabitat scales.

4.6. Leveraging emerging remote sensing platform for habitat monitoring

Land use changes, coupled with climate change, play a crucial role in influencing species distribution by modifying habitat suitability. Habitat loss and fragmentation resulting from deforestation and urbanization lead to population declines and genetic isolation, altering species interactions and distributions (Fahrig, 2003). Moreover, climate change is causing species to move their habitats toward the poles and to higher elevations as they seek more suitable temperature and precipitation conditions (Parmesan and Yohe, 2003). In this context, remote sensing offers valuable insights into habitat dynamics, enabling the detection of current changes and the projection of future trends.

This, in turn, facilitates the development of informed conservation strategies to safeguard biodiversity in the face of environmental challenges. The recent implementation of species distribution models in the Google Earth Engine platform may be valuable, especially for less economically developed countries, for monitoring and analyzing changes in habitats over time (Crego et al., 2022). This integration of advanced platforms like Google Earth Engine, along with frameworks such as GEE_xtract, facilitates the preparation of time series data (Gorelick et al., 2017). Researchers can utilize this to understand how habitats evolve by processing satellite data time series, enabling the detection and quantification of changes in vegetation, water bodies, and other habitat features (Valerio et al., 2024). This advancement enhances the capability to track and predict shifts in species distributions and habitat suitability for environmental management. Despite habitat suitability, the application of species distribution modeling techniques within an ecological framework provides several advantages and implications. These include establishing priority zones for management, identifying crucial environmental drivers, predicting range shifts due to climate change (Khwarahm, 2020), as well as monitoring population dynamics and biotic interactions (Guisan and Thuiller, 2005). Hence, these models can inform proactive management strategies to support biodiversity conservation and mitigate climate change impact (Hama and Khwarahm, 2023).

5. Conclusion

Nowadays the distribution of *Pica mauritanica* is discontinuous, especially with more isolated populations in the northeast of Africa due to the fragmentation of its natural habitats caused by various factors. In this critical situation, there is an urgent need to provide information regarding the current distribution of the species across North Africa to assess the distribution and habitat vulnerability of Maghreb Magpie. Our study discussed the outcomes concerning the relationship between habitat preferences and habitat vulnerability of *Pica mauritanica* at North Africa scale based on the environmental variables used in the model. The discontinuity of the remaining high suitability habitat patches, which is more fragmented in the real-world situations, explains the vulnerability of the species. However, recognizing the limitations, our study employs a habitat model acknowledged for its simplicity, relying on restricted data. Despite these inherent limitations, the model serves as a proactive initiative for rapid assessment and mapping of potential suitable habitats for *Pica mauritanica*. Future research could explore the effectiveness of identifying more influential variables on the bird species at different habitat scales. Based on these potential distribution results, further extensive fieldwork is still needed to explore microhabitat requirement and estimate population sizes, thereby determining the vulnerability and conservation status of Maghreb populations across North Africa. In addition, genetic studies might be useful for understanding the diversity within populations and potential connectivity between different populations.

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