

Biodiversity

ISSN: 1488-8386 (Print) 2160-0651 (Online) Journal homepage: www.tandfonline.com/journals/tbid20

Habitat suitability modelling of red-billed quelea (*Quelea quelea*) in Malawi, southern Africa

Jéssica da Carolina Antónia Manuel, Luwaga Denis, Bruno Kokouvi Kokou & Tiwonge I. Mzumara

To cite this article: Jéssica da Carolina Antónia Manuel, Luwaga Denis, Bruno Kokouvi Kokou & Tiwonge I. Mzumara (2026) Habitat suitability modelling of red-billed quelea (*Quelea quelea*) in Malawi, southern Africa, Biodiversity, 27:2, 206-217, DOI: 10.1080/14888386.2026.2636803

To link to this article: https://doi.org/10.1080/14888386.2026.2636803

Published online: 07 Apr 2026.

Submit your article to this journal

Article views: 117

View related articles

View Crossmark data

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=tbid20

BIODIVERSITY
2026, VOL. 27, NO. 2, 206–217
https://doi.org/10.1080/14888386.2026.2636803

Check for updates

Habitat suitability modelling of red-billed quelea (*Quelea quelea*) in Malawi, southern Africa

Jéssica da Carolina Antónia Manuel [a,b], Luwaga Denis [a,c,d], Bruno Kokouvi Kokou [a,e,f,g] and Tiwonge I. Mzumara [h]

[a]African Centre of Excellence in Neglected and Underutilised Biodiversity (ACENUB), University of Mzuzu, Mzuzu, Malawi; [b]Department of Biological Sciences, Mzuzu University, Mzuzu, Malawi; [c]Department of the Built Environment, Mzuzu University, Mzuzu, Malawi; [d]Department of Environmental Studies, Uganda Martyrs University, Kampala, Uganda; [e]Agrisciences Department, Mzuzu University, Mzuzu, Malawi; [f]Laboratory of Botany and Plant Ecology (LBPE), Botanical Department, Faculty of Sciences (FDS), University of Lom´e (UL), Lom´e, Togo; [g]Togolese Institute of Agronomic Research (ITRA – Togo), Lome, Togo; [h]Biological Sciences Department, Malawi University of Science, Technology, Limbe, Malawi

ABSTRACT

The distribution of pest species like *Q. quelea*, a major threat to cereal crops, may shift due to climate change, requiring predictive modelling to guide management strategies. This study used the maximum entropy (MaxEnt) model to predict current and future suitable habitats for *Q. quelea* in Malawi, incorporating nine bioclimatic variables, elevation, and soil type. Model performance was robust (Area under the ROC curve, AUC = 0.813). Key variables influencing distribution included maximum temperature of the warmest month (30.1%), elevation (19.1%), and temperature seasonality (16.2%). Currently, 12,880.8 km^2 is highly suitable, 47,421.5 km^2 moderately suitable, and 57,610.2 km^2 exhibits low suitability. Under future climate scenarios (Shared Socioeconomic Pathways, SSP3–7.0 and SSP5–8.5), moderately and highly suitable habitats are projected to expand, especially under SSP5–8.5. These findings suggest increased risks to agriculture in Malawi's Central and Southern regions. The study offers essential insights for developing adaptive management, early warning systems, and control strategies to safeguard food security.

KEY POLICY INSIGHTS

- The distribution of *Q. quelea* in Malawi is primarily influenced by climatic and topographic factors. This underscores the importance of integrating environmental data into national pest risk assessments.
- Projections under future climate scenarios suggest a likely expansion of *Q. quelea* habitats, particularly under the high-emission SSP5–8.5 pathway, posing increased risks to agricultural productivity in previously less affected regions of Central and Southern Malawi.
- These findings reinforce the need for climate-responsive policies, including adaptive pest management plans, early warning systems, and sustainable control measures to mitigate the growing threat of *Q. quelea* to national food security.

ARTICLE HISTORY
Received 8 October 2025
Accepted 20 February 2026

KEYWORDS
Quelea quelea; species distribution modelling; highrisk areas; MaxEnt; Malawi

Introduction

The red-billed quelea (*Quelea quelea*), a nomadic granivorous bird, poses a significant threat to the livelihoods of small grain farmers in southern African countries (Cheke and Sidatt 2019), including Malawi. These abundant birds have a dynamic distribution, breeding colonially where conditions permit (seasonal rainfall and seed availability), travelling long distances to find breeding habitat or to avoid food shortages, making their movements unpredictable and management strategies difficult (Cheke, Venn, and Jones 2006, 2007).

Climate change is exacerbating these challenges, as it increases the frequency and intensity of extreme weather events (Dobson et al. 2024), altering the migration timing (Tøttrup et al. 2012), changing patterns of rainfall, and expanding suitable habitat into new regions (Cheke, Venn, and Jones 2006; Nguru, Leong, and Ismail 2023). The fluctuations in rainfall may affect the germination of grasses and, consequently, the movements and breeding cycles *of Q. quelea* (Cheke, Venn, and Jones 2007; Cheke 2009). Regions like Malawi, which depend on smallholder agriculture (Bhatti et al. 2021) and where food production is dependent on rainfall, are susceptible to droughts and inconsistent rainfall (You et al. 2011), which may subsequently increase the vulnerability to *Q. quelea* infestations.

CONTACT Jéssica da Carolina Antónia Manuel jessicamanuel407@gmail.com African Centre of Excellence in Neglected and Underutilised Biodiversity (ACENUB), University of Mzuzu, P/Bag 201, Mzuzu, Malawi

© 2026 Biodiversity Conservancy International

To reduce this growing burden of *Q. quelea* infestations, researchers have developed forecasting models that are based on satellite-derived rainfall and vegetation indices, which indicate that a threshold of 60 mm of rain over 2 weeks and 300 mm within 6 weeks spurs the germination of grass seeds, forcing the migration of *Q. quelea* in search of fresh seeds (Cheke, Venn, and Jones 2006). Another recent advance is the application of dynamic species distribution models (D-SDMs) and near-term forecasting to anticipate *Q. quelea* distribution changes during extreme weather events (Dobson et al. 2024).

The future impact of climate change and global warming on the geographical distribution of species remains uncertain, making it important to use technology that can predict potential suitable habitats for pests in advance, hence minimizing the damage caused by changes in the environment. Habitat suitability index (HSI) models are mostly used in wildlife management and conservation practices to classify areas from the most suitable to the least suitable. These models are derived from species distribution models (SDMs), which link a species' occurrence data with a specific location to inform environmental predictor variables (Unglaub et al. 2015). SDMs help to determine whether certain species are present or absent in a specific area by predicting and evaluating the spatial distribution and redistribution of species in response to environmental changes (Elith and Leathwick 2009).

The utilization of SDMs has significantly advanced recently due to the availability of species occurrence data and environmental datasets through a variety of online platforms, such as WorldClim and the Global Biodiversity Information Facility (GBIF) (Kokou et al. 2025). Among these models, the maximum entropy (MaxEnt) model is one of the most popular tools because of its flexibility, robustness, and efficacy, even with incomplete data or presence-only data (Phillips, Anderson, and Schapire 2006; Pearson et al. 2007; Lissovsky and Dudov 2021). MaxEnt implements maximum entropy theory to obtain coordinates that identify the closest model variable attributed to the occurrence coordinates of a target species (Hwang et al. 2022). This method has been applied to modelling plants (Qin et al. 2017; Tuan et al. 2021; Kokou et al. 2025), animals (Khosravi et al. 2016; Jafari, Zamani-Ahmadmahmoodi, and Mirzaei 2018; Na et al. 2018), microhabitats for endemic species (Moreno et al. 2011), endangered species (Ashraf et al. 2016), and pests (Hwang et al. 2022).

Although efforts in modelling to predict *Q. quelea* distribution on a large scale have been conducted across southern Africa, there is still a gap that remains concerning the fine-scale analysis of habitat suitability within individual countries, particularly Malawi, a country where the bird causes crop losses (Government of Malawi 2015), making data from the predictive model needed. This study tries to fill this gap by using the MaxEnt modelling to predict habitat suitability and identify the potential areas of distribution of *Q. quelea* in Malawi. The approach will help to identify areas of high risk of *Q. quelea* presence and inform strategic intervention.

Materials and methods

Study site

The study was conducted in Malawi, a landlocked country located in sub-Saharan Africa, between latitudes 9°22′ and 17°03′ south of the equator, and longitudes 33°40′ and 35°55′ east of the Greenwich Meridian (Figure 1). The country covers a total area of 188,484 km^2, of which 28,000 km^2 (nearly 20%) is occupied by Lake Malawi (Chimonyo et al. 2023).

Malawi has a subtropical climate, which is strongly affected by Lake Malawi and altitudes. There are two distinct seasons: the rainy season from October to April, with mean temperatures between 17 and 27°C, and the dry season from May to October, with average temperatures between 25 and 37°C. The rainfall varies across the country; it ranges from 500 mm in the lower Rift Valley areas to 3000 mm in the highlands (Saka et al. 2012). Studies have shown that the mean temperature is continuously rising, particularly in the northern and southern regions, because of climate change (Amosi and Anyah 2024).

Study species

Quelea quelea is a small and highly gregarious passerine bird, widely distributed across semi-arid regions of sub-Saharan Africa. With an estimated post-breeding population of 1.5 billion individuals (Cheke 2022), it is considered the most abundant wild bird species globally. The species inhabits tropical and subtropical savannahs, thorny shrublands, and cultivated fields, with movements and breeding closely tied to seasonal rainfall (Cheke, Venn, and Jones 2007). The birds' diet consists mainly of wild grass seeds and cereal crops such as sorghum, millet, and rice (Markula, Hannan-Jones, and Csurhes 2016; Ngazero 2013). Each bird consumes up to its own body weight (approximately 18 g) in grain daily (Mtobesya 2012). Due to their massive flock sizes and high consumption rates, *Q. quelea* poses a serious threat to agriculture, particularly to smallholder farmers who rely on rainfed cereal production. A single flock of

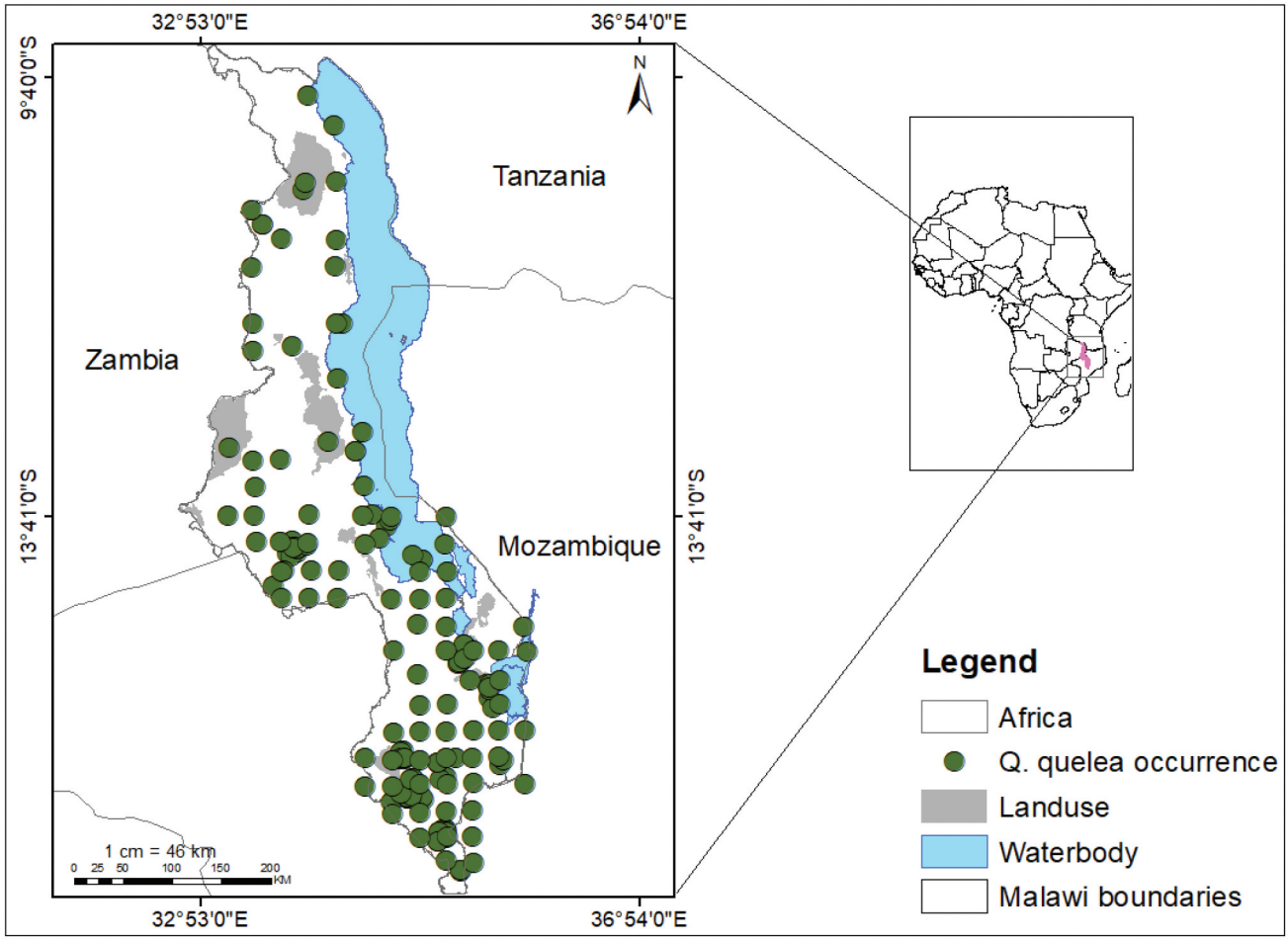


Figure 1. Map of *Quelea quelea* distribution in Malawi.

one million birds can consume up to 10 tonnes of grain per day, while severe infestations can cause 50–100% yield losses in affected fields (Dayoub et al. 2021; Markula, Hannan-Jones, and Csurhes 2016; Ngazero 2013). Crop damage is most severe when natural seed availability is low, forcing birds to target maturing crops during dry periods (Ward 1965). The economic burden extends beyond yield losses, as governments invest millions in control efforts such as aerial pesticide spraying, monitoring, and management logistics (Cheke et al. 2000). *Quelea quelea*'s increasing abundance, driven by expanding agriculture and habitat availability, represents a growing challenge for food security and rural livelihoods (Jaleta and Tekalign 2023; Zitsanza 2008).

Data sources and methods

Occurrence records of *Q. quelea* were obtained from multiple reliable sources, such as the GBIF (www.gbif.org), an atlas, and a handbook by Dowsett-Lemaire and Dowsett (2006). Field survey locations (coordinates) were acquired using a Garmin GPS in December 2024 and May 2025. All occurrence records were reviewed to ensure georeferencing accuracy and temporal relevance. Duplicate records, incorrect occurrences, and those without coordinates were removed. The final dataset included 180 unique occurrence points, where 49.4% were from GBIF, 44.4% from the atlas and handbook, and 6.2% from the field survey. Subsequently, the data was entered into Microsoft Excel, coded accordingly, and saved in CSV format. The coded data was exported into the ArcGIS environment for further geoprocessing. Secondary data was used due to limitations in research funds and time.

Data processing

Climatic factors influence species distribution, and species can quickly adapt to changes (Chen et al. 2011). Keeping this in view, different global circulation models (GCMs) that represent a group of bioclimatic predictor variables (Bio1–Bio19) were downloaded from the CHELSA

(Climatologies at high resolution for the earth's land surface areas) (https://chelsa-climate.org/). The elevation data were obtained from version 2.1 of the WorldClim database (https://www.worldclim.org/data/worldclim21.html) (Fick and Hijmans 2017). The data on soil type were downloaded from version 1.2 of the Harmonized World Soil Database http://www.fao.org/land-water/databases-and-software/hwsd/en/ (FAO and ISRIC 2012). To account for the effect of anthropogenic activities on the distribution of the target species, Sentinel-2 10 m Land Use/Land Cover (LULC) classes for Malawi were downloaded from the Morocco Africa geoportal (https://morocco.africageoportal.com/apps/esri::sentinel-2-land-cover-explorer/explore) (Karra et al. 2021).

The evaluation of the effects of climate change at a given time scale is carried out by looking at a variety of scenarios, such as low, moderate, and high (Harris et al. 2014). In this context, the modelling was conducted using the most recent future climate scenarios based on the Shared Socioeconomic Pathways (SSPs). According to Riahi et al. (2017), SSPs were created to provide consistent narratives of future societal change in order to enable climate impact assessments. Therefore, to project the future climate scenarios, the SSP3–7.0 (stabilization in greenhouse gas emissions at a similar rate to the current one) and SSP5–8.5 (continuous increase in greenhouse gas emissions) scenarios were used. The data was downloaded from the GCM (MPI-ESM1.2-HR) as it has a well-balanced radiation budget, and its climate sensitivity is explicitly tuned to 3 K (Kokou et al. 2025). The data from SSP were downloaded for the year 2055 (2041–2060).

Before running the variables in the MaxEnt model, Pearson's correlation was performed using R software to examine the cross-correlation, and highly correlated bioclimatic factors (Pearson's $|r| \geq 0.75$) were removed to avoid multicollinearity of variables (Ejigu and Tassie 2020). After correlation analysis, only 11 variables were retained (Table 1; Figure S1). All have the same geographical dimensions: 30 arc-seconds (~1 km^2) resolution, columns and rows, coordinate system, and extent.

Table 1. Environmental variables used.

Variables	Units
bio02: Mean diurnal range (mean of monthly (max temp – min temp)	°C
bio04: Temperature seasonality (standard deviation * 100)	°C
bio05: Max temperature of warmest month	°C
bio06: Min temperature of coldest month	°C
bio07: Temperature annual range (BIO5–BIO6)	°C
bio14: Precipitation of the driest month	mm
bio15: Precipitation seasonality (coefficient of variation)	mm
bio16: Precipitation of wettest quarter	mm
bio19: Precipitation of the coldest quarter	mm
elev: Elevation	m
hwsd: Harmonized World Soil Database	

bio02 = Mean Diurnal Range (mean of monthly maximum temperature - minimum temperature); bio04 = Temperature Seasonality; bio05 = Maximum Temperature of the Warmest Month; bio06 = Minimum Temperature of the Coldest Month; bio07 = Temperature Annual Range (maximum temperature of the warmest month minus minimum temperature of the coldest month); bio14 = Precipitation of the Driest Month; bio15 = Precipitation Seasonality; bio16 = Precipitation of the Wettest Quarter; bio19 = Precipitation of the Coldest Quarter; elev = Elevation; HWSD = Harmonized World Soil Database; °C = degrees Celsius; mm = millimetres; m = metres.

Species distribution modelling

MaxEnt software version 3.4.3 (Philips et al. 2018) was used to estimate suitable habitats for *Q. quelea* in Malawi. MaxEnt is a machine-learning method used for SDM from presence-only species records and background data, which represents a sample of available habitats (Elith et al. 2011; Liu et al. 2013; Na et al. 2018).

MaxEnt was chosen because of its advantages, including (1) the need for only presence data to generate the probability of presence on a scale of 0 to 1 and environmental information for the entire study area; (2) that it can utilize both continuous and categorical data and incorporate interactions between various variables; (3) that it will work with a small sample size; (4) its utility in situations where presence–absence data collection is not feasible; (5) its superior performance even when the number of geographic records is low; (6) that it utilizes both continuous and categorical data and incorporates interactions between several variables; (7) that it is a good choice for predicting the distribution of endangered and rare species; (8) that it can be used to create a spatially explicit map for habitat suitability with easy interpretability; and (9) that it uses the jackknife test to measure the importance of each environmental variable in terms of gain (Elith et al. 2011; Kumar 2012; Liu et al. 2013; Jha and Jha 2021).

Jackknife tests and cross-validation were applied to measure the contribution and relative importance of individual environmental factors (Luo, Wang, and Lyu 2017; Ejigu and Tassie 2020). Occurrence data was split into 75% for training and 25% allocated as a test set for validation (Luo, Wang, and Lyu 2017). A cross-validation process was employed using 10 replicates, each with a cap of 500 iterations, and a maximum of 10,000 background points.

MaxEnt model performance evaluation

The MaxEnt model's performance was evaluated using the receiver operating characteristic (ROC) area under the curve (AUC). The AUC values range from 0 to 1, where values >0.7 indicate acceptable performance, those >0.8 indicate good performance, and those >0.9 reflect excellent model accuracy (Tuan et al. 2021). Values below 0.5 suggest the model is no better than random results (Na et al. 2018).

Habitat suitability mapping

By converting the probability distribution values, which range from 0 to 1, a classification of locations as appropriate or unsuitable for the species was done (Pearson et al. 2007), and a 10-percentile training presence threshold was used to convert continuous suitability scores into binary 1–0 (presence–absence) predictions of suitable and unsuitable areas. Pixels with values below the threshold value were classified as unsuitable, moderate suitability encompassed intermediate values up to (but not including) 0.5, and high suitability was assigned to values ≥ 0.5 (Ramirez-Reyes, Bateman, and Radeloff 2016; Ejigu and Tassie 2020). ArcGIS (10.5) software was used for the conversion of index-based MaxEnt maps to a version presentable as raster files representing the current scenario.

Future habitat projection

The same set of uncorrelated environmental variables used for the current model was applied to the future climate scenarios (SSP3–7.0 and SSP5–8.5). Each scenario was processed in MaxEnt using identical parameters (10 replicates, 500 iterations, cross-validation) to ensure comparability. The resulting raster outputs were reclassified into low, moderate, and high suitability using the 10-percentile training presence threshold and mapped in ArcGIS 10.5 to visualize projected distribution shifts between current and future conditions. In ArcGIS, the area (km^2) of each suitability class was calculated to quantify habitat changes. These values were used to determine the gain and loss in habitat suitability areas between scenarios, and the respective graphs were made using GraphPad Prism.

Results

Model performance

The prediction accuracy of the model demonstrated a good performance for estimating the potential distribution of *Q. quelea* in Malawi. The AUC was 0.813 for the training data and 0.797 for the test data, meaning the model was able to differentiate between the suitable and unsuitable areas (Figure S2). The regularized training gain was 0.609, while the unregularized test gain was 0.550.

Variable importance for Q. quelea distribution

The potential distribution model for *Q. quelea* was developed using 11 environmental variables, including bioclimatic aspects, soil characteristics, and elevation. The predictive variable that contributed the most to the MaxEnt model was the mean maximum temperature of the warmest month (bio05), at 30.1%. *Quelea quelea* had moderately favourable occurrence conditions between 28.8 and 29.5°C, with an increase in their presence of occurrence at high values around 30.8°C. The second variable was elevation (19.1%) (Table 2). The probability of *Q. quelea* occurrence was below 1000 m, peaking at around 300 m, and gradually decreasing with a bit of fluctuation after that (Figure S3). The third variable was temperature seasonality (bio04), which measures the variation in temperature throughout the year. *Quelea quelea* showed the highest suitability in areas with moderate seasonality (24–26°C), which suggests very high or low seasonality reduces the suitability of the species (Figure S3). In terms of precipitation, the precipitation of the coldest quarter (bio19) and precipitation of the driest month (bio14) constitute the fourth and fifth most important variables influencing species occurrence. The increase in the precipitation of the coldest quarter gradually reduces the occurrence of the species with values below 500 mm, predicting their presence, while the increase in the precipitation of the driest month also increases the species occurrence, though *Q. quelea* responds to temperature and precipitation variation. The rest of the variables that were examined had neither a high percentage contribution nor permutation importance.

The environmental variable with the highest gain when used in isolation is bio05, which appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is bio19, which appears to have the most information that is not present in the other variables (Figure 2).

Current and future distribution of Q. quelea

The results from the simulation of the *Q. quelea* ecological suitability area under three different scenarios (current, SSP3–7.0, and SSP5–8.5) are presented in Figure 3.

The habitat suitability distribution for *Q. quelea* in Malawi indicates that, under the current scenario, a total area of 57,610.2 km^2 is classified as having low suitability, 47,421.5 km^2 as moderately suitable, and 12,880.8 km^2 as having high suitability (Table 3). The

Table 2. AUC value and permutation contribution (%) of the most important variables influencing the distribution of *Q. quelea* in the MaxEnt model.

AUC	Code	Percent contribution
0.813	bio05	30.1%
	Elev	19.1%
	bio04	16.2%
	bio19	4.8%
	bio14	2.3%

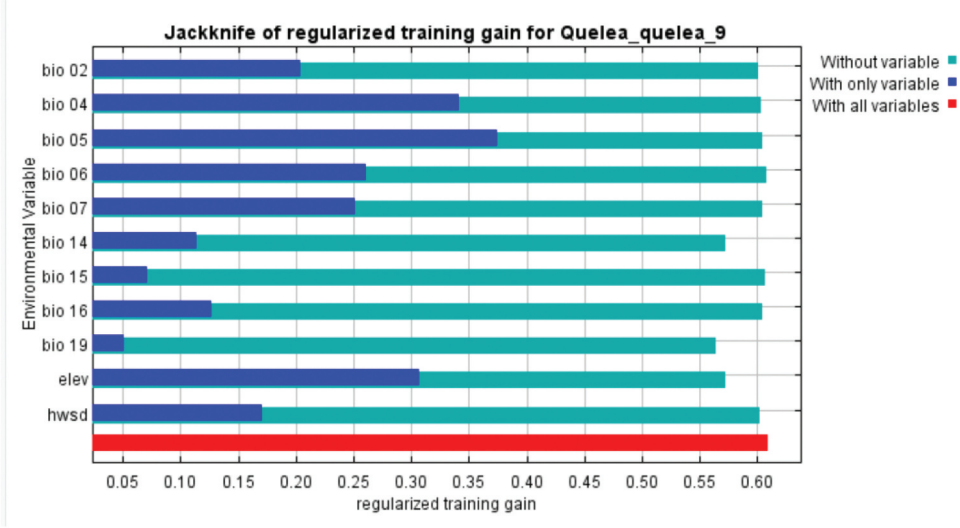


Figure 2. Jackknife test of variable importance in modelling the distribution of *Q. quelea*.

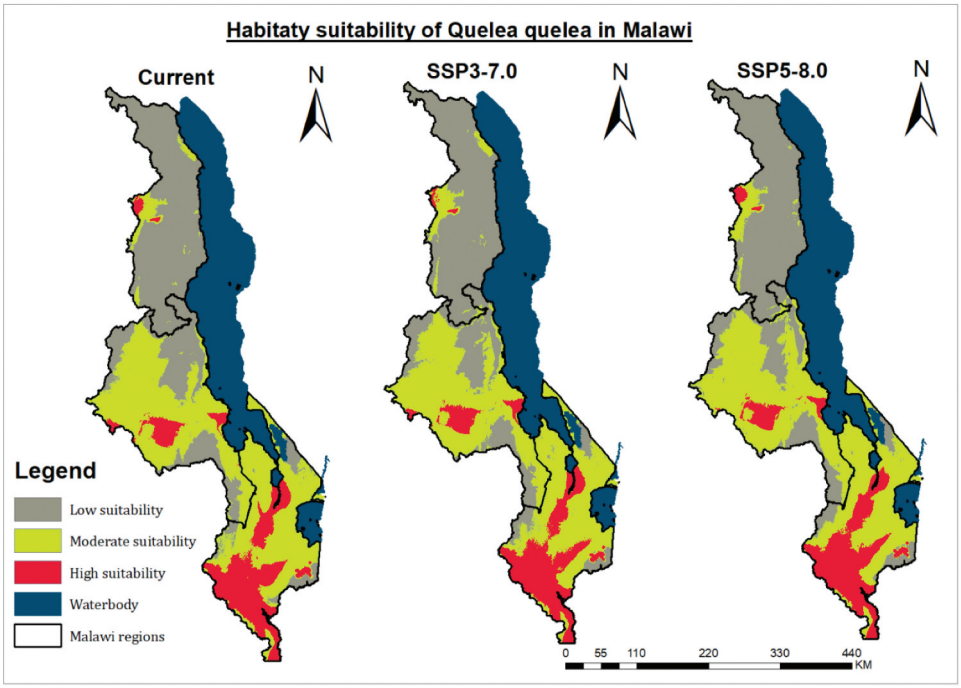


Figure 3. Potential current and future suitable habitats of *Q. quelea* in Malawi.

latter areas are predominant in the southern and central regions of Malawi, where highly suitable habitats are present around the lower Shire Valley in Nsanje, Chikwawa, and Chiranzulo, as well as in some parts of Zomba, Machinga, Balaka, Salima, Lilongwe, and Rumphi (Figure 4).

Under the SSP3–7.0 scenario, a slight decline in high-suitability habitat was observed, reaching 12,867.3 km^2, while moderate suitability expanded to 48,382.1 km^2, indicating a transition from low and high to moderate suitability in some areas (Table 3). The highly suitable areas persist in the same locations (Figure 4).

In the SSP5–8.5 scenario, an increase in both moderately and highly suitable habitats was

Table 3. Changes in geographic distribution in km^2 for *Q. quelea* under different scenarios.

	Current	SSP370	SSP585
Low suitability	57,610.2 km^2	56,669.8 km^2	55,579.7 km^2
Moderate suitability	47,421.5 km^2	48,382.1 km^2	49,161.8 km^2
High suitability	12,880.8 km^2	12,867.3 km^2	13,184.7 km^2

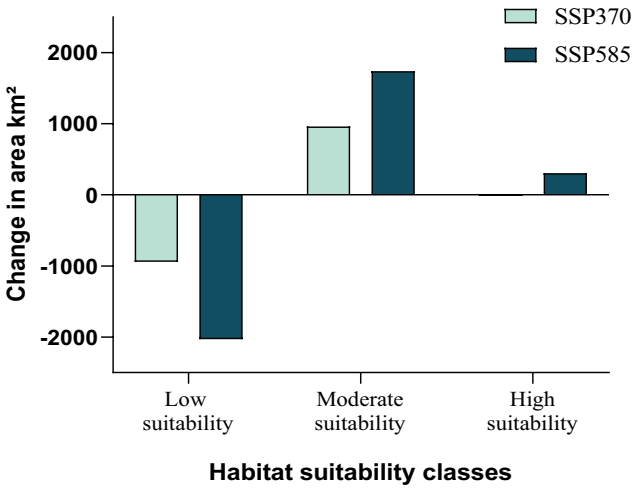


Figure 4. Redistribution of the habitat suitability of *Q. quelea* under future scenarios.

observed, to 49,161.8 km^2 and 13,184.7 km^2, respectively. The map reflects the large zones of moderate suitability in both central and southern areas, the persistence of high-suitability areas in the south, and the presence of unsuitable areas in the north, which decrease under both scenarios (Figure 4).

The results in general reveal that although the total extent of suitable habitat remains consistent across scenarios, climate change will cause important shifts in the quantity of suitable areas.

From the current situation to the SSP3–7.0 scenario, moderate-suitability habitat presented an expansion of approximately 960.6 km^2, at the expense of both low-suitability areas (loss of ~940.4 km^2) and high-suitability zones (loss of ~13.5 km^2). Likewise, under SSP5–8.5, the shifts are more visible, with a gain of approximately 1740.3 km^2 in moderate suitability and 303.9 km^2 in high suitability. In comparison, a significant loss of about 2030.5 km^2 in the low-suitability area was observed (Figure 4).

Discussion

MaxEnt modelling is a widely used species distribution modelling approach that predicts where a species is likely to occur based on known observation locations and environmental conditions. This modelling approach has been used to model SDM for other bird species, such as the red-crowned crane (Na et al. 2018), red-cockaded woodpecker (Lawrence 2024), Amazona lilacina (Biddle et al. 2021), and African white-backed vulture (Zvidzai et al. 2024). In MaxEnt modelling, the AUC is a statistical measure of model performance that expresses how well the model distinguishes between suitable and unsuitable habitat for a species. The AUC value found here was 0.813, which suggests the model has a strong ability to differentiate suitable from unsuitable habitat, as suggested by Tuan et al. (2021).

Factors influencing the current habitat suitability and distribution of Q. quelea

The results revealed that *Q. quelea* distribution in Malawi is influenced by a combination of temperature, precipitation, and elevation. These factors, when combined, can create favourable conditions for *Q. quelea* breeding, foraging, and nesting. These results are consistent with the findings from other bird species' distribution, where the same variables are dominant predictors (Céspedes Arias, Wilson, and Bayly 2022).

The maximum temperature of the warmest month (bio05) made the highest contribution (30.1%), with suitable areas concentrated in regions where temperatures reached 28.8–30.8°C. This supports the known thermotolerance of the species, which can withstand body temperatures above 48°C (Freeman et al. 2020). These temperature thresholds correspond to the lowland and mid-elevation zones of Malawi, particularly the central and southern regions, where the most suitable habitats were identified.

Elevation, as the second most important variable, showed a negative relationship with *Q. quelea* occurrence. The probability of *Q. quelea* presence declined gradually above 1000 m, suggesting that the species prefers lowland environments such as the Lower Shire Valley and areas around Lake Chilwa and Lake Malawi. These regions offer open grasslands and croplands that provide conditions for *Q. quelea* to breed and forage. Similar altitudinal preferences have been reported in southern Africa, where *Q. quelea* colonies concentrate below 1500 m during the breeding season (Cheke 2022; Dowsett-Lemaire and Dowsett 2006; Ministry of Agriculture and Livestock Development 2025). In contrast, the north comprises areas of high elevation, making these highlands less susceptible to the birds' abundant presence (Munthali et al. 2017).

The temperature seasonality (bio04) reflects the variation of the temperature throughout the year and is the third most important variable. *Quelea quelea* showed occurrence in the range where the seasonal temperature is between 24°C and 26°C, declining outside this interval. This suggests that species stay in regions with moderate thermal fluctuations, avoiding environments with extreme variability or excessive stability. Such thermal regimes may promote grass seed availability, which is critical for feeding and breeding.

The precipitation variables also played an important role in the *Q. quelea* distribution. The bio19 variable showed an inverse relationship with species occurrence, where areas with precipitation above 500 mm during the coldest quarter had a reduced probability of occurrence. In contrast, habitat suitability increased with the increase of precipitation of the driest month (bio14). This suggests that *Q. quelea* avoid extremely wet cold-season environments but require minimum moisture levels even during dry periods. These findings are consistent with previous research showing that rainfall acts as a key stimulus for breeding and migration, as grass seed production and insect abundance peak shortly after rainfall events (Lloyd 1999).

Climate change influence on Q. quelea *distribution*

Under both future scenarios (SSP3–7.0 and SSP5–8.5), suitable habitats for *Q. quelea* are projected to expand. These reveal that climate change will not necessarily lead to habitat contraction but may instead stimulate a redistribution of suitability in the landscape. In the SSP3–7.0 scenario, we identified an expansion of the moderately suitable areas and some presence of highly suitable areas towards regions of Lake Chilwa, Lake Mlawi, and Lower Shire, as *Q. quelea* always stays within about 30 km from the water for everyday drinking (Markula, Hannan-Jones, and Csurhes 2016). The SSP5–8.5 scenario represents a more extreme climate pathway, where the spatial impacts are more pronounced. Both moderately and highly suitable areas increase in this scenario, and a significant reduction in the low-suitability habitats is observed. These patterns may be explained by the warming and altered precipitation that can possibly improve the quality of the areas that are already favourable, while the areas that are now marginalized may, in the future, shift towards greater suitability.

The high dependence of *Q. quelea* on grass seeds, as well as its breeding synchronization with rainfall, spurs the formation of large flocks that usually move in groups of several hundred and consume an extensive quantity of crops (Sabastian 2023). This has led to the red-billed quelea being characterized as the most significant avian pest in sub-Saharan Africa (Cheke 2022; De Mey, Demont, and Diagne 2012). Thus, habitat suitability modelling like that presented in this study is important for informing predictive control measures, mainly due to the increase in climate variability.

Additionally, land-use change, particularly agricultural expansion, may further enhance *Q. quelea* distribution in Malawi, as observed in Tanzania, where similar transformations favoured their presence (Mmbaga et al. 2025). Although *Q. quelea* constitutes a risk to food security (Mtobesya 2012; Mpala et al. 2015; Mmbaga et al. 2025), this species is also vital for seed dispersal and as prey for raptors (McWilliam and Cheke 2004). Consequently, the application of control strategies must be balanced with biodiversity conservation.

Conclusion

The study aimed to assess the current and future potential distribution of *Q. quelea* in Malawi under different climate change scenarios. The findings revealed that the species' distribution is strongly influenced by climatic and topographic factors, particularly the maximum temperature of the warmest month (bio05), elevation, temperature seasonality (bio04), and precipitation during the driest (bio14) and coldest (bio19) quarters. These results indicate that future climatic shifts may cause a slight contraction of highly suitable habitats under SSP3–7.0, but a potential expansion under the warmer SSP5–8.5 scenario, increasing the risk of pest outbreaks in new areas. This work contributes to a better understanding of the ecological determinants of *Q. quelea* distribution and provides valuable information for agricultural planning, pest management, and food security strategies in Malawi. Despite some limitations, such as the exclusion of behavioural and ecological predictors (e.g. bird movement, breeding colonies, and seed resource availability), the study provides useful insights for early warning systems and risk assessment frameworks. Further research should focus on integrating dynamic ecological data and developing a climate-based *Q. quelea* alert system to strengthen prevention and rapid response measures against future outbreaks.

Author contributions

CRediT: **Jéssica da Carolina Antónia Manuel**: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft; **Luwaga Denis and Bruno Kokouvi Kokou**: Formal Analysis, Review and Editing, Validation; **Tiwonge I Mzumara**: Supervision, Validation.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the World Bank under the African Centre of Excellence in Neglected and Underutilized Biodiversity (ACENUB) Master's program.

Notes on contributors

Jéssica da Carolina Antónia Manuel is a researcher specializing in species ecology and biodiversity conservation. She holds a Bachelor's degree in Ecology and Conservation of Terrestrial Biodiversity and is currently pursuing a Master's degree in Biodiversity Conservation and Management at Mzuzu University, Malawi. Her research interests include species distribution modelling, climate change impacts on biodiversity, and sustainable ecosystem management.

Luwaga Denis is a member of the academic staff at Uganda Martyrs University, where he teaches courses in Geographic Information Systems (GIS), Remote Sensing, and Information Technology, and supervises student research in these areas. He is currently a Doctor of Philosophy (PhD) candidate in Geoinformatics at Mzuzu University, Malawi. His research interest is in the application of geospatial technologies for environmental conservation and climate change mitigation, with a particular focus on digital innovation for sustainable natural resource management. He holds a Master of Science in Geographic Information Systems (GIS) from the University of Nairobi, Kenya, a Bachelor of Information Technology from Ndejje University, and a Diploma in Computer Science from Uganda Martyrs University.

Dr. Bruno Kokouvi Kokou is a Postdoctoral Researcher specializing in plant ecology, biodiversity conservation, and climate change. His research focuses on plant systematics, ethnobotany, plant genetic resources valorization, and sustainable ecosystem management in Sub-Saharan Africa. He has conducted several studies on biodiversity, ecosystem services, land-use change, and the ecology and regeneration of indigenous fruit trees, particularly Uapaca kirkiana. His work also addresses climate change impacts on vegetation distribution and the sustainable management of natural resources and food systems.

Tiwonge I. Mzumara is a Senior Lecturer in Ecology in the Biological Sciences Department at the Malawi University of Science and Technology. She is an ecologist by training and an activist by passion. She holds a PhD in Ecological Sciences from the University of KwaZulu Natal. MSc in Conservation Biology from the University of Cape Town, under the Graca Machel Scholarship, 2009.. She graduated from the University of Malawi, Chancellor College with a BSc in Biology and minor in statistics. She was the first female ornithologist in Malawi. She is currently training many more to build the skill in Malawi. She is an energetic and passionate researcher teaching both undergraduate and post-graduate courses.

ORCID

Jéssica da Carolina Antónia Manuel http://orcid.org/0009-0006-8268-7791
Luwaga Denis http://orcid.org/0009-0001-9580-0734
Bruno Kokouvi Kokou http://orcid.org/0009-0006-0852-1232
Tiwonge I. Mzumara http://orcid.org/0000-0002-5364-9853

Data availability statement

The data will be made available from the corresponding author upon reasonable request.

References

Amosi, N., and R. O. Anyah. 2024. "Trends of Precipitation and Temperature Extremes over Malawi and Mozambique During the Recent Decades from Models and Observations." *Theoretical and Applied Climatology* 155 (2): 783–804. https://doi.org/10.1007/s00704-023-04659-y.

Ashraf, U., H. Ali, M. N. Chaudry, I. Ashraf, A. Batool, and Z. Saqib. 2016. "Predicting the Potential Distribution of *Olea ferruginea* in Pakistan Incorporating Climate Change by Using Maxent Model." *Sustainability* 8(8): 722. https://doi.org/10.3390/su8080722.

Bhatti, M. A., S. S. Godfrey, R. H. Ip, C. Kachiwala, H. Hovdhaugen, L. J. Banda, M. Limuwa, P. C. Wynn, T. Ådnøy, and L. O. Eik. 2021. "Diversity of Sources of Income for Smallholder Farming Communities in Malawi: Importance for Improved Livelihood." *Sustainability* 13 (17): 9599.

Biddle, R., I. Solis-Ponce, M. Jones, S. Marsden, M. Pilgrim, and C. Devenish. 2021. "The Value of Local Community Knowledge in Species Distribution Modelling for a Threatened Neotropical Parrot." *Biodiversity and Conservation* 30(6): 1803–1823. https://doi.org/10.1007/s10531-021-02169-9.

Céspedes Arias, L. N., S. Wilson, and N. J. Bayly. 2022. "Community Modeling Reveals the Importance of Elevation and Land Cover in Shaping Migratory Bird Abundance in the Andes." *Ecological Applications* 32(1): e02481. https://doi.org/10.1002/eap.2481.

Cheke, R. 2009. Models of *Quelea* Movements and Improved Control Strategies. *Final Technical Report*.

Cheke, R. 2022. "*Quelea Quelea* (Weaver Bird)." In *CABI Compendium*. Wallingford, UK: CABI International.

Cheke, R. A., L. J. Rosenberg, and M. E. Kieser. 2000. *Workshop on Research Priorities for Migrant Pests of Agriculture in Southern Africa, Plant Protection Research Institute, Pretoria, South Africa, 24-26 March 1999*. Plant Protection Research Institute.

Cheke, R. A., and M. E. H. Sidatt. 2019. "A Review of Alternatives to Fenthion for Quelea Bird Control." *Crop Protection* 116: 15–23. https://doi.org/10.1016/j.cropro.2018.https://doi.org/10.005.

Cheke, R. A., J. F. Venn, and P. J. Jones. 2006. "A Spatio-Temporal Model for Predicting When and Where Red-billed Quelea Will Breed in Southern Africa." *Journal of Ornithology* 147(1): 147.

Cheke, R. A., J. F. Venn, and P. J. Jones. 2007. "Forecasting Suitable Breeding Conditions for the Red-Billed Quelea *Quelea Quelea* in Southern Africa." *Journal of Applied Ecology* 44(3): 523–533. https://doi.org/10.1111/j.1365-2664.2007.01295.x.

Chen, I.-C., J. K. Hill, R. Ohlemüller, D. B. Roy, and C. D. Thomas. 2011. "Rapid Range Shifts of Species Associated with High Levels of Climate Warming." *Science* 333(6045): 1024–1026. https://doi.org/10.1126/science.1206432.

Chimonyo, V. G. P., T. Mabhaudhi, F. K. Muthoni, and G. Chavula. 2023. *Context Assessment for Mixed Farming Systems in Malawi*. Ibadan, Nigeria: International Institute of Tropical Agriculture (IITA).

Dayoub, M., R. J. Birech, M.-H. Haghbayan, S. Angombe, and E. Sutinen. 2021. "Co-Design in Bird Scaring Drone Systems: Potentials and Challenges in Agriculture." In *Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2020*, 598–607.

De Mey, Y., M. Demont, and M. Diagne. 2012. "Estimating Bird Damage to Rice in Africa: Evidence from the Senegal River Valley." *Journal of Agricultural Economics* 63(1): 175–200. https://doi.org/10.1111/j.1477-9552.2011.00323.x.

Dobson, R., S. G. Willis, S. Jennings, R. A. Cheke, A. J. Challinor, and M. Dallimer. 2024. "Near-Term Forecasting of Terrestrial Mobile Species Distributions for Adaptive Management under Extreme Weather Events." *Global Change Biology* 30(11): e17579. https://doi.org/10.1111/gcb.17579.

Dowsett-Lemaire, F., and R. J. Dowsett. 2006. *The Birds of Malawi: An Atlas and Handbook*. Liège, Belgium: Tauraco & Aves.

Ejigu, D., and N. Tassie. 2020. "Present and Future Suitability of the Lake Tana Biosphere Reserve in Ethiopia for the Nile Monitor (*Varanus niloticus*) Using the MaxEnt Model." *Environmental Systems Research* 9(1): 1–15. https://doi.org/10.1186/s40068-020-00197-y.

Elith, J., and J. R. Leathwick. 2009. "Species Distribution Models: Ecological Explanation and Prediction Across Space and Time." *Annual Review of Ecology, Evolution, and Systematics* 40 (1): 677–697. https://doi.org/10.1146/annurev.ecolsys.110308.120159.

Elith, J., S. J. Phillips, T. Hastie, M. Dudík, Y. E. Chee, and C. J. Yates. 2011. "A Statistical Explanation of MaxEnt for Ecologists." *Diversity and Distributions* 17(1): 43–57. https://doi.org/10.1111/j.1472-4642.20https://doi.org/10.00725.x.

FAO, I., and ISRIC, I. 2012. "JRC: Harmonized World Soil Database (Version 1.2)." Rome, Italy: FAO; Laxenburg, Austria: IIASA.

Fick, S. E., and R. J. Hijmans. 2017. "WorldClim 2: New 1-km Spatial Resolution Climate Surfaces for Global Land Areas." *International Journal of Climatology* 37(12): 4302–4315. https://doi.org/10.1002/joc.5086.

Freeman, M. T., Z. J. Czenze, K. Schoeman, and A. E. McKechnie. 2020. "Extreme Hyperthermia Tolerance in the World's Most Abundant Wild Bird." *Scientific Reports* 10(1): 13098. https://doi.org/10.1038/s41598-020-69997-7.

Government of Malawi. 2015. *Malawi Floods Emergency Recovery Project (MFERP) (Environmental and Social Management Framework for Credit IDA 1431)*. Lilongwe, Malawi: Ministry of Finance, Economic Planning and Development.

Harris, J. B. C., D. D. Putra, S. D. Gregory, B. W. Brook, D. M. Prawiradilaga, N. S. Sodhi, D. Wei, and D. A. Fordham. 2014. "Rapid Deforestation Threatens Mid-Elevational Endemic Birds But Climate Change Is Most Important at Higher Elevations." *Diversity and Distributions* 20(7): 773–785. https://doi.org/10.1111/ddi.12180.

Hwang, J. H., S.-H. Kim, S. Yoon, S. Jung, D. H. Kim, and W.-H. Lee. 2022. "Evaluation of Spatial Distribution of Three Major *Leptocorisa* (Hemiptera: Alydidae) Pests Using MaxEnt Model." *Insects* 13(8): 750. https://doi.org/10.3390/insects13080750.

Jafari, A., R. Zamani-Ahmadmahmoodi, and R. Mirzaei. 2018. "Persian Leopard and Wild Sheep Distribution Modeling Using the MaxEnt Model in the Tang-e-Sayad Protected Area, Iran." *Mammalia* 83(1): 84–96.

Jaleta, M., and W. Tekalign. 2023. "Crop Loss and Damage by Primate Species in Southwest Ethiopia." *International Journal of Ecology* 1–9. https://doi.org/10.1155/2023/8332493.

Jha, K. K., and R. Jha. 2021. "Study of Vulture Habitat Suitability and Impact of Climate Change in Central India Using MaxEnt." *Journal of Resources and Ecology* 12(1): 30–42. https://doi.org/10.5814/j.1674-764x.2021.01.004.

Karra, K., C. Kontgis, Z. Statman-Weil, J. C. Mazzariello, M. Mathis, and S. P. Brumby. 2021. "Global Land Use/Land Cover with Sentinel-2 and Deep Learning." In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, 4704–4707. Brussels, Belgium: IEEE. https://doi.org/10.1109/IGARSS47720.2021.9553499.

Khosravi, R., M. R. Hemami, M. Malekian, A. Flint, and L. Flint. 2016. "MaxEnt Modeling for Predicting Potential Distribution of Goitered Gazelle in Central Iran: The Effect of Extent and Grain Size on Performance of the Model." *Turkish Journal of Zoology* 40(4): 574–585. https://doi.org/10.3906/zoo-1505-38.

Kokou, B. K., M. Ulemu, W. Atakpama, S. Biaou, S. C. Teteli, S. K. Raoul, F. Mnthambala, T. Mavuto, P. Munyenyembe, and F. Noulèkoun. 2025. "Climate Change Reduces and Shifts Suitable Habitats of *Uapaca Kirkiana* Müll. Arg. to Higher Altitudes in Malawi." *Trees, Forests and People* 20: 100884. https://doi.org/10.1016/j.tfp.2025.100884.

Kumar, P. 2012. "Assessment of Impact of Climate Change on *Rhododendrons* in Sikkim Himalayas Using MaxEnt Modelling: Limitations and Challenges." *Biodiversity and Conservation* 21(5): 1251–1266. https://doi.org/10.1007/s10531-012-0279-1.

Lawrence, B. 2024. "Lidar-Based MaxEnt Models to Support Conservation Planning for Endangered Red-Cockaded Woodpeckers in Urbanizing Environments." *Remote Sensing Applications: Society and Environment* 34: 101190. https://doi.org/10.1016/j.rsase.2024.101190.

Lissovsky, A. A., and S. V. Dudov. 2021. "Species-Distribution Modeling: Advantages and Limitations of Its Application. 2. MaxEnt." *Biology Bulletin Reviews* 11(3): 265–275. https://doi.org/10.1134/S2079086421030087.

Liu, C., M. White, G. Newell, and R. Pearson. 2013. "Selecting Thresholds for the Prediction of Species Occurrence with Presence-Only Data." *Journal of Biogeography* 40(4): 778–789. https://doi.org/10.1111/jbi.12058.

Lloyd, P. 1999. "Rainfall as a Breeding Stimulus and Clutch Size Determinant in South African Arid-Zone Birds." *Ibis* 141(4): 637–643. https://doi.org/10.1111/j.1474-919X.1999.tb07371.x.

Luo, M., H. Wang, and Z. Lyu. 2017. "Evaluating the Performance of Species Distribution Models Biomod2 and MaxEnt Using the Giant Panda Distribution Data." *Ying*

Yong Sheng Tai Xue Bao = The Journal of Applied Ecology 28(12): 4001–4006. https://doi.org/10.13287/j.1001-9332.201712.011.

Markula, A., M. Hannan-Jones, and S. Csurhes. 2016. *Red-Billed Quelea: Pest Animal Risk Assessment*. Queensland Government: Invasive Plants and Animals Biosecurity.

McWilliam, A. N., and R. A. Cheke. 2004. "A Review of the Impacts of Control Operations against the Red-Billed Quelea (*Quelea Quelea*) on Non-Target Organisms." *Environmental Conservation* 31(2): 130–137. https://doi.org/10.1017/S0376892904001213.

Ministry of Agriculture and Livestock Development. 2025. *Red-billed Quelea Birds*. Kenya: Government of Kenya.

Mmbaga, N., F. Chebby, L. Gayo, and K. Ngongolo. 2025. "Land Use Changes and the Distribution of the Red-Billed Quelea (*Quelea Quelea*) in Chemba District, Tanzania." *Discover Sustainability* 6(1): 313. https://doi.org/10.1007/s43621-025-01177-x.

Moreno, R., R. Zamora, J. R. Molina, A. Vasquez, and M. Á. Herrera. 2011. "Predictive Modeling of Microhabitats for Endemic Birds in South Chilean Temperate Forests Using Maximum Entropy (Maxent)." *Ecological Informatics* 6(6): 364–370. https://doi.org/10.1016/j.ecoinf.2011.07.003.

Mpala, C., P. Sibanda, M. Dlamini, and B. Sibanda. 2015. "Are Quelea Birds Really a Menace? Innovative Use of Indigenous Knowledge Systems in the Harvesting and Utilisation of Quelea, *Quelea Quelea Lathamii*, Hwange District of Matabeleland North Province." *International Journal of Agricultural Sciences* 5: 71–82.

Mtobesya, B. N. 2012. "Non-Chemical Control of the Red-Billed Quelea (Quelea Quelea) and Use of the Birds as a Food Resource." MPhil diss., University of Greenwich.

Munthali, M., P. Nalivata, W. Makumba, E. Mbewe, H. Manase, G. Oduor, M. Macharia, and K. Kayuki. 2017. "Optimizing Nutrient Use Efficiency and Returns from Soybean Production under Smallholders in Three Agro-Ecologies of Malawi." *Agricultural Sciences* 8(8): 801–815. https://doi.org/10.4236/as.2017.88059.

Na, X., H. Zhou, S. Zang, C. Wu, W. Li, and M. Li. 2018. "Maximum Entropy Modeling for Habitat Suitability Assessment of the Red-Crowned Crane." *Ecological Indicators* 91: 439–446. https://doi.org/10.1016/j.ecolind.2018.04.013.

Ngazero, A. K. 2013. "Levantamento da Vegetação das Zonas de Reprodução do Pardal-de-Bico Vermelho (Quelea quelea) e Efeito de Produtos Químicos como Repelentes no Seu Controlo." Tese de mestrado, Universidade Eduardo Mondlane.

Nguru, M. I., P. C. Leong, and M. Ismail. 2023. "Habitat Suitability Analysis for Red-Billed Quelea (*Quelea Quelea*) Using Analytic Hierarchy Process (AHP) and Geospatial Techniques in Hadejia-Nguru Wetlands Area of North-East Nigeria, Implications for Management." *International Journal of Agriculture and Agricultural Technology* 2 (2). https://cambridgeresearchpub.com/ijaat/article/view/65.

Pearson, R. G., C. J. Raxworthy, M. Nakamura, and A. T. Peterson. 2007. "Predicting Species Distributions from Small Numbers of Occurrence Records: A Test Case Using Cryptic Geckos in Madagascar." *Journal of Biogeography* 34(1): 102–117. https://doi.org/10.1111/j.1365-2699.2006.01594.x.

Phillips, S. J., R. P. Anderson, and R. E. Schapire. 2006. "Maximum Entropy Modeling of Species Geographic Distributions." *Ecological Modelling* 190(3–4): 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026.

Phillips, S. J., M. Dudík, and R. E. Schapire. 2018. *MaxEnt Software for Modeling Species Niches and Distributions*. Amsterdam, Netherlands: Elsevier.

Qin, A., B. Liu, Q. Guo, R. W. Bussmann, F. Ma, Z. Jian, G. Xu, and S. Pei. 2017. "MaxEnt Modeling for Predicting Impacts of Climate Change on the Potential Distribution of *Thuja Sutchuenensis* Franch. an Extremely Endangered Conifer from Southwestern China." *Global Ecology and Conservation* 10: 139–146. https://doi.org/10.1016/j.gecco.2017.02.004.

Ramirez-Reyes, C., B. L. Bateman, and V. C. Radeloff. 2016. "Effects of Habitat Suitability and Minimum Patch Size Thresholds on the Assessment of Landscape Connectivity for Jaguars in the Sierra Gorda, Mexico." *Biological Conservation* 204: 296–305. https://doi.org/10.1016/j.biocon.2016.https://doi.org/10.020.

Riahi, K., D. P. Van Vuuren, E. Kriegler, J. Edmonds, B. C. O'Neill, S. Fujimori, N. Bauer, K. Calvin, R. Dellink, and O. Fricko. 2017. "The Shared Socioeconomic Pathways and Their Energy, Land Use, and Greenhouse Gas Emissions Implications: An Overview." *Global Environmental Change* 42: 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009.

Sabastian, M. M. 2023. "Evaluation of the Food of Red-Billed Quelea (Quelea Quelea) During Cropping Season in Gyawana and Environs, Adamawa State, Nigeria." *GSC Biological and Pharmaceutical Sciences* 24 (3): 140–148.

Saka, J. D., P. Siable, S. Hachigonta, L. M. Sibanda, and T. S. Thomas. 2012. *Southern African Agriculture and Climate Change: A Comprehensive Analysis - Malawi*. Washington, DC: International Food Policy Research Institute (IFPRI).

Tøttrup, A. P., R. H. G. Klaassen, M. W. Kristensen, R. Strandberg, Y. Vardanis, Å. Lindström, C. Rahbek, T. Alerstam, and K. Thorup. 2012. "Drought in Africa Caused the Delayed Arrival of European Songbirds." *Science* 338(6112): 1307. https://doi.org/10.1126/science.1227548.

Tuan, N. T., I. Gliottone, M. P. Pham, and D. D. Vu. 2021. *Current and Future Predicting Habitat Suitability Map of Cunninghamia konishii Hayata Under Climate Change in Northern Vietnam*. Lawrence, Kansas, USA: European Journal of Ecology (KU Academic Publishing, University of Kansas).

Unglaub, B., S. Steinfartz, A. Drechsler, and B. R. Schmidt. 2015. "Linking Habitat Suitability to Demography in a Pond-Breeding Amphibian." *Frontiers in Zoology* 12 (1): 9. https://doi.org/10.1186/s12983-015-0103-3.

Ward, P. 1965. "Feeding Ecology of the Black-Faced Dioch Quelea Quelea in Nigeria." *The Ibis* 107 (2): 173–214. https://doi.org/10.1111/j.1474-919X.1965.tb07296.x.

You, L., C. Ringler, U. Wood-Sichra, R. Robertson, S. Wood, T. Zhu, G. Nelson, Z. Guo, and Y. Sun. 2011. "What Is the Irrigation Potential for Africa? A Combined Biophysical and Socioeconomic Approach." *Food Policy* 36(6): 770–782. https://doi.org/10.1016/j.foodpol.2011.09.001.

Zitsanza, E. 2008. "Manual do Curso Nacional de Maneio do Gafanhoto Vermelho." In *Programa de Formação da Organização Internacional para o Controlo do Gafanhoto Vermelho nas Regiões Central e Austral de África (IRLCO-CSA)*, 40. Caia-Sofala.

Zvidzai, M., F. M. Zengeya, M. Masocha, A. Murwira, and P. Tagwireyi. 2024. "Projected Climate Scenarios Reveal an Expanding Suitable Habitat for the Critically Endangered African White-Backed Vulture *Gyps Africanus*." *Integrative Conservation* 3(4): 398–409. https://doi.org/10.1002/inc3.81.