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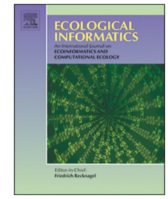

Analysis of potentially suitable habitat within migration connections of an intra-African migrant-the Blue Swallow (*Hirundo atrocaerulea*)

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ABSTRACT

Bird species that occupy highly specialised ecological niche are susceptible to environmental and climatic change. These species can easily be moved into extinction by small anthropogenic or natural changes to their habitat. It is paramount to understand and assess the uncertainties of the impacts of climate change on the species to adopt adaptation strategies and provide revised management actions. Based on two emission scenarios Representative Concentration Pathway (RCP2.6 and RCP8.5) set by the Intergovernmental Panel on Climate Change (IPCC), we predicted the potential distribution of Blue Swallows (*Hirundo atrocaerulea*) habitat suitability under current and future scenarios using a maximum entropy (MaxEnt) model. Eight variables were selected from 21 bioclimatic, elevation and land use/ land cover covariates based on their model percentage contribution in MaxEnt and correlation analysis. Our results demonstrate that maximum temperature of the warmest month (Bio5) and precipitation of the warmest quarter (Bio18) are the most important variables in determining the distribution of potentially suitable habitat for the Blue Swallow. Furthermore, our results suggest that Blue Swallow suitable habitat will decrease with increase in latitude while decreasing with an increase in longitude due to climate change. The predicted fundamental niche was much larger than the realised niche, suggesting that other anthropogenic and ecophysiological parameters may limit occupation of the suitable habitat; thus, the actual distribution extents may continue to decline in the future. We conclude that there is a negative impact of climate change on the distribution of Blue Swallow habitat and any increase in temperature results in the surge of unsuitable areas. Therefore, unless strict protection is awarded to the current suitable habitat, the suitable habitat and population of the Blue Swallow will continue to decline. Our results can be used by Blue Swallow conservationists and decision-makers to draft adaptive countermeasures to cope and mitigate for climate change.

1. Introduction

Climate change is an indisputable phenomenon, currently experienced at different scales globally (Rong et al., 2019). The global annual temperature has increased by between 0.6° and 0.85°C between 18th and the 21st century with probable chances of increasing soon. The atmospheric concentrations of CO_2, CH_4, and N_2O have reached their highest in the last 800,000 years (Zhang et al., 2019). Africa is considered the most vulnerable continent to the impacts of climate change as the continent's temperature is anticipated to increase faster than the rest of the world because of its already warmer baseline climate, low precipitation and limited ability to adapt (IPCC, 2014; Kotir, 2010). Climate projections for Africa suggest that temperatures will increase by between 3° and 6°C from the temperatures experienced at end of the 20th century, particularly in the in-land sub-tropics (Serdeczny et al., 2016). These increases in temperature are likely to trigger extreme heat events, increased aridity and extreme changes in precipitation across the whole continent particularly the arid and semi-arid regions such as north Africa and south western South Africa, Botswana and Namibia (Kotir, 2010; Niang et al., 2014; Serdeczny et al., 2016). While southern and north Africa will become more arid, east Africa is anticipated to become wetter and receive extreme rainfall (Niang et al., 2014). Additionally, in high topography regions such as the Ethiopian highlands, projections indicate that these areas will likely receive increased

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rainfall by the end of the 21st century (Kotir, 2010; Niang et al., 2014)

These changes will unequivocally alter both animal and plant species diversity, structure, ecosystem functions, and distribution. Currently, species have already begun to show substantial changes in species richness, composition and abundance in response to the 0.6°C increase during the past century with considerable effects likely to occur soon (Abolmaali et al., 2017; Chunco et al., 2013). Several studies have attempted to simulate current and potential future occurrences of species to enhance preparedness for the uncertainties provided by these environmental deviations (Abolmaali et al., 2017; Azrag et al., 2018; Makori et al., 2017).

Birds are one of the most diverse taxa within the animal kingdom and are easily moved into extinction by small anthropogenic or natural changes in the environment. The Blue Swallow, is one of the birds threatened with extinction because of its decreasing global population of less than 1500 breeding pairs and loss of suitable habitat (Evans et al., 2015). It is classified as "Vulnerable" due to its low population and has been on the BirdLife International and the IUCN Red List since 2010 (BirdLife International, 2019).

The Blue Swallow (*Hirundo atrocaerulea*) is an intra-African migrant bird species with a known range spanning ten African countries. Seven of these countries are its breeding range (South Africa, Eswatini, Tanzania, Malawi, Mozambique, Zambia and Zimbabwe) while it forages during the wintering season in Uganda, Kenya and Democratic Republic of Congo (DRC) (Evans et al., 2015; Ndang'ang'a, 2007). It is habitat specific, requiring mountainous rolling mist grasslands and spends over 80% of its forage time in these wetland habitats and grasslands (Mudereri et al., 2009; Wakelin et al., 2018). However, anthropogenic activities in the urban and agroecological systems have seriously transformed, fragmented and threatened the habitats of these birds in all its migration range. Blue Swallow foraging and breeding sites have been turned into human settlements and agricultural land, disintegrating their habitat in the process (Evans and Bouwman, 2010a). Threats in the breeding, non-breeding zones and/or along migration routes constitute the highest cause for most population declines in migratory birds (Wakelin et al., 2011). However, there is insufficient data on current population numbers, quantification of their habitat status, breeding trends and the impact of climate change on the suitable habitat for this highly specialised bird throughout all its migratory connections.

The Blue Swallow is characterised by a declining population, a limited geographic range, and habitat specialisation; therefore, it is highly sensitive to climate change. We hypothesise that climate change will further alter the distribution and migration ranges which might ultimately send the species into extinction. Understanding the transformed distribution ranges of the Blue Swallow is crucial for providing bases for revised management actions and protection strategies aimed at maintaining ecological services.

Predicting the possible species distribution using Species Distribution Models (SDMs) involves combining current location presence data of a species with appropriate environment variables (Ayebare et al., 2018; Merow et al., 2013). SDMs are widely used for many purposes in conservation biology, biogeography and ecology (Elith et al., 2010a). Most of the frequently used SDMs such as the Ecological Niche Factor Analysis (ENFA), Genetic Algorithm for Rule-set Prediction (GARP), Random Forests (RFs) and Maximum Entropy (MaxEnt) are designed to predict species distribution under current and potential future climate change (Biber-freudenberger et al., 2016). Globally, these models have been validated in various applications to predict for habitat suitability for countless species (Abolmaali et al., 2017; Jácome et al., 2019; Khadka and James, 2017; Padalia et al., 2014; Rong et al., 2019; Sang et al., 2016; Stockwell and Peters, 1999; Zhang et al., 2019).

Contrasted with other models, MaxEnt is reliably better in its predictive performance and usefulness as evidenced by over 1000 ecological applications published since 2006 (Merow et al., 2013). This utilisation of MaxEnt model is attributable to: (1) ease of use which allows modellers to view and manipulate default settings in MaxEnt; (2) interpretability of outputs and a gentle learning curve; (3) requiring presence only data which is often overwhelmingly available for greater proportion of the Earth's biodiversity; (4) consistent outputs for research conducted with large or small sample sizes; (5) simultaneous use of continuous and discrete input data and (6) generating a continuous probabilistic output, that is befitting to classify species suitability (Elith et al., 2010a; Zhang et al., 2019).

Despite the extensive use of MaxEnt, relatively few studies have applied it to bird species predictions research (Moreno et al., 2011). Herein, we use MaxEnt modelling to predict the suitability of the vulnerable Blue Swallow habitat throughout its connected migratory route in Africa using the currently known presence records contrasted with the elevation, land use/ land cover (LULC), current and future environmental covariates from WorldClim (http://www.worldclim.org/). The specific objectives of the study were to: (1) predict the suitability of habitat for the species in all its African range (breeding and wintering) and (2) estimate its suitability areas under the two future scenarios: 2050 and 2070 in Africa.

2. Materials and methods

2.1. Study area

Predictions of the occurrence of the Blue Swallow were conducted on the entire African continent. Our target was to test all the potential habitat suitability areas of the Blue Swallow within and outside of its current known territory Fig. 1.

2.2. Reference occurrence data

The reference distribution data of Blue Swallows was collated by conducting a literature search in reports, journal publications of surveys and research on the Blue Swallow (Matsvimbo and Wachi, 2014; Ndang'ang'a, 2007; Ogoma, 2012; Wakelin et al., 2018). We also obtained additional occurrence points from the Global Biodiversity Information Facility (GBIF: GBIF (2019)). Additional data for validation of the realised niche was provided by Birdlife International as polygons (BirdLife International and Handbook of the Birds of the World, 2018). The "presence-only" samples acquired from the literature search and GBIF were verified on Google Earth® for positional accuracy. A total of 956 samples were subjected to positional accuracy and spatial filtering using a standard distance of 5 km between points. The point data were examined to eliminate redundant and overlapping samples (Elith et al., 2010a). A total of 850 records were eliminated and we retained 106 presence points that were representative of the entire distribution range of the Blue Swallow. Although the points appear to be few compared to the total area of the African continent, research has established that MaxEnt is effective when predictions are conducted with few data points (Bean et al., 2012). Furthermore, MaxEnt accuracy is greater for species with small geographic range and limited environmental tolerance (Bean et al., 2012; Hernandez et al., 2006), which are the typical ecological characteristics of the Blue Swallow. Thus, these points were enough for use in MaxEnt to predict the occurrence of the Blue Swallow in Africa. The occurrence points were arranged and formatted for input in MaxEnt.

2.3. Environmental variables

We used a combination of bioclimatic, elevation and LULC variables to determine the key environmental variables influencing the distribution of Blue Swallows in all its range. The current climate data (1950–2000) and the future climate data for the minimum and maximum emission representative concentration pathways (RCP2.6 and RCP8.5) for carbon dioxide concentrations predicted for 2050 (average

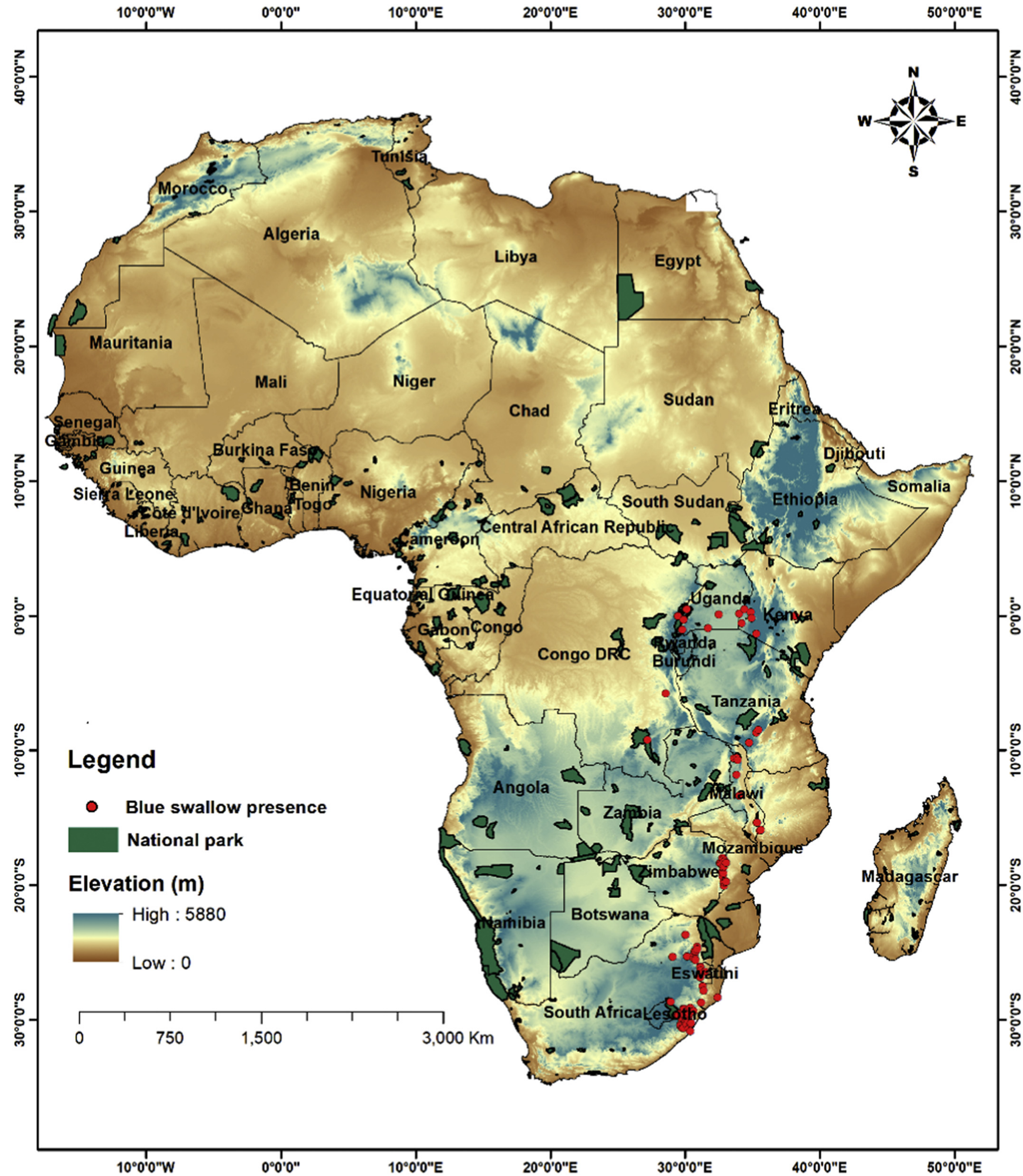


Fig. 1. Current distribution of the occurrence of the Blue Swallow in all its migratory range and the location of protected areas i.e. National parks in Africa. The data is overlaid on the SRTM 90 m elevation map of Africa.

of predictions for 2041–2060) and 2070 (average of predictions for 2061–2080) were used as predictors in our analysis (Abdelaal et al., 2019). We downloaded the current and future bioclimatic variables at 2.5 arc-minutes from WorldClim (www.worldclim.org). Four representative concentration pathways (RCPs) were set by the Intergovernmental Panel on Climate Change (IPCC) using the total radio-active forcing of values 2.6, 4.5, 6 and 8.5 watt/m^2 (IPCC, 2014).

The elevation data was downloaded from http://srtm.csi.cgiar.org/ in tiles of 30 × 30-degree ESRI ASCII files and mosaicked to cover the entire African continent. The Shuttle Radar Topographic Mission

(SRTM) data is available as 3 arc *sec* (~ 90 m resolution) Digital Elevation Models (DEMs) with a vertical error margin of less than 16 m (CGIAR-CSI, 2019). The elevation data was very relevant as a predictor since Blue Swallows have been reported to occur in high altitude regions (Evans and Bouwman, 2010a; Mudereri et al., 2009; Wakelin et al., 2018). We resampled the DEM to similar pixel size of the other 19 bioclimatic variables in preparation for input in MaxEnt.

We included the LULC data in our analysis since the Blue Swallow is a rare and habitat specific species. We used the Africa land cover, version 2 data which is downloadable from https://www.usgs.gov/media/images/africa-land-cover-characteristics-data-base-version-20. The Africa land cover data comprises 197 legend attributes of the LULC classes available in Africa. This categorical data was formatted and resampled to the same standards of the bioclimatic variables for input in the MaxEnt model.

A multi-collinearity test was conducted on the 21 variables to reduce redundancy and overfitting of the model brought by highly correlated variables using the Pearson correlation coefficient ($r \geq 0.85$) and the overall percentage contribution of the variables (Merow et al., 2013). In cases where two predictors were correlated, only ecologically viable predictors were retained. This reduction of predictor variables resulted in only 8 variables for modelling, which are highlighted in bold in Table 1. These selected variables included: annual mean temperature range (Bio1), maximum temperature of the warmest month (Bio5), mean temperature of the warmest quarter (Bio10), annual precipitation (Bio12), precipitation of the driest month (Bio14), precipitation of warmest quarter (Bio18), elevation and the LULC variables.

Additionally, we corrected for sampling bias (Støa et al., 2018) using the identified uncorrelated variables (i.e. the 6 selected bioclimatic variables plus elevation and LULC: $n = 8$) and the spatially filtered Blue Swallow occurrence points ($n = 106$) as inputs. We employed the kernel density estimator i.e. "kde2d" function of the "MASS" package (Venables and Ripley, 2002) using the "block" sampling approach in R-software (R Core Team, 2018). The "kde2d" function provides a two-dimensional kernel density estimate based on the coordinates of the occurrence points to generate a raster bias file (Venables and Ripley, 2002). It is important to correct for sampling bias particularly for rare and highly specialised species as often spatial bias leads to environmental bias (Kramer-Schadt et al., 2013; Merow et al., 2013), more so when using GBIF data (Beck et al., 2014). MaxEnt modelling allows the inclusion of bias files in the modelling which facilitates the choice of background data within similar bias as the occurrence data (Phillips et al., 2009).

Table 1
Environmental variables used in the MaxEnt models for the Blue Swallow suitable habitat prediction. The variables in bold were used in the final prediction after eliminating the correlated variables.

BioClim Code	Environmental variable	Unit
Bio1	**Annual Mean Temperature**	**°C**
Bio2	Mean Diurnal Range [Mean of monthly (max temp–min temp)]	°C
Bio3	Iso-thermality (Bio2/Bio7) (×100)	
Bio4	Temperature Seasonality (standard deviation ×100)	
Bio5	**Maximum Temperature of Warmest Month**	**°C**
Bio6	Min Temperature of Coldest Month	^{0}C
Bio7	Temperature Annual Range (Bio5–Bio6)	^{0}C
Bio8	Mean Temperature of Wettest Quarter	^{0}C
Bio9	Mean Temperature of Driest Quarter	^{0}C
Bio10	**Mean Temperature of Warmest Quarter**	**°C**
Bio11	Mean Temperature of Coldest Quarter	^{0}C
Bio12	**Annual Precipitation**	**mm**
Bio13	Precipitation of Wettest Month	mm
Bio14	**Precipitation of Driest Month**	**mm**
Bio15	Precipitation Seasonality (Coefficient of Variation)	mm
Bio16	Precipitation of Wettest Quarter	mm
Bio17	Precipitation of Driest Quarter	mm
Bio18	**Precipitation of Warmest Quarter**	**mm**
Bio19	Precipitation of Coldest Quarter	mm
Elevation	**Elevation**	**m**
Land use/land cover	**Landcover**	**Categorical**

2.4. MaxEnt model implementation and accuracy evaluation

In our study, we used the MaxEnt algorithm (version 3.4.1) (Phillips et al., 2006). MaxEnt has been widely used to predict species distribution because of its statistical robustness procedures, adaptability to various environments, sample sizes and its high performance across several niche modelling methods for presence-only data (Marchioro and Krechemer, 2018). We used the "ENMevaluate" function in the package "ENMeval" (Muscarella et al., 2014) available in R-software (R Core Team, 2018) to derive optimum tuning and parameter settings for our MaxEnt models. This approach calculates multiple metrics to aid in selecting optimum model settings that balance goodness-of-fit and model complexity (Muscarella et al., 2014). This approach has been recommended by many studies (Arthur et al., 2019; Bohl et al., 2019; Marchioro and Krechemer, 2018). We used the following model parameters derived from "ENMeval" to perform the Blue Swallow habitat suitability modelling in Africa: linear/quadratic/product: 0.141, categorical: 0.250, threshold: 1.320, hinge: 0.500, Multivariate Environmental Similarity Surface (MESS) analysis, clamping, extrapolate and fade with clamping. The MESS analysis in MaxEnt quantifies the measure of projection uncertainty by calculating the similarity of each point in the projected region to a set of reference points (Mesgaran et al., 2014). We also cooperated our generated bias file in all the current and future projection models while the rest of the settings were used as default.

Furthermore, using the above-mentioned setting parameters, we replicated our model 10 times and used the average of the 10 probability outputs to determine the optimum habitat suitability and performance of the models. We used 70% ($n = 74$) of the occurrence points for training while 30% ($n = 32$) were retained for testing the model (Dube et al., 2014; Mudereri et al., 2019). The comparative relevance of each environmental predictor for the models of Blue Swallow was evaluated using the overall percentage contribution, permutation importance of each variable and Area Under the Curve (AUC) of the Jackknife test, all available in MaxEnt (Merow et al., 2013; Phillips et al., 2006). The Jackknife test analysis has been reported to be the best comparative index for small sample sizes (Abdelaal et al., 2019).

The prediction precision was validated using the AUC of the Receiver Operating characteristic Curve (ROC) (Allouche et al., 2006; Phillips et al., 2006). The sensitivity (true positives) was plotted against specificity (false positives) to generate AUC. The values of AUC range between 0 and 1. AUC values closer to 1, suggest perfect performance of the model whereas an AUC value of 0.50 indicates that model did not perform better than random (Qin et al., 2017). Herein, we report the AUC of the current climate scenario, since there are no future occurrence points to validate our future predictions. However, we assume that if the model performs well with the current available data it would replicate the same strength when used to project predictions into the future.

The chief graphic outputs of MaxEnt application includes maps, highlighting the habitat suitability of Blue Swallows with values ranging from 0 (unsuitable) to 1 (optimum). We mapped the area for optimum distribution and spatially compared the model predictions with the current polygons provided by Birdlife International of the Blue Swallow occurrence recognised sites (BirdLife International and Handbook of the Birds of the World, 2018). We estimated and intercompared the percentages of the suitability area predicted within the different climate scenarios.

Further, we intercompared the shift in the probability of occurrence

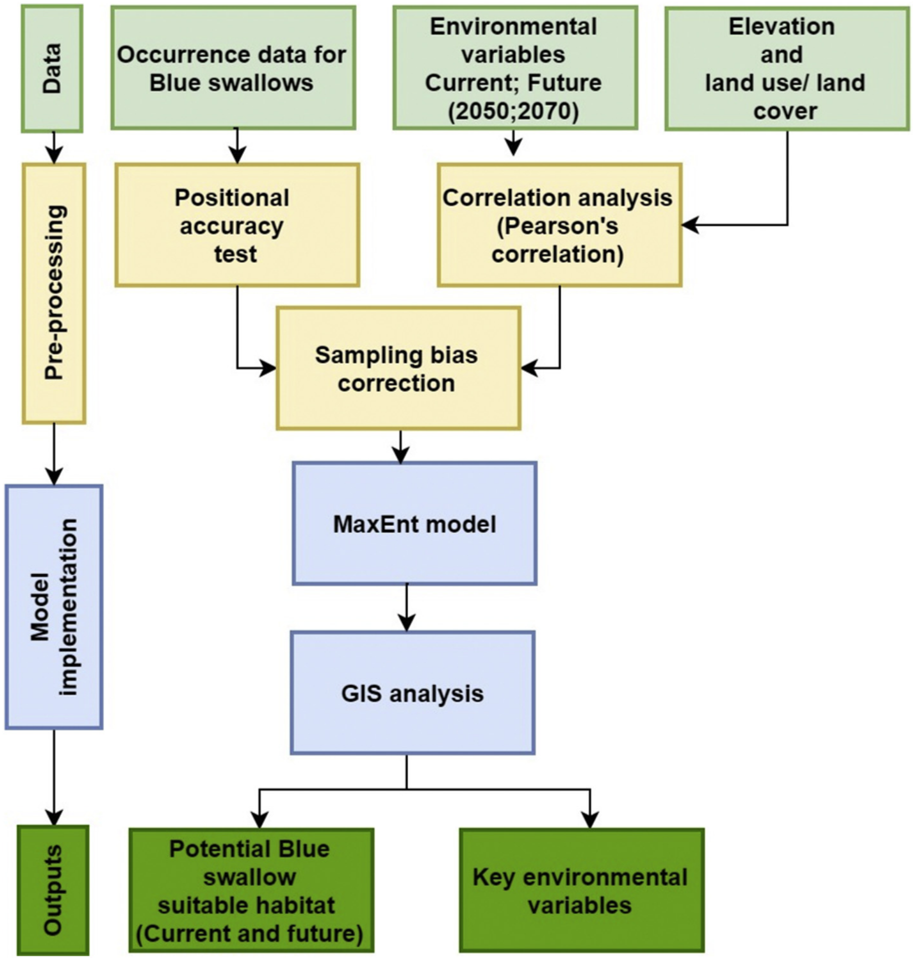


Fig. 2. Flowchart of the processing chain for the determination of current and future habitat suitability for the Blue Swallow.

as influenced by the longitude and latitudinal location. We used trend graphs to represent the anticipated decrease in suitability between the current and future climate scenarios along longitudes and latitudes. We used up and down bars to quantify and show the magnitude of the loss for each individual location for all the 106 presence data locations used in this study. We however, only report the comparison between the current climate scenario with the RCP 8.5: 2070 as we noted that the trend is the same for other scenarios studied.

We statistically tested for correlation and significant differences in the probability of occurrence in the current and future climate scenarios using the Person correlation coefficient (r^2) and the Analysis of Variance (ANOVA). These statistics were calculated in R-software using the "agricolae" package (de Mendiburu, 2019). We conducted a Tukey post hoc test to check and determine the groups that were significantly different.

2.5. Procedure used to determine the current and future habitat suitability for the Blue Swallow

Full workflow that provided the basis for the analysis conducted by this study is summarised in Fig. 2.

3. Results

3.1. MaxEnt models evaluation

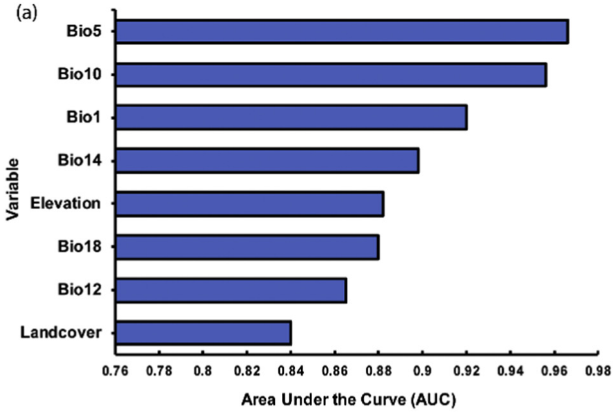
All the MaxEnt models for the prediction and projection of the Blue Swallow potential habitat using the current and future (RCP2.6: 2050; RCP8.5: 2050; RCP2.6: 2070 and RCP8.5: 2070) provided satisfactory results (AUC > 0.96), for all the test and training datasets. This demonstrates that our models show good predictive performance.

Temperature based variables were the most relevant predictors compared to precipitation, elevation and LULC. Maximum temperature of the warmest month (Bio5) contributed the most to the models and was consistently the most relevant in the modelling as pointed by all the measures used in our analysis (i.e. Jackknife AUC, overall percentage contribution and permutation importance). Based on the Jackknife results, Bio5 recorded the highest gain when used in isolation for the five tested scenarios and therefore, appears to provide the most useful information individually (Fig. 3). Similarly, Bio18 contributed the most among the precipitation variables and had a relatively high permutation importance (10.1).

3.2. Variable response curves

The response of the occurrence of the Blue Swallow to the temperature variables i.e. Bio1; Bio5 and Bio10 demonstrated that the suitable habitat for the Blue Swallow ranged between 10° and 25°C in all its migratory range. Further, Blue Swallows were predicted within very high precipitation regions with rainfall ranges between ~ 1000 mm and 2500 mm/year (Fig. 4). Thus, the model indicates that it prefers low temperatures and higher precipitation rates. Under climate change more areas are projected to lose these conditions especially in east Africa. Our results of the response of Blue Swallows occurrence predicted that the most suitable habitat occurs in high altitude regions ranging between 1500 m–3000 m a.s.l. However, a decrease in

(a)



(b)

Variable	Percentage contribution	Permutation importance
Bio5	26.5	58.4
Bio14	19.8	9.2
Bio18	18.8	10.1
Bio1	15.2	2
Elevation	9.5	3
Landcover	8	1.3
Bio12	1.6	16
Bio10	0.6	0

Fig. 3. Relative contribution and importance of the environmental variables used in the MaxEnt modelling of the Blue Swallow habitat suitability in Africa as measured by (a) contribution towards Area under the curve (AUC) derived from the Jackknife analysis in MaxEnt and (b) the percentage contribution and permutation importance of each individual variable.

occurrence was observed beyond the 3000 m altitude. The model predicted that the most dominant LULC classes were open grasslands and mixtures of grasslands and shrub lands. On the contrary, probability of occurrence of Blue Swallows within the other classes such as the Miombo woodland, cropland and closed forests was very low i.e. probabilities values of 0.1, 0.1 and 0.3 respectively (Fig. 4).

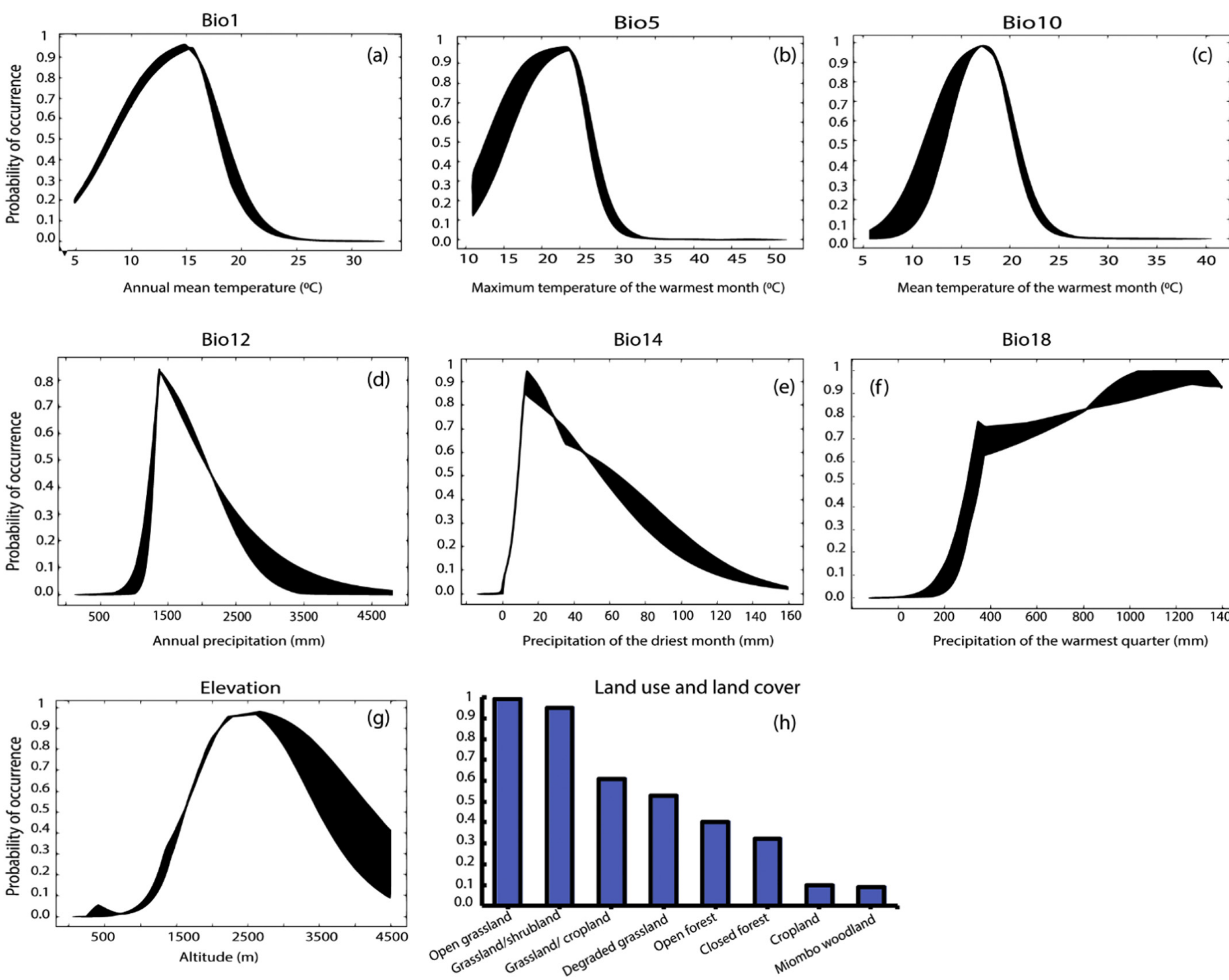


Fig. 4. Response curves derived from MaxEnt Models showing influence of environmental variables: (a) Bio1; (b) Bio5; (c) Bio10; (d) Bio12; (e) Bio14; (f) Bio18; (g) elevation and (h) land use and land cover on probability of occurrence of the Blue Swallow in Africa.

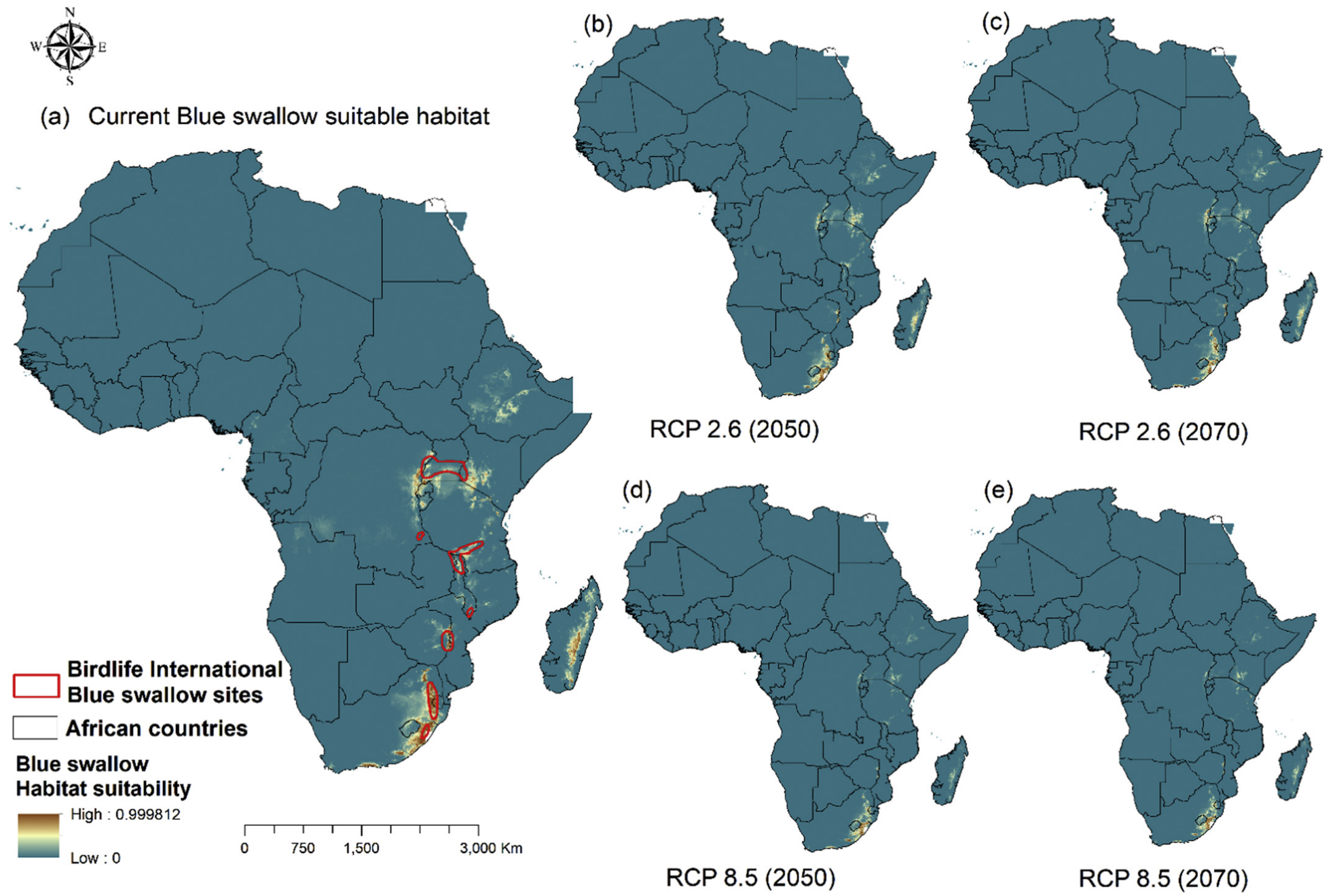


Fig. 5. Prediction of the Blue swallow habitat suitability for: (a) current and (b-e) future climate scenarios. The future predictions are based on two representative concentration pathways (RCP2.6 and RCP8.5) for 2050 (b, d) and 2070 (c, e).

Table 2
Pairwise comparison using the Person correlation coefficient for the five groups of probabilities predicted under the current climate scenario, RCP 2.6 (2050), RCP 2.6 (2070), RCP 8.5 (2050) and RCP 8.5 (2070).

Scenario	Current	RCP 2.6 (2050)	RCP 2.6 (2070)	RCP 8.5 (2050)	RCP 8.5 (2070)
Current	1				
RCP 2.6 (2050)	86	1			
RCP 2.6 (2070)	85	91	1		
RCP 8.5 (2050)	65[a]	84	70[a]	1	
RCP 8.5 (2070)	63[a]	80	69[a]	97	1

[a] Significant at $p = .01$.

3.3. Habitat suitability under current and future climate conditions

Current potential suitable habitat for the Blue Swallow was predicted in 15 African countries namely: DRC, Ethiopia, Eswatini, Kenya, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Reunion Island, Rwanda, South Africa, Tanzania, Uganda and Zimbabwe. Most of the identified locations coincided with the sites already recognised by BirdLife International (Fig. 5). Notably, additional suitable habitats were identified by our model, based on similar climate envelope. These additional habitats were predicted in Ethiopia, Lesotho, Madagascar, the Reunion and Mauritius. However, differences were noted in the spatial extent covered by the Birdlife International polygons in the known sites in South Africa, Uganda, Tanzania and Kenya suggesting a difference in the fundamental and realised niche of the Blue Swallow. Notably most of the sites and suitable habitat was outside strict conservation or protected areas.

Although the location and pattern of the future potential habitat of Blue Swallows is similar to the current potential distribution, our models' results suggest that the geographic extents would generally shrink under the tested scenarios of climate change (Fig. 5). The greatest losses in suitable habitat were observed for the RCP 8.5 for both 2050 and 2070 when compared to the RCP 2.6 for both 2050 and 2070. Our results suggest that South Africa shall remain the sole and most suitable location for Blue Swallow breeding while most of the wintering season sites shall diminish because of climate change as demonstrated by Fig. 5.

The Pearson correlation coefficients demonstrated that there were very high correlations between the RCP 8.5 of 2050 and RCP 8.5 of 2070 ($r^2 = 0.97$). Similarly, the r^2 value for the RCP 2.6 of 2050 and RCP 2.6 of 2070 was also very high ($r^2 = 0.91$). Nonetheless, relatively low r^2 (0.65 and 0.63) values were observed for the correlation between the current climate scenario with the two RCP 8.5 scenarios for both periods (Table 2). The results of the one-way ANOVA (F (20.32), $p = .000018$) and the Tukey post hoc test showed that there were significant differences between the RCP8.5 of 2050 and 2070 with the current climate scenario.

3.4. Predicted habitat suitability along the longitude and latitude

Blue Swallows were particularly predicted to exist within the bounds above the 30°S latitude but below the 1°N and between the longitudes 27°E − 38°E (Fig. 6). Generally, Fig. 6 shows that the trend of the suitable area and probability of occurrence is likely to decline along the longitude and latitude. The general trend shows that the most

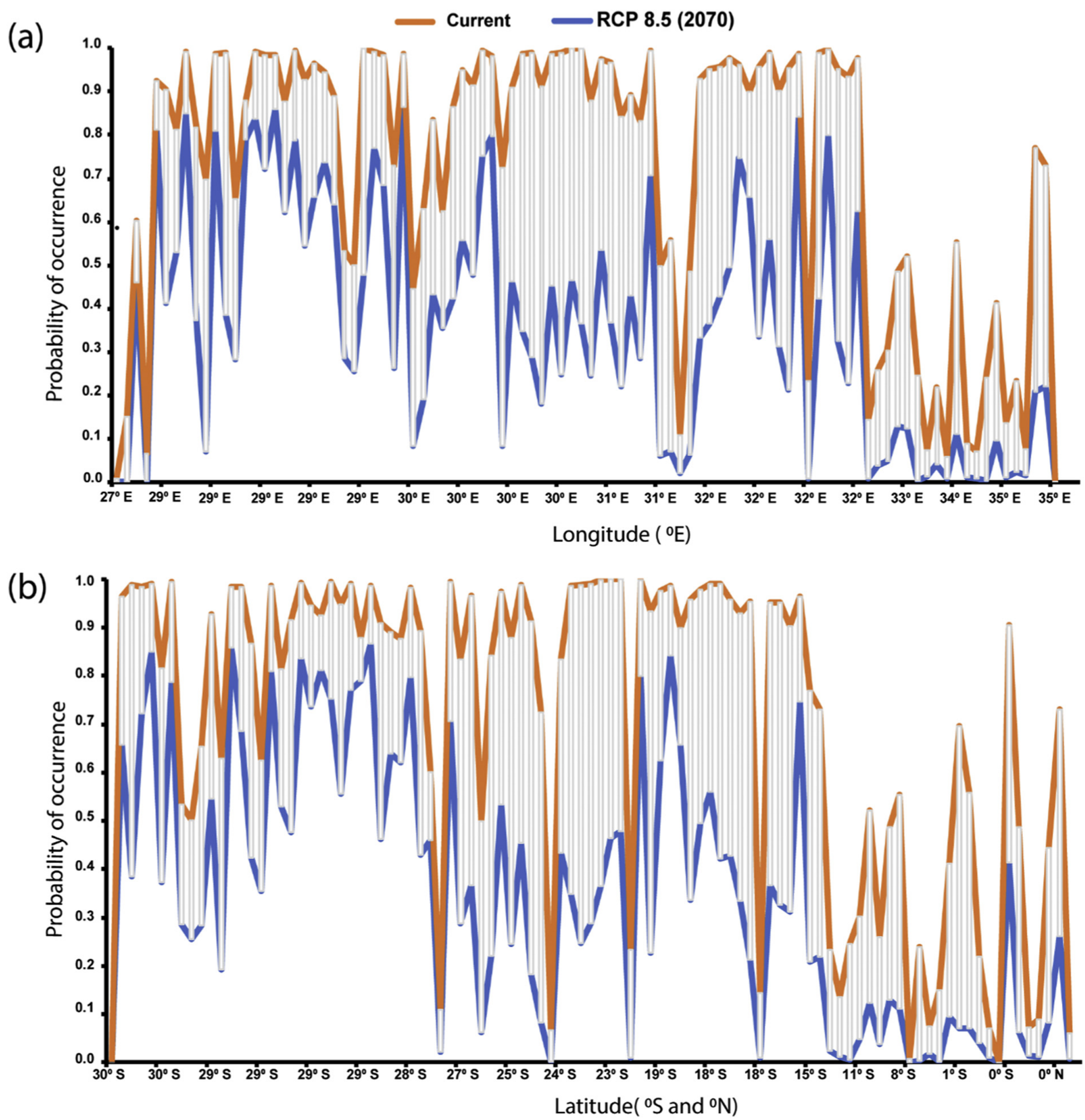


Fig. 6. Comparative analysis of the Probability of occurrence of the Blue Swallow using the current climate scenario and the future (RCP 8.5: 2070) based on the (a) longitude and (b) latitude location of the 106 presence-only data used in this analysis. The up and down bars show the magnitude of the reduction in habitat suitability at every point. Longer bars show huge declines in the Blue Swallow suitability while shorter bars represent small variations in the habitat suitability.

suitable habitat exists in the southern hemisphere, with South Africa having the most suitable and widespread habitat for the Blue Swallow than any other country. There is however a consistent suitability from the 30°S latitude until 28°S. Thereafter, there is a steady decline in suitability beyond the 28°S latitude until 18°S where the decline is evidently high towards the equator. The longitudes between 27°E and 30°E show very high probability of occurrence for the Blue Swallow, while very low probability of occurrence is shown between the longitudes 32°E and 35°E. Although the current climate scenario shows high probability of occurrence between the 30°E and 32°E there is a huge decline in the probability of occurrence using the RCP 8.5 scenario within the same longitudes bounds. Quantitative losses between the current and future climate scenarios are shown by the up and down bars in Fig. 6. The up and down bars further demonstrated that there were no anticipated suitability gains due to climate change in the whole of Africa.

4. Discussion

Climate change impacts on the Blue Swallow habitat pose major threat to its continued survival in all its migratory and foraging range. Huge future habitat losses, shrinkage and fragmentation were anticipated, suggested and flagged by our MaxEnt modelling. The Blue Swallow population in Africa will continue to decline and hang in a balance if sufficient and appropriate habitat is not set aside and strictly protected to safeguard sustainable populations (Evans and Bouwman, 2010b). It is essential to recognise the spatial dependencies between the geographic range size of species and the potential threats of habitat loss may cause high species extinction risk under global climate change scenarios (Rong et al., 2019). This is a crucial step in adaptive management of habitat conservation and sustainability of current species populations and the future. The adaptation, through better conservation management of the current available habitat and decision making with consideration of climate change is influenced by the availability of information on climate change impacts (Biber-freudenberger et al., 2016).

Therefore, in this study we used environmental variables in combination with presence records obtained from multiple sources to assess the impact of climate change on the distribution of the vulnerable Blue Swallow species in Africa. Using SDMs is one of the most reliable and central tools for determining species distribution and habitat suitability for threatened species particularly MaxEnt which uses presence-only data (Chunco et al., 2013; Padonou et al., 2015). MaxEnt performs better compared to other presence-only models in predicting range shifts for species (Elith et al., 2010b). We ensured accurate predictions by cooperating a sampling bias file and using the MESS predictions approach as highly recommended for small samples and biased location points when projecting to new environments or time space (Elith et al., 2010b; Kramer-Schadt et al., 2013; Mesgaran et al., 2014; Owens et al., 2013; Zurell et al., 2012)

Additionally, model accuracy assessment is an essential component of any computer-based species distribution modelling (Elith et al., 2010a). It ensures that the species distribution models represent the reality on the ground and can be validated by ground truth data (Merow et al., 2013). Generally, AUC is selected as an accuracy assessment standard for MaxEnt models (Khadka and James, 2017; Mbatudde et al., 2013; Padalia et al., 2014). Models with AUC values larger than 0.7 generally suggest good model performance (Elith et al., 2010a). In our study, AUC values for all the training and testing models were greater than 0.969, demonstrating that the models were excellent for simulating the distribution of the species and its present and future potential habitat. The mean of the replicated models exhibited small standard deviations which signified perfect fitting of the models. Therefore, the fundamental findings and outputs from this study can be relied on.

SDMs reflect the deep interrelationships between species and their habitat. Our results showed that the variables related to air temperature (Bio5), precipitation (Bio18) and elevation were central in defining the suitable habitat for Blue Swallows. Comparatively, previous studies have demonstrated that distribution of the species is affected by altitude, temperature and precipitation (Evans et al., 2015; Wakelin et al., 2018). Temperature and precipitation influence the range availability and range size for the Blue Swallow as it tolerates a strict temperature and precipitation as highlighted by our study. The response curves of these variables showed that temperature below 20°C and above 30°C is not conducive for the occurrence and survival of this species. These variables are associated with influencing the availability of mist grasslands on very high altitudes providing the necessary aerial arthropod feed requirements necessary for the Blue Swallows survival (Evans and Bouwman, 2010b). In addition, Blue Swallows have been identified to forage more in wetland-grasslands areas more than plain grasslands (Evans and Bouwman, 2010b). This explains why high precipitation averages greatly influence the availability and potential habitat of the species. Therefore, increased temperatures due to climate change shall lead to a decrease in the distribution of the species while extremely low or very high temperature cause localised extinctions of the species. This is constant with results of earlier studies, which suggested that climate change will have adverse effects on species distribution ranges (Qin et al., 2017; Rong et al., 2019).

The comparison between RCP2.6 and RCP8.5 for the two periods 2050 and 2070 showed that suitable area for the Blue Swallow decreased under RCP8.5 much larger than the RCP2.6 due to different changes of temperature. RCP2.6 is the lowest carbon emission scenario, and RCP8.5 is an extreme carbon emission scenario (IPCC, 2014). This is attributed to the fact that the increase in temperature was much greater under RCP8.5 than RCP2.6. Therefore, adaptation strategies could focus on maintaining and avoiding invasion of the current sites by agriculture activities or other land use types that do not promote survival of Blue swallows as also suggested by Ndang'ang'a (2007). We suggest that the current areas be formally upgraded to conservation protection status, particularly the Zimbabwean and Malawian breeding ranges that have been reported to have the best survival option regarding available population (Evans and Bouwman, 2010b). Although approximately 60% of the Blue Swallow breeding population is reported to be in strict protected areas while the wintering regions are chiefly unprotected (Evans and Bouwman, 2010b), there is urgent need to readdress the previous known locations based on climate change through intensive surveys and ultimately upgrade the protection status of these suitable regions or areas.

Further, these seasonal variations, increases in temperature and decline in precipitation will alter the food supply, photoperiod and circannual rhythms of these birds (Gwinner, 2003). This will influence their migratory regimes including arrival and breeding dates thus, reducing hatching success and driving population declines (Ndang'ang'a, 2007; Wakelin et al., 2018). Thus, studies of microclimates become very relevant to establish microclimate envelopes that will cause or have already caused local extinctions in localities like Busia in Kenya, parts of Uganda and South Africa where the Blue Swallows have previously existed (Ndang'ang'a, 2007; Wakelin et al., 2018). We suggest that governmental environmental institutions and other organisations working in these areas perform intensive localised analysis and also adopt citizen science and crowd sourcing information of sites and breeding successes of this species for effective monitoring. It is necessary to inspect and record nesting and breeding success to initiate designation of such areas for protection and championing conservation resources for environmental monitoring of negative activities such as bush encroachment or invasion by alien species which are likely to increase and encroach into the suitable grasslands because of climate change.

Our results show that the suitable habitat will decline as we move from the 30°S towards the equator because of climate change. This concurs with the climate predictions reported by Niang et al. (2014) who reported the temperature in the entire continent to continue rising particularly areas that already have high temperature. Additionally, these areas are likely to receive intensive rainfall which is not conducive for Blue Swallow breeding. Since our results suggest that South Africa will remain relatively suitable for the occurrence of the Blue Swallow, we recommend that current sites may be extensively and consistently surveyed for the presence and probable nesting and breeding success of the species. Prescribed burning of these areas can improve and promote the growth of various grass species, disturb bush encroachment and promote introduction of insect for the species to feed on (Mudereri et al., 2009).

The elevation variable revealed that altitudes between 1000 and 3000 m above sea level were the optimum for the existence of the Blue Swallow (Evans and Bouwman, 2010b). We discovered that the trend in the occurrence of Blue Swallows followed the high-altitude areas within the Afro-montane biome covered by moist savannah in Africa such as the Drakensberg mountains in South Africa, the Eastern Highlands in Zimbabwe, the Mitumba mountain ranges in DRC among others. These results are comparable to some of the ranges identified by BirdLife International (BirdLife International, 2019). However, these moist savannah grasslands have limited foraging range for Blue Swallows. The areas are often preferred for cash crop agriculture and horticulture production such as potato farming and tea (Mudereri et al., 2009). According to Evans and Bouwman (2010b) the preferred minimum radius for foraging by Blue Swallows is 1.5 km around the nest which might be reduced due to habitat fragmentation brought by these agricultural activities. Therefore, although our results show vast potential habitat for the Blue Swallow in Africa, the actual occurrence and survival could be determined by the local environment, the surrounding anthropogenic conditions and availability of sinkholes and aardvark holes for nesting (Mudereri et al., 2009). Wakelin et al. (2018) reported that Blue Swallows prefer the ecotones of wetlands and grasslands compared to agricultural areas in South Africa. We therefore, recommend localised management plans to consider protecting and conserving natural habitats and maintaining mosaic of grassland and wetland to take full advantage of ecotones within conserved areas. Our results also suggest the occurrence of Blue Swallows to be associated with open grasslands and shrub lands. The slight difference compared to the results of Wakelin et al. (2018) could be attribute to the broad legend of LULC classes used by the Africa land cover data that was used in our study as a proxy for the vegetation and habitat specific characterisation for the Blue Swallow.

In this study, we used bioclimatic variables to characterize environmental conditions in combination with elevation and LULC. However, other important environmental variables, such as distance to water sources, availability of food sources, soil properties, and conservation management interventions (Important Bird Areas: IBAs) which can influence species distribution were not considered in this study. While we agree that these variables are key to assess the final distribution of Blue Swallows, in this study, we however, emphasise on the necessity to assess only climate change impact to their fundamental habitat since their distribution very much depends on strict climate conditions. Hence, we decided to focus on assessing climate change effects on the habitat suitability only. However, conservation strategies at local nesting sites and along the migratory corridors and stop over sites remains vague but are significantly a crucial step in establishing other threats to the survival of the Blue Swallow. Furthermore, future studies could improve our modelling approach by conducting a country by country analysis and cooperating actual population sizes in their modelling or modelling specifically for breeding and wintering regions independently. These future studies could also explore influence of localised changes in LULC to the Blue Swallow species. This was not possible in this study as we could not secure the current precise population data which to our understanding is currently spatially limited and not current.

5. Conclusions

Our study modelled the potential habitat and distribution of Blue Swallows for the current and future climate change scenarios. Our results confirm the hypothesis that climate change will modify the distribution ranges of the species, which is crucial for understanding the dynamics of Blue Swallows under climate change scenarios. We recommend conservation and restoration prioritisation measures in the currently known sites and the locally extinct localities where Blue Swallows used to forage. These conservation prioritisation areas include the predicted suitable areas which have real distribution of the species such as the Eastern highlands of Zimbabwe, Eswatini, South Africa and DRC. Additionally, the restoration areas are the places where the predicted suitable area has no real distribution but historically used to house the species such as Busia grasslands of Kenya and Uganda. Furthermore, the unexplored very high suitability areas identified in Ethiopia, Mauritius and Madagascar can be earmarked for new introductions in the future. Our results could be used to provide reliable information on devising adaptive responses for the sustainable management of the Blue Swallows in all its migration range. This can help secure the limited range left for the Blue Swallow from any further urban development or agricultural expansion. The maps produced by our study can be used as an orientation guide to warrant conservation protection status for these areas. Integrating SDMs and climate scenarios into land management decision making can ultimately help decrease biodiversity losses or this species from going into extinction.

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