Habitat Suitability and Distribution Patterns of Rouget’s rail (Rougetius rougetii Guérin-méneville, 1843) in Ethiopia.

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Abstract

Geographical distribution and diversity patterns of bird species are influenced by climate change. The Rouget’s rail (Rougetius rougetii) is a ground-dwelling endemic bird species distributed in Ethiopia and Eritrea. It is a near-threatened species menaced by habitat loss, one of the main causes of population declines for bird species. The increasing effects of climate change may further threaten the species’ survival. So far, the spatial distribution of this species is not fully documented. With this study, we develop current potential suitable habitat and predict the future habitat shift of R. rougetii based on environmental data such as bioclimatic variables, population density, vegetation cover, and elevation using ten algorithms. We evaluated the importance of environmental factors in shaping the bird’s distribution and how it shifts under climate change scenarios. We used 182 records of R. rougetii from Ethiopia and nine bioclimatic, population density, vegetation cover, and elevation variables to run the 10 model algorithms. Among 10 algorithms, eight were selected for ensembling models according to their predictive abilities. The current suitable habitats for R. rougetii were predicted to cover an area of about 82,000 km² despite being highly fragmented. The model suggested that temperature seasonality (bio4), elevation, and mean daily air temperatures of the driest quarter (bio9) contributed the most to delimiting suitable areas for this species. R. rougetii is sensitive to climate change associated with elevation, leading to a large, shrinking distribution of suitable areas. The projected spatial and temporal pattern of habitat loss of R. rougetii suggests the importance of climate change mitigation and implementing long-term conservation and management strategies for this threatened endemic bird species.

INTRODUCTION

Habitat suitability is important for the survival of organisms, reproduction, and population development (Matthiopoulos et al., 2015; Spear et al., 2010). Several environmental factors including local resource availability, elevation, and levels of habitat disturbance, determine the distribution pattern and degree of habitat suitability of different bird species (Dunning et al., 1992; Evans et al., 2009; Garden et al., 2006; Saab, 1999). Thus, understanding a species’ biology and natural history should focus on studying the distribution in its habitat (Guisan et al., 2017). In this regard, Species Distribution Models (SDMs) are used to predict how the world’s biota will respond to climate change and other environmental factors. In addition, SDM helps to understand environmental predictors that could affect the range and distribution of species and also help identify where suitable habitats are distributed in space and time (Feng et al., 2019; Jetz et al., 2007). In the face of climate change where predicting how the natural environment and habitat affect ecosystems is increasingly difficult, SDMs are used as a critical tool for predicting these changes.
Climate change is one of the main causes of change in the spatial arrangement of suitable habitats for bird species in either direct or indirect ways (Stewart et al., 2022). Limiting factors affecting species distribution have been studied by researchers on species dispersal ability (Dormann, 2007), land use type (Sirami et al., 2017), availability of resources, soil condition, topography, and landscape structure (Franklin, 2013). Birds may adapt to the effects of climate change by gradually shifting their geographic ranges to track better thermal conditions, even if the habitat type and other resources might not perfectly match their ecological requirements (Bosco et al., 2022). Birds have adapted to changing habitats through evolutionary processes (morphological or phenological adaptation) (Sexton et al., 2009). They can adapt morphologically by increasing or decreasing in body mass to regulate heat better, or phenologically by adjusting the time they perform life events like mating, reproduction, hibernation, and migration (McWhorter et al., 2018; Sauve et al., 2021).

Animals adapt when habitats and natural cycles alter due to climate change. It is this ability to adapt that allows the majority of species to evolve over millions of years. However, it has recently been suggested that contemporary plants and animals will not be able to adapt quickly enough to keep up with the rate of human-driven climate (Radchuk et al., 2019). This is because, rapid climate change has the potential to affect survival or fitness by interfering with the energy required by organisms to maintain their basic levels of activity and conditions, reproduction, as well as their breeding, and migratory timing (Hoffmann et al., 2019; Huey & Buckley, 2022; IPCC, 2021).

Species distribution models are used to understand how species’ observed distribution is affected by a suite of environmental predictors and to subsequently predict how the potential distribution of the target species could change across space and time under different conditions, for instance, following climate change. It consisted of different tools and protocols that link the species presence to environmental factors like temperature and precipitation (Datta et al., 2020; Evans et al., 2009; Feng et al., 2019; Jetz et al., 2007; Thuiller et al., 2022). By studying the data and analyzing the distribution of a species, researchers can learn where the species may be located in the future in relation to climate change (Mason et al., 2019; Zuckerberg, 2017).

It is known that global climate change is a rapidly occurring phenomenon (IPCC, 2021) and it is primarily driven by anthropogenic greenhouse gas emissions that change Earth’s climate dynamics. This alteration has the potential to significantly impact organisms, from the genetic level to entire ecosystems. Specifically, climate change and intensive land use following population pressure are the major threats to high-altitude species in both protected and unprotected areas (Israel et al., 2016).

To study such changes and estimate the conditions suitable for a species to inhabit a given area, statistical models have been used to connect known species locations to a suit of environmental variables. Different studies have found that species distribution models can produce varied results based on different factors, such as the selected algorithms and predictors. It has been shown that no single species distribution model framework is best for all species and environments. Thus, it is important to be cautious when selecting the species distribution model to implement, because various modelling choices affect the accuracy of the obtained predictions. Comparison of multiple species distribution models is fundamental to selecting the models, or the combination of models (i.e., ensemble modelling), permitting minimal prediction error (Guisan et al., 2017). Most studies compare more than one model to minimize error and get the best result (Brown et al., 2014; Zeng et al., 2016). Some studies advise using presence-absence models, while others suggest presence-only models. Despite these differences, the selection of suitable models depends on the type of application, the extent to which models are calibrated, and the spatial resolution of the environment and the environmental predictors.

The family Rallidae contains 152 species (Gill et al., 2020). Africa hosts six endemic genera of Rallidae, with 23 endemic species distributed all over the continent, except in the areas that are deserts and ice-covered mountains. In Ethiopia, nine genera consisting of 12 extant species, some of which being resident, are reported, of which Rouget’s rail (\textit{Rougetius rougetii} ) is an endemic species to East Africa (Eritrea and Ethiopia) (Asefa et al., 2017). \textit{R. rougetii} population has drastically declined in the last few decades, and hence, it has been listed as near-threatened by the International Union for Conservation of Nature (IUCN).
since 1994 (http://www.birdlife.org). Currently, most Rallidae species inhabit a heavily degraded habitat, as they have lost much of their former suitable habitats and breeding sites (BirdLife International, 2023). In addition, they are observed in urban areas as feeding and breeding grounds along swampy and river streams with struggling anthropogenic pressures (BirdLife International, 2023).

We used species distribution models for prioritizing conservation areas that can support a considerable population of this near-endemic and threatened bird. In this regard, different individual distribution models were compared to predict the habitat suitability of *R. rougetii*. The present study gives empirical evidence on their current distribution and the prediction of future distribution (2056 and 2086) in Ethiopia. Hence, the present study aims at (1) identifying the most important environmental variables influencing model predictions, (2) determining the potential distribution of *R. rougetii* in the current and future climate conditions, and (3) estimating the range change of *R. rougetii*, and synthesizing the potential effect of climate changes. To support the conservation efforts of this near-threatened species, this study offers vital insights regarding the distribution and characteristics of *R. rougetii*’s natural habitats, highlighting both the species’ existing distribution and future appropriate habitats. Intending to efficiently reduce habitat loss and promote conservation efforts, this study forecasts future viable habitats in addition to mapping the current distribution.

**MATERIALS AND METHODS**

**Occurrence data**

We used primary and secondary occurrence data of *R. rougetii* to study the current habitat distribution and predict the future in Ethiopia using an ensemble modeling approach (Fig. 1). The primary species occurrence data were recorded during field surveys (October, 2021-December, 2022) in the southeastern (6029-7010 N and 39028-39058 E) and central (8045-9049 N and 38039-38054 E) highlands of Ethiopia. A total of 98 occurrence points were recorded from the selected areas (Bale Mountains National Park, Goba town, and Addis Ababa city), and the minimum distance between the occurrence points was one kilometer which is aligned to a one-kilometer square raster grid resolution of bioclimatic variables.

Secondary occurrence data were downloaded from the online source Global Biodiversity Information Facility (GBIF) (http://www.gbif.org/). A total of 1161 occurrence points were downloaded and 84 occurrences of data were selected for this study. The data were filtered using the year of occurrence point recorded (included only recorded data after 1981) and included those outside of the primary data collection areas. We rarefied and aligned to a one-kilometer square raster grid resolution of bioclimatic variables using “Spatially Rarefy Occurrence Data for SDMs” in the SDM Toolbox v. 2.5 (ArcGIS v. 10.7) to reduce spatial autocorrelation among all occurrence points. We randomly generated 10,000 pseudo-absence points within the study area, excluding presence points using the Biomod2 package in R (Thuiller et al., 2022) because it has a significant impact on the power of prediction to identify the predictor variable (Barbet-Massin et al., 2012).

Overall, we generated a sample with data (SWD) by combining and rarifying 182 occurrences and 10,000 pseudo-absence points to predict this bird species’ current geographical distribution and future suitable areas. We used sufficient occurrence data because the predictive power of habitat suitability models is affected by numerous factors, of which occurrence data is the major one (Guisan et al., 2017).
Ecological predictor variables

We used 19 bioclimatic variables of current climate downloaded from Climatologies at high resolution for the earth’s land surface areas (CHELSA) version 2.1 (available at http://envicloud.wsl.ch/) with the highest resolution of 30 arc seconds (~1 km), which are the average for the years 1981-2010 (Karger et al., 2017). Not only bioclimatic variables but also downloaded elevation (from the Shuttle Radar Topography Mission digital elevation model; SRTM-DEM; https://srt.csi.cgiar.org/), population (*R. rougetii* habitat which includes urban areas, therefore it is important to understand human disturbances) (from https://www.ciesin.org/), and vegetation (from https://landscapeportal.org/layers/geonode:veg_ethiopia) (see Table 1). To avoid the effect of multi-collinearity among predictor variables, we used pairwise Pearson’s correlation coefficients (r < |0.7|) (Guisan et al., 2017) and a variance inflation factor (VIF < 10) (Thuiller et al., 2004). Accordingly, out of the total downloaded variables 12 variables were selected for this study (see summary in Table 1). Also, we downloaded the future climate projections under three shared socio-economic pathway (SSP) scenarios (i.e. ssp126, ssp470, and ssp585), from CHELSA for two periods 2041-2070 and 2071-2100 at a spatial scale resolution of 30s arc (~1km²) which has the same spatial resolution of current period data. Since the future model prediction only depicts the constraints of climate change, the elevation, population, and vegetation variables used are the same as those used in the current suitable area prediction.

Model fitting and evaluation

We used an ensemble modeling approach, to develop an accurate projection for *R. rougetii* in Ethiopia (Grenouillet et al., 2011; Marmion et al., 2009; Norberg et al., 2019; Oppel et al., 2012; Stohlgren et al., 2010). The presence and pseudo-absence data were set randomly and we used 70% of the points for training and the remaining 30% for model tests. The training data set and selected environmental variables were used for the 10 algorithms test, including the generalized Linear Model (GLM), Generalized Boosting Method (GBM), Generalized Additive Model (GAM), Classification Tree Analysis (CTA), Artificial Neural Network (ANN), Surface Range Envelope (SRE), Flexible Discriminant Analysis (FDA), Multivariate Adaptive Regression
Splines (MARS), Random Forests (RF), and Maximum Entropy (MAXENT) (Thuiller et al., 2022) (available at https://cran.r-project.org/web/packages/biomod2.pdf). To evaluate the predictive performances of these algorithms, we used true skill statistics (TSS) and area under the receiver operating characteristics curve (AUC) (Allouche et al., 2006; Datta et al., 2020). Considering results of TSS ≥ 0.7 and AUC ≥ 0.9 were chosen (Fig. 3) for the prediction of the habitat suitability under present and future projected climates using the Biomod2 package in R (Guisan et al., 2017).

After selecting the best-performed models based on TSS and AUC scores, we employed these models for predicting the distribution of the study bird species. We used the “BIOMOD_EnsembleModelling” function to build ensemble models (Marmion et al., 2009; Thuiller et al., 2004). We opted for two ensemble methods, namely committee averaging and weighted mean, in order to reduce the number of outputs and minimize the algorithm’s bias effects in the individual predictions. However, upon comparing these ensemble options, it became evident that committee averaging provided a slightly better evaluation than the weighted mean option. Consequently, we chose committee averaging to present the results (Thuiller et al., 2022).

For the current and future projections (Dormann et al., 2007; Thuiller et al., 2004), we used the functions BIOMOD_Projection and BIOMOD_Ensemble forecasting, respectively. To build the individual models, we used the same environmental raster cells (spatial scale resolution of 30 arc seconds), either current projection or future projections (under different scenarios, i.e., ssp126, ssp470, and ssp585). To estimate the change in the range distribution size of *R. rougetii*, the number of raster cells was counted and classified as the stables areas (suitable/unsuitable), loss and gain areas by comparing suitable habitats under current and future climate conditions (Datta et al., 2020; Guisan et al., 2017; Guo et al., 2021; Thuiller et al., 2022). All analyses were performed in R software version 4.2.2 (R Core Team) and followed standard protocol for reporting species distribution models (Zurell et al., 2020).

RESULTS

Model performances and contributions of predictor variables

The selected eight SDM algorithms (GLM, GBM, GAM, CTA, ANN, SRE, FDA, MARS, RF, MaxEnt) were used to build an ensemble model (evaluation metric quality threshold = 0.7) based on their good predictive performance using TSS and AUC values (Fig. 2). Model performance was evaluated based on the full run of each algorithm. The mean AUC varied between 0.79 ± 0.026 (SRE) and 0.96 ± 0.018 (GBM), and also the mean TSS varied between 0.58 ± 0.052 (SRE) and 0.87 ± 0.085 (RF). The SRE and FDA algorithms displayed weaker predictive performances than the others, excluding them from the final ensemble model (Fig. 2).

![Figure 2. Evaluation of the predictive potential of ten species distribution models (SDMs) algorithms (GLM, GBM, GAM, CTA, ANN, SRE, FDA, MARS, RF, MaxEnt) for estimating habitat suitability of *R. rougetii* based on True Skill Statistics (TSS) and Area under the receiver characteristic curve (AUC) scores. Temperature-related factors’ (total contribution of 44.75%) were the most influential in determining suitable](image-url)
conditions for *R. rougetii*, and the precipitation-related factor contribution was the second, totaling 29.48%. Individually, the mean of variable importance by algorithm showed that bio4 (19.73 ± 1.28) was the most influential variable in limiting the habitat suitability of *R. rougetii*. The elevation (elev) and bio9 were also the second and third significant variables in limiting the suitability of habitats of *R. rougetii* accounting for 16.62 ± 2.41 and 15.99 ± 2.30, respectively (Fig. 3). Consequently, the elevation and temperature-related factors were prominent factors in determining the habitat suitability of this threatened bird species.

Figure 3. Percent contributions of the 12 selected predictor variables in the ensemble model of habitat suitability for *R. rougetii*

**Habitat suitability under present and future climates**

According to the ensemble model projection, the currently suitable areas for *R. rougetii* are mainly located in the highlands of Ethiopia, covering almost 80,000 km² (Fig. 4). Several suitable areas were predicted in the eastern mountainous areas, most of the central highlands, and southeastern Ethiopia (the chain of Arsi-Bale Mountains). Further, a continuous “core” suitable area emerged in most of the central and southeastern Ethiopian highlands. Some suitable habitats are shown to be fragmented in the southwest, the Central Rift Valley, and the northern region of the country. Similar fragmented areas were observed in the northern part of the country.
The ensemble model projections suggested that the suitable areas for *R. rougetii* will be reduced significantly under both the future time horizons considered (2041-2070 and 2071-2100), with varying extent of lost suitable areas depending on the shared socio-economic pathway scenarios (SSPs) used to predict future climatic conditions. The predicted suitable habitats of *R. rougetii* under SSP126, SSP370, and SSP585 covered about 61,000 km$^2$, 41,000 km$^2$, and 43,000 km$^2$, respectively in 2041-2070 and 56,000 km$^2$, 35,000 km$^2$, and 36,000 km$^2$, respectively in 2071-2100 (Fig. 5; Table 2).
Figure 5. Predicted habitat suitability for the R. rougetii under future climate conditions in 2041-2070 and 2071-2100 was produced using SSP126, SSP370, and SSP585 scenarios.

The results of range size change in R. rougetii in 2041-2070 and 2071-2100 indicated a reduction under future climate conditions, and a big loss was observed in areas in the northern and lowland areas of the country (Fig. 6). Comparing current suitability maps with future suitability maps showed that significant portions of the suitable areas have been lost, reduced, and changed in the north, central, and eastern Ethiopian highlands.

Figure 6. Current and future habitat suitability range changes in R. rougetii; “lost” = habitat loss, “pres” = remain suitable, “abs” = remain unsuitable, and “gain” = unsuitable habitat changed to suitable.

The habitat suitability projections for R. rougetii under future climatic conditions varied based on the shared socio-economic pathway scenarios (SSPs) used (Table 2). The highest loss in habitat range change is observed under SSP585 (58%) in 2071-2100 revealing a significant loss of suitable areas for the bird from the current situation to future climate change.
DISCUSSION

This study examined the extent of suitable habitat of *Rougetius rougetii* under present and future climatic conditions. Furthermore, the variables influencing the geographical distribution of *R. rougetii* in Ethiopia were examined and ensemble models were built to predict current and future habitat suitability. A practical conservation strategy begins with discovering suitable habitats for vulnerable species (Zhang et al., 2012) such as *R. rougetii*. The ensemble model projection under current conditions showed that the suitable areas for *R. rougetii* in Ethiopia are far smaller than the geographic range reported for this species by BirdLife International (www.datazone.birdlife.org). On the basis of the current habitat suitability map, the species is likely to occur in Ethiopia’s highlands and fragmented localities in the Central Rift Valley. The model predicted *R. rougetii* will lose a significant proportion of its suitable habitat in the future despite some newly suitable areas predicted to be gained. The results of this study demonstrate that *R. rougetii* is sensitive to climate change, where a significant portion of suitable habitat loss in its previous range was observed. The habitat specialists, particularly those with comparatively weak colonization potential are poorly adapted to the changing climate and fragmentation of habitat (Travis, 2003). This bird species may be in danger of extinction due to habitat loss under different climate scenarios, suggesting future climate conditions (Ansley et al., 2023).

Among the twelve variables adopted in the model, bio4, bio9, and elevation have highly contributed to estimating the potential distribution of *R. rougetii*. This prediction is supported by a similar study in Great Britain where few climate change variables affected the distribution of bird species (Araújo et al., 2005). In the current study, in addition to climate change, other important variables such as elevation, population, and vegetation also affected the distribution of the species. High human population density can affect the distribution of threatened bird species such as *R. Rougetii*, which has a restricted range, poor ability to move, and a declining population, posing significant conservation challenges (Wuebbles et al., 2018).

Bird populations are declining globally and losing their suitable habitats due to climate change (Mason et al., 2019; Parmesan, 2006; Thackeray et al., 2010; Zuckerberg, 2017). Several SDMs have been developed to predict the suitability of their habitat under projected climatic conditions. Climate change is not only directly causing population declines for many bird species, but it may also promote new biotic interactions (Clavero et al., 2011).

Climate change may affect birds by changing the suitability of areas they currently inhabit forcing them to colonize new sites to find suitable habitats (Kuussaari et al., 2009). Finding such suitable habitats, however, depends on the dispersal ability of the bird species. Otherwise, birds may adjust phenologically or physiologically to cope with the challenge of climate change (Chmura et al., 2019; Quratulann et al., 2021; Scridel et al., 2018). If warming is neither too fast nor too pronounced, birds can adapt to rising temperatures through microevolution, i.e. by modifying the genetic structure of the population (Gienapp et al., 2008).

There is a significant difference between the suitable area under the current and the future scenario. Compared to the current projection, more than half of the suitable area is lost in the future predictions, except in SSP126. It has been suggested that climate change may be the reason behind these future predictions or potential impacts on the ecosystem (Bellard et al., 2012; Malhi et al., 2020). Climate change has a detrimental impact on many species’ appropriate regions, but it may also expand the suitable area for some species (Malhi et al., 2020; Martay et al., 2017). The assumptions made regarding dispersion capacities in abiotic and biotic interactions can have a substantial impact on the forecasts of species distribution models (Zuckerberg, 2017). We made the premise of limitless dispersion potential in our work, and our SDMs estimates suggest that the appropriate habitat for *R. rougetii* will probably diminish significantly. The high rate of increase in human population coupled with habitat disruptions may lead to the extinction of the species despite the presence of suitable habitats (CBD, 1992). Climate change interacts with and intensifies human modifications to the landscape, altering ecosystem structure and function, biodiversity, and species distributions (Rinawati et al., 2013).

The present study suggests that *R. rougetii* is vulnerable to climate change, which will lead to a large range
shift of suitable habitats under future climatic conditions. However, large amounts of currently suitable habitat may disappear because of land-use change and habitat loss due to the rapid growth of the human population in the highlands of Ethiopia. Implementing long-term conservation and management strategies in the *R. rougetti* distribution range, along with mitigation strategies to buffer climate change effects, is mandatory to preserve this threatened bird species from extinction.

**AUTHOR CONTRIBUTIONS**

**Hailu Tilahun Argaw**: Conceptualization (lead); data collection and curation (lead); formal analysis (lead); investigation (lead); methodology (lead); project administration (lead); validation (lead); writing original draft (lead); writing review and editing (lead).

**Bezawork Afework Bogale**: Conceptualization (equal); supervision (lead); project administration (lead); validation (lead); writing review and editing (lead).

**Afwork Bekele**: Conceptualization (equal); supervision (lead); project administration (lead); validation (lead); writing review and editing (equal).

**Anagaw Atickem**: Formal analysis (equal); writing review and editing (support).

**Diress Tsegaye**: Writing review and editing (support).

**Nils Chr. Stenseth**: Writing review and editing (support).

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**CONFLICT OF INTEREST STATEMENT**

The authors declare that there is no conflict of interest.

**DATA AVAILABILITY STATEMENT**

All important data are included in the main manuscript. The data supporting the findings is available upon request in the hands of the first (Hailu Tilahun Argaw) authors.

Location records and environmental variables used to generate the models are made available on Dryad. https://doi.org/10.5061/dryad.547d7wmfq.

Modelling procedures reported followed the ODMAP protocol (Zurell et al., 2020, Ecography, 43(9), 1261–1277. https://doi.org/10.1111/ecog.04960).

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REFERENCES


Table 1. Summary of selected ecological predictor variables used for modeling the habitat suitability of *R. rougetii* with their category, code, unit of measurement, data sources and variance inflation factor (VIF). We included only those variables that show < 10 VIF

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<th>Category</th>
<th>Variables</th>
<th>Code</th>
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<td></td>
<td>Mean daily mean air temperatures of the driest quarter</td>
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Table 2. Range size change in *R. rougetii* under three shared socio-economic pathway scenarios (SSPs) in 2056 and 2086.

<table>
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<td></td>
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