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Combining species distribution models and moderate resolution satellite information to guide conservation programs for reticulated giraffe

R. D. Crego[1,2], J. Fennessy[2], M. B. Brown[1,2], G. Connette[1], J. Stacy-Dawes[3], S. Masiaine[4] & J. A. Stabach[1]

1 Conservation Ecology Center, Smithsonian National Zoo, Conservation Biology Institute, Front Royal, VA, USA
2 Giraffe Conservation Foundation, Windhoek, Namibia
3 Conservation Science & Wildlife Health, San Diego Zoo Wildlife Alliance, Escondido, CA, USA
4 Twiga Walinzi, Loisaba Conservancy, Nanyuki, Kenya

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Correspondence
Ramiro D. Crego, Conservation Ecology Center, Smithsonian National Zoo, Conservation Biology Institute, 1500 Remount Rd, Front Royal,VA 22630, USA.
Email id:
Email: ramirocrego84@gmail.com

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Abstract

The conservation of threatened and rare species in remote areas often presents two challenges: there may be unknown populations that have not yet been documented and there is a need to identify suitable habitat to translocate individuals and help populations recover. This is the case of the reticulated giraffe (*Giraffa reticulata*), a species of high conservation priority for which: (a) there may be unknown populations in remote areas, and (b) detailed maps of suitable habitat available within its range are lacking. We implemented a species distribution modeling (SDM) workflow in Google Earth Engine, combining GPS telemetry data of 31 reticulated giraffe with Landsat 8 OLI, Advanced Land Observing Satellite Phased Arrayed L-band Synthetic Aperture Radar, and surface ruggedness layers to predict suitable habitat at 30-m spatial resolution across the potential range of the species. Models had high predictive power, with a mean AUC-PR of 0.88 (SD: 0.02; range: 0.86–0.91), mean sensitivity of 0.85 (SD: 0.04; range: 0.80–0.91), and mean precision was 0.81 (SD: 0.02; range: 0.79–0.83). Model predictions were also consistent with two independent validation datasets, with higher predicted suitable habitat values at known occurrence locations than at a random set of locations ($P < 0.01$). Our model predicted a total of 5519 km^2 of potentially suitable habitat in Kenya, 963 km^2 in Ethiopia, and 147 km^2 in Somalia. Our results indicate that is possible to combine moderate spatial resolution imagery with telemetry data to guide conservation programs of threatened terrestrial species. We provide a free web app where managers can visualize and interact with the 30 m resolution map to help guide future surveys to search for existing populations and to inform future reintroduction assessments. We present all analysis code as a framework that could be adapted for other species across the globe.

Introduction

A major component of the biodiversity crisis is the extirpation of wildlife populations across ecosystems globally (Dirzo *et al.*, 2014). Often, the defaunation of species is so severe that remnant populations go unnoticed for decades, or longer, by the scientific community before the potential for discovery (Scheffers *et al.*, 2011). Creation and management of protected areas, increasing connectivity across fragmented populations, and reduction of anthropogenic pressures can, in many cases, protect species from extinction. However, reversing the defaunation process for many species requires extreme measures, including species translocations, to reestablish populations across their distributional range (Seddon *et al.*, 2014).

With more than 600 mammal species on the brink of extinction (Macdonald, 2019), the translocation of individuals to establish new populations and secure viable metapopulations is increasingly becoming an important component of conservation management strategies (IUCN, 2013). Along with social and economic factors, the identification of large areas with adequate habitat to meet the metabolic needs of translocated animals is critical to the success of translocations (IUCN, 2013). In this regard, species distribution models (SDMs), a popular statistical tool for linking occurrence data with environmental variables to predict the potential distribution of species (Guisan & Zimmermann, 2000; Guisan & Thuiller, 2005; Araújo *et al*., 2019), have emerged as a valuable tool for identifying suitable areas for conservation translocations of threatened species (Cilliers *et al*., 2013; Payne & Bro-Jørgensen, 2016; Draper, Marques, & Iriondo, 2019; Bellis *et al*., 2020; Eyre *et al*., 2022). Most analyses rely on coarse spatial resolution explanatory variables (i.e., ~1000 m); however, species relationships with the environment can be poorly captured in analyses with a coarse spatial grain (Mertes & Jetz, 2018), limiting their utility to inform reintroduction assessments.

Recent studies have introduced the concept of using unclassified multispectral satellite imagery as predictor variables to assess suitable habitat for species (Lahoz-Monfort *et al*., 2010; Shirley *et al*., 2013; St-Louis *et al*., 2014; Remelgado *et al*., 2018; Oeser *et al*., 2020; Zhang *et al*., 2022). This analytical approach provides a strategy to account for fine spatiotemporal variation in habitat characteristics and supports fine-scale habitat suitability predictions (He *et al*., 2015). Incorporating raw spectral information can also result in more informative SDMs than using subjective land-cover classifications as predictor variables, which are frequently derived from satellite imagery with varying degrees of error (Bradley & Fleishman, 2008; Oeser *et al*., 2020). However, processing large amounts of satellite data at large spatial scales requires high computing capacity. A recent workflow for fitting SDMs in Google Earth Engine (Crego, Stabach, & Connette, 2022), a cloud-based spatial analysis platform that provides free access to a high-performance computational infrastructure (Gorelick *et al*., 2017), has reduced the barrier to using raw satellite information as predictor variables for SDMs.

We explored the utility of combining satellite data within a SDM framework in GEE for identifying potential suitable habitat for reticulated giraffe (*Giraffa reticulata*) (Fennessy *et al*., 2016; Winter, Fennessy, & Janke, 2018; Coimbra *et al*., 2021) across its geographic range. This species is distributed mainly across northeast Kenya (O'Connor *et al*., 2019; Brown *et al*., 2022). Like many other giraffe populations across East, Central, and West Africa, reticulated giraffe have experienced a sharp decline in abundance and a contracting distribution in recent decades. As a result, reticulated giraffe are listed as endangered on the IUCN Red List (Muneza *et al*., 2018; Brown *et al*., 2022). The decline in this species is largely due to habitat loss, fragmentation, and degradation (Muneza *et al*., 2018). Recent reviews of the status of reticulated giraffe populations indicate an increase in estimated abundance (Brown *et al*., 2022) and a 14% increase in estimated range size, mostly within northeast Kenya (O'Connor *et al*., 2019). Both increases are likely due to improved data quality, rather than an actual increase in abundance or distribution. However, a detailed understanding of the extent of their range and potential habitat remaining is limited despite how critical this information is for future conservation efforts, such as targeted surveys, corridor development, and conservation translocations.

Translocations of different giraffe species have occurred within and across numerous African range and non-range states for decades (Chege, 2008; Malyjurkova *et al*., 2014; Flanagan *et al*., 2016; Muller *et al*., 2020; Gippoliti, Robovský, & Angelici, 2021). In recent years, detailed information on best practices for giraffe translocation assessments has been developed that includes capture, handling, transportation, and monitoring (Fennessy *et al*., 2022). In this study, we aimed to model the potential habitat suitability of reticulated giraffe across the species' range by combining moderate-resolution satellite imagery data with telemetry data. Our fine-scale mapping of current habitat suitability provides an important tool for determining the suitability of areas identified for giraffe conservation translocations, guiding the decision-making process. Maps will also be valuable to guide future giraffe surveys across remote areas. This study provides a model for how habitat suitability modeling based on satellite imagery can provide an additional tool for guiding surveys and conservation translocations of other threatened species.

Materials and methods

Species telemetry data

We assembled a telemetry dataset of thirty-one (31) reticulated giraffe fitted with solar-powered GPS devices in central and northern Kenya during 2019–2020. Devices, manufactured by Savannah Tracking Ltd, Kilifi, Kenya, were programmed to collect hourly fixes with an average positional accuracy of 12.8 m (Hart *et al*., 2020). Animals were tracked for an average of 209 days (range: 8–462). As part of the data cleaning processes, aberrant or abnormal GPS fixes were removed following Bjørneraas *et al*. (2010). We also excluded all points collected by devices up to 24 h after the animal capture and 24 h before the last recorded location (Northrup, Anderson, & Wittemyer, 2014). To reduce temporal autocorrelation, we randomly selected one fix per day for each individual (Holloway & Miller, 2017; Oeser *et al*., 2020; McCabe *et al*., 2021). We set the spatial resolution of our analysis to 30 m, rarifying the telemetry dataset further to maintain a standard of one observation per pixel, resulting in 5778 presence points for modeling (Veloz, 2009; Boria *et al*., 2014; Fourcade *et al*., 2014).

Predictor variables

We modeled giraffe habitat suitability using atmospherically corrected Landsat 8 OLI surface reflectance (SR) collection 2, Advanced Land Observing Satellite (ALOS) Phased Arrayed L-band Synthetic Aperture Radar (PALSAR) information, and surface roughness as predictor variables. We filtered the Landsat 8 SR collection from the GEE catalog to retain only images that overlapped our area of interest, and which were collected from 01 January 2019 to 31 December 2020, to match the temporal interval of the telemetry data. Only images with <20% cloud cover were considered for analyses. For each of the 482 resulting Landsat-8 images, we masked out low-quality pixels (i.e., clouds, cloud shadows, and saturated pixels) using a cloud mask and rescaled pixel values with the appropriate scaling factors (USGS, 2022). We selected the blue, red, green, near-infrared (NIR), shortwave infrared 1 (SWIR1), and shortwave infrared 2 (SWIR2) bands for analysis. For each image, we also derived two indices to account for key ecological interactions more specifically. First, we calculated the Normalized Difference Vegetation Index $\left(\mathrm{NDVI}:\frac{(\mathrm{NIR}-\mathrm{Red})}{(\mathrm{NIR}+\mathrm{Red})}\right)$. Vegetation indexes derived from satellite imagery have been proved useful in predicting habitat use of large herbivores in general and giraffe in particular (Ryan *et al*., 2012; Borowik *et al*., 2013; Pettorelli *et al*., 2014; Tyrrell, Russell, & Western, 2017; Brown & Bolger, 2020; Crego *et al*., 2020). Second, we derived a Bare Soil Index (BSI; $\left(\frac{(\mathrm{Red}+\mathrm{SWIR1})-(\mathrm{NIR}+\mathrm{Blue})}{(\mathrm{Red}+\mathrm{SWIR1})+(\mathrm{NIR}+\mathrm{Blue})}\right)$; Rikimaru, Roy, & Miyatake, 2002). We incorporated BSI based on the assumption that areas overgrazed with livestock will present high bare soil cover (Figure S1: Appendix S1) and are likely to be avoided by giraffes when livestock densities are high (Crego *et al*., 2020). We created a composite for each band by calculating the median pixel value of all unmasked pixels across all Landsat images in our filtered time series. Similarly, we created a second composite for each band with the standard deviation of all unmasked pixels to account for the temporal variability in spectral reflectance.

Our models also incorporated ALOS-PALSAR HH and HV polarization data because of their recognized value for identifying woody vegetation (Shimada *et al*., 2014), the main source of forage for giraffe (Kartzinel *et al*., 2019; Brown & Bolger, 2020). We filtered the ALOS-PALSAR dataset to retain mosaics for 2019–2020 and calculated the median pixel value for each pixel of the HH and HV bands. We also calculated surface ruggedness, an important variable determining suitable habitat for ungulates (Killeen *et al*., 2014). For this, we obtained elevation data from the 30 m Shuttle Radar Topography Mission (SRTM; Farr *et al*., 2007) and calculated the standard deviation of elevation in a moving window of a 5-pixel radius. Rugged terrain would show a greater difference in elevation among neighboring pixels, resulting in higher standard deviations, whereas areas with lower standard deviations (closer to 0) represent smoother terrain.

From the list of covariables, we masked out all pixels containing permanent water using the global water surface product (Pekel *et al*., 2016). The final multi-band image for species distribution modeling consisted of 18 bands: median composites for Landsat-8 bands 2 to 7, NDVI and BSI, standard deviation composites for each of these bands, median composites for ALOS-PALSAR HH and HV bands, and surface ruggedness. All giraffe tracking data and the covariates incorporated for modeling purposes can be visualized directly in GEE (https://gcfspatial.users.earthengine.app/view/reticulatedgiraffesdm).

Model fitting and k-fold spatial block cross-validation

We modeled potential habitat suitability for reticulated giraffe using random forest classifiers and a repeated (5-fold) spatial block cross-validation technique (Roberts *et al*., 2017; Valavi *et al*., 2019). We defined 10 × 10 km spatial blocks and randomly split the blocks five times, with 70% of each split used for model training and 30% for model validation ensuring spatial independence between training and validation datasets. Blocks were created in an area defined by the known geographic range as first identified by O'Connor *et al*. (2019). At each iteration, occurrence points within the set of training blocks were used for model training. The remaining occurrence points were used for validation. We generated an equal number of pseudo-absences as occurrence data for each of the five datasets used for model fitting and for model validation given random forest performance is better with balanced datasets (Evans *et al*., 2011; Barbet-Massin *et al*., 2012; Sillero *et al*., 2021). We limited the area to create pseudo-absences at distances larger than 100 m from any occurrence point (Figure S2: Appendix S1). Five replicates have been shown to be sufficient for datasets with >1000 and <10 000 pseudo-absences (Barbet-Massin *et al*., 2012). We fitted a random forest model (500 trees) to each individual training dataset. We examined the relative importance of each of the 18 covariates in predicting habitat suitability by calculating the average proportional contribution of each band indicated by the GINI index from across the five separate estimates produced by each random forest classifier.

We made separate predictions for each of the five iterations of model fitting and generated a final map by calculating the mean pixel value from across the five model outputs. We also estimated pixel-specific standard deviation from the five model iterations as a measure of model prediction uncertainty. We assessed model accuracy for each model iteration by calculating the threshold-independent Area Under the Precision-Recall Curve (AUC-PR; Sofaer, Hoeting, & Jarnevich, 2019). The AUC-PR ranges from 0 to 1, with 1 indicating a perfect prediction of presence data, and the prevalence of presence locations in the dataset (0.5 for a balanced dataset) indicating predictions are not better than random (Sofaer, Hoeting, & Jarnevich, 2019). This metric is not influenced by the number of absences and provides a better indication of the ability of the model to correctly predict presence locations (Sofaer, Hoeting, & Jarnevich, 2019). Additionally, we calculated the threshold-dependent sensitivity (the true positivity rate) and precision (true positives divided by the sum of true positives and false positives) for each model iteration (Fielding & Bell, 1997) as additional information on model performance. We calculated the threshold habitat suitability value that maximized the sum of sensitivity and specificity (Liu, Newell, & White, 2016). We reclassified the final averaged habitat suitability map into a binary potential distribution map using the average threshold among the five individual models. We used this binary distribution model to quantify potential suitable habitat within the 'known' and 'possible' reticulated giraffe range, as identified by O'Connor *et al*. (2019), and an extra 50 km buffer to the north, east, and west of this distributional range to include areas where giraffe potentially occur in Somalia and Ethiopia. We did not extend the buffer to the south as those areas correspond to the known range of the Masai giraffe (*G.*

tippelskirchi) (Fennessy *et al*., 2016; Winter, Fennessy, & Janke, 2018; Coimbra *et al*., 2021). All model scripts are available at: https://code.earthengine.google.com/?accept_repo=users/gcfspatial/RetGirManuscript.

Independent model validation

We further assessed model accuracy using two independent reticulated giraffe occurrence datasets. First, we downloaded all reticulated giraffe i-Naturalist records from the Global Biodiversity Information Facility (GBIF) dataset (GBIF.org (28 July 2022); https://doi.org/10.15468/dl.vrr7r8) from 2019 to 2020, matching the dates of all remote sensing data included in our analyses. For each observation, we inspected the metadata and associated photos to ensure all observations were correctly identified, resulting in 36 records for model validation. Second, we incorporated giraffe observations recorded during the months of May 2015 as part of the Great Elephant Census (GEC) aerial survey across Laikipia and Samburu Counties, Kenya (Chase *et al*., 2016). Although the GEC was designed specifically to count African savanna elephant (*Loxodonta africana*), other large mammal sightings were also recorded, including all giraffe species. Animals were counted within a 150–200 m strip width on each side of a plane. Coordinate locations of the plane were recorded at each observation. Further details on the standardized protocol used during the GEC are provided in Chase *et al*. (2016). The GEC dataset for model validation consisted of 335 reticulated giraffe records. We used our fitted models to predict reticulated giraffe distribution using a 2-year composite of Landsat-8 with images from 1 year before and after the survey month (May 2015) and ALOS-PALSAR annual composites for 2014 and 2015.

Given that the reticulated giraffe is a taxon of conservation concern, the coordinates reported in GBIF are associated with uncertainty for security reasons. To account for the lack of precision in the coordinates of both the GBIF and GEC data, compared to the 30 m resolution of model predictions, we buffered each giraffe record by a 100 m radius. We then extracted the mean habitat suitability prediction within each buffer polygon from the final averaged habitat suitability index (HSI) model output. We then tested whether HSI at the observed giraffe locations was higher than HSI at random locations. We hypothesized that model predictions were a good representation of reticulated giraffe habitat if the predicted HSI at the actual animal locations was significantly higher than random locations. To obtain a good representation of background HSI across the area, we used 1000 random locations. We created random points within the bounding box (maximum extent of all validation points) plus a 1000 m buffer. This process was repeated for both validation datasets (GBIF and GEC) to generate separate sets of random points within the known giraffe distribution. For each random location, we followed the same procedure as with the validation points for calculating the mean habitat suitability within a surrounding 100 m buffer. We then tested whether mean habitat suitability for the validation points was higher than for the random points, using a Welch's *t*-test due to the heteroscedasticity of both datasets. We also calculated the same tests using 100, 250, and 500 random points to ensure that results were not dependent on the number of random locations selected (see Table S1: Appendix S1). Additionally, we calculated sensitivity, precision, and AUC-PR for both independent validation datasets. For calculating sensitivity and precision, we used the same threshold than before. Because we lack reliable absence data, and to maintain a balanced testing dataset, we calculated precision and AUC-PR 100 times, each time selecting a new random set of absence points equal to the number of presence points from the previously created 1000 random points. We reported precision and AUC-PR mean and standard deviation from the 100 iterations. The validation analysis was conducted in R (R Core Team, 2022). The R code used for conducting the analyses is provided in Appendix S2.

Results

Model runs were consistent, with low standard deviation among individual model predictions (Fig. 1). Models also exhibited high predictive power. The mean AUC-PR for the five model iterations was 0.88 (SD: 0.02; range: 0.86–0.91), mean sensitivity was 0.85 (SD: 0.04; range: 0.80–0.91), and mean precision was 0.81 (SD: 0.02; range: 0.79–0.83). Bare soil was the most influential covariate on average across model iterations (8.32%), followed by NDVI (7.95%), the Landsat 8 blue band (7.63%), and surface ruggedness (6.85%). The contributions of other covariates ranged from 3.27 to 6.08% (Fig. 2).

On average, the HSI for the independent GBIF dataset was higher than the HSI of 1,000 random locations (Mean GBIF HSI = 0.61; mean random locations = 0.49; *P*-value = 0.003; Fig. 3a). Sensitivity was 0.77, mean precision was 0.58 (SD: 0.03), and mean AUC-PR was 0.66 (SD: 0.04). Similarly, the mean HSI for the independent GEC dataset was higher than the mean HSI of a 1,000 random set of locations (mean GEC HSI = 0.51; mean random locations = 0.41; $P < 0.001$; Fig. 3b). Sensitivity was 0.60, mean precision was 0.60 (SD: 0.01), and mean AUC-PR was 0.47 (SD: 0.01).

Model predictions highlight large areas of suitable habitat for reticulated giraffe across the western section of the potential distribution in Kenya (Fig. 1). Specifically, the binary model predicted 4736 km^2 of potential suitable habitat within the 'known' Kenyan range (19.7%) and 783 km^2 of potential suitable habitat within the possible Kenyan range (11.8%; Fig. 4). Suitable habitat was also identified along the northwest border between Kenya and Ethiopia, and along much of the border between Kenya and Somalia. The binary model also predicted 963 km^2 in Ethiopia (38.4% of the Ethiopian possible range; Fig. 4) and 147 km^2 in Somalia as potential suitable habitat (18.9% of the Somalia possible range; Fig. 4). Finally, 1418 km^2 of potential suitable habitat was identified within the 50 km buffer from the potential range into the west of Kenya, further north in Ethiopia, and further east into Somalia (Fig. 4).

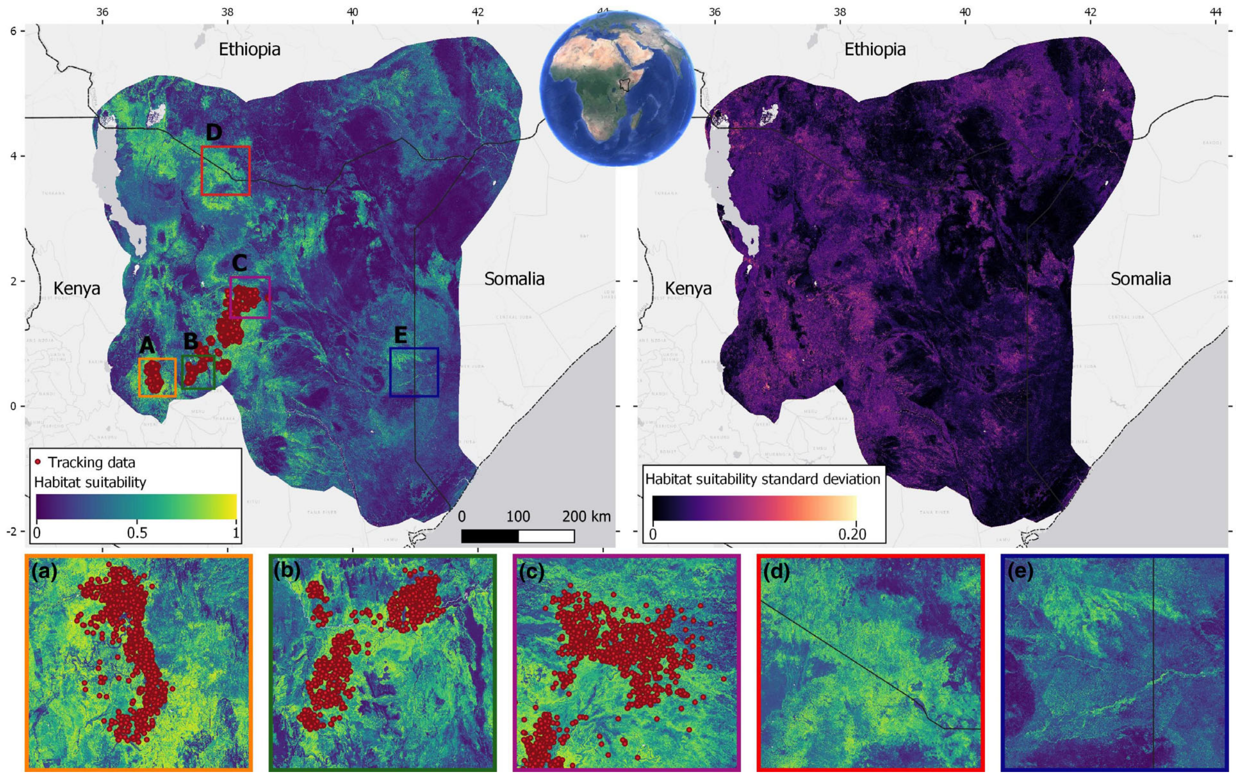

Figure 1 Mean (left) and standard deviation (right) of habitat suitability predictions from 5-fold model fitting for reticulated giraffe at 30 m spatial resolution using 2019–2020 Landsat-8, ALOS-PALSAR composites, and surface ruggedness as predictor variables. The insets (colored boxed) show finer details of habitat suitability predictions.

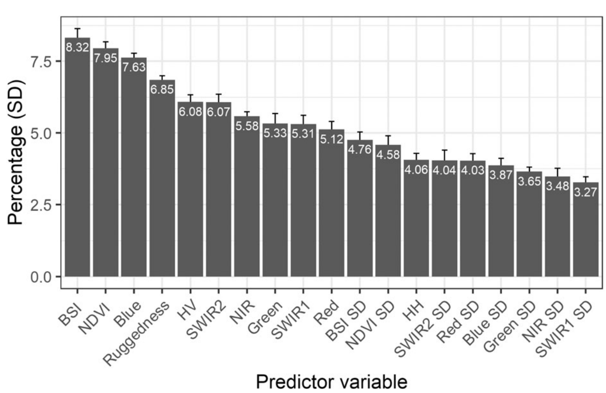

Figure 2 Mean (+1 SD) random forest variable importance percentage contribution from five-fold model fitting. Higher values indicate a greater ability of the variable to separate suitable from unsuitable habitat based on the training dataset.

Discussion

Habitat suitability models derived from moderate-resolution satellite data can be valuable tools for conservation management. We modeled habitat suitability for the entire range of the endangered reticulated giraffe at 30 m spatial resolution. We obtained high average model accuracy from across five iterations of model fitting with different partitions of training and validation data (AUC-PR > 0.86). Predicted habitat suitability was higher for known giraffe locations than on random locations on two independent giraffe occurrence datasets. This study demonstrates the potential of combining tracking data with moderate spatial resolution satellite imagery to model habitat suitability at large spatial scales ($\sim$ 378 400 km^2) to guide conservation actions of endangered species. The method relies on free imagery, free software, with results viewable on a free web application (https://gcfspatial.users.earthengine.app/view/reticulatedgiraffesdm), opening the opportunity to work collaboratively with governments and institutions and expand on similar research worldwide.

Species distribution models combined with coarse resolution predictor variables, generally climatic variables, have been used extensively to identify suitable habitats to guide translocations or surveys (e.g., Cilliers *et al.*, 2013; Payne & Bro-Jørgensen, 2016; Eyre *et al.*, 2022). Such climatic variables are valuable for purposes such as understanding how climate change can affect suitable habitats at large spatial scales (Bellis *et al.*, 2020). However, coarse-resolution maps do not necessarily provide the fine-scale information required to support translocation assessments by identifying the distribution and spatial arrangement of suitable habitat. Our modeling framework combining moderate-resolution satellite

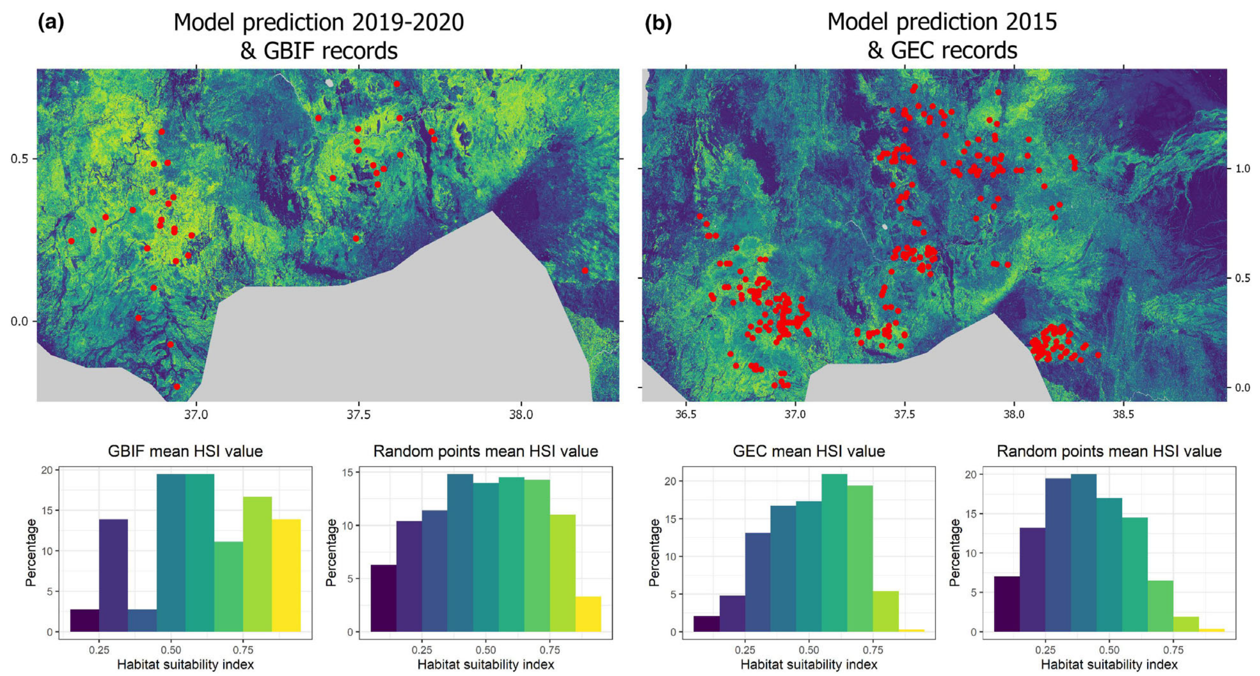

Figure 3 Independent model validation. Map A shows predicted habitat suitability for 2019–2020 and the locations of 36 giraffe records obtained from Global Biodiversity Information Facility (GBIF). Map B shows predicted habitat suitability for 2015 and the 335 giraffe records obtained from the Great Elephant Census (GEC). Histograms show mean habitat suitability values distribution for each independent validation dataset and 1000 random locations (see methods description on how random locations were created).

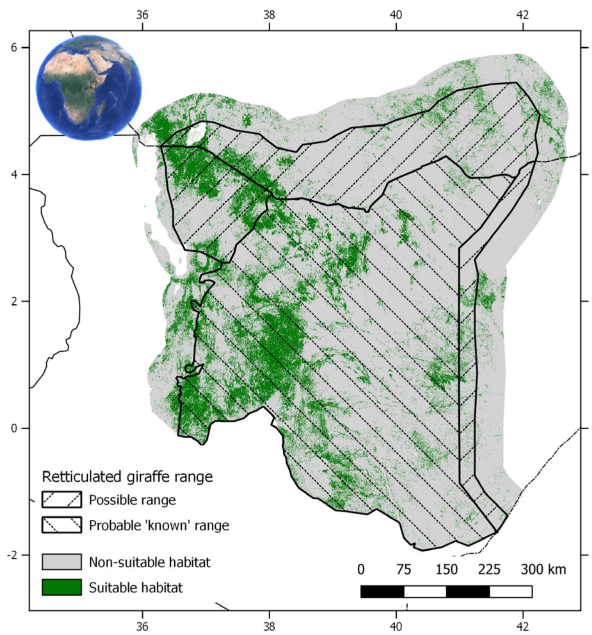

Figure 4 Potential habitat suitability predictions in a binary format (suitable/non-suitable) for reticulated giraffe at 30 m spatial resolution for 2019–2020. The binary map was created based on the average threshold that maximized the sum of sensitivity and specificity from across a five-fold model fitting with different training-validation data splits.

imagery with telemetry data can be a valuable tool for guiding future translocations of reticulated giraffe or for targeting future surveys to locate groups of animals persisting in remote or less-studied areas. Moreover, the visualization of patches of suitable habitat can help identify and prioritize areas for reintroducing individuals that maintain linkages, or habitat corridors, to known populations. This would help ensure the necessary connectivity and gene flow between known populations and future introduced populations to maintain genetic variation for the species (Willi *et al.*, 2022). Similarly, maps can help mitigate negative impacts by identifying locations where corridors will be needed to mitigate fragmentation by planned linear infrastructure, such as the Lamu Port–South Sudan–Ethiopia Transport (LAPSSET) corridor program, that are and will be built across the reticulated giraffe range (Aalders *et al.*, 2021).

When predicting a different year (2015) from which the model was trained (2019–2020), independent validation showed the capacity of the model to predict areas used by giraffe, with higher predicted HSI in known giraffe locations than random locations (Fig. 3b). This result supports the idea that our model can be used to predict habitat suitability on the year in which a translocation is planned, accounting for temporal variability in habitat suitability. The code provided could be edited to incorporate satellite data from different years of interest. Predicting across long spans of time to assess changes in suitable habitat (e.g., Betts *et al.*, 2022) will be limited by the ALOS-PALSAR dataset in our case, for which annual composites start in 2007. Other studies using Landsat imagery as predictor variables in SDMs have used coefficients to harmonize the different Landsat sensors (Roy *et al*., 2016; Betts *et al*., 2022). However, such types of analysis have only been done in forest ecosystems. Spectral variability in images due to vegetation structure variation across savanna ecosystems makes analyses using multispectral satellite imagery more challenging (Ribeiro *et al*., 2020), but we foresee this as an area of potential future development to improve habitat suitability predictions across these ecosystems.

In the random forest classifiers, no covariable presented a clear higher importance in distinguishing suitable from unsuitable habitat. As expected, given the effect that foraging availability and livestock abundance have on giraffe occurrence (Tyrrell, Russell, & Western, 2017; Brown & Bolger, 2020; Crego *et al*., 2020), our spectral indices attempting to capture these impacts, NDVI and BSI, were the most important variables across the random forest models. The Landsat blue band was also important, also expected given its spectral response to soil characteristics (Rikimaru, Roy, & Miyatake, 2002). This suggests vegetation availability and soil degradation are important factors determining habitat suitability. Surface ruggedness was also identified as an important variable in the model, likely corresponding with the tendency for giraffe tracking locations to fall in relatively smoother terrain. Despite the focus of our modeling technique on maximizing the predictive accuracy of the models rather than understanding the drivers of giraffe habitat selection (Araújo *et al*., 2019), the variable importance results can be valuable for future studies that aim to investigate the specific roles that soil and vegetation characteristics have on the ecology of reticulated giraffe.

Biological interactions can play important roles in determining habitat use by giraffe and importantly, the outcome of a conservation translocation (Muller *et al*., 2020; Fennessy *et al*., 2022). Incorporating biological interactions into habitat suitability modeling frameworks, however, is challenging (Kissling *et al*., 2012). The inclusion of BSI in our model indirectly accounted for the negative effect that high livestock abundance can have on reticulated giraffe occurrence (Crego *et al*., 2020). However, our models do not account for the effect of predators, competition with other herbivores, illegal hunting, traffic levels on roads, and other effects that can affect giraffe habitat (e.g., Valeix *et al*., 2009; Muller, 2018). When it is not possible to include such biological interaction variables, caution is needed when interpreting habitat suitability model predictions. For instance, model predictions at 30 m resolution can identify small patches of suitable habitat in a matrix of small farming lands. Despite the small patch appearing suitable in our predictive map, giraffe rarely would use such habitats due to the overall presence of human activities and their fragmented nature (Fig. 5).

The Twiga Tracker Initiative (https://giraffeconservation.org/programmes/twiga-tracker/) is one of the most ambitious programs in animal movement, aiming to tag and monitor individuals of all giraffe species across the diverse ecological

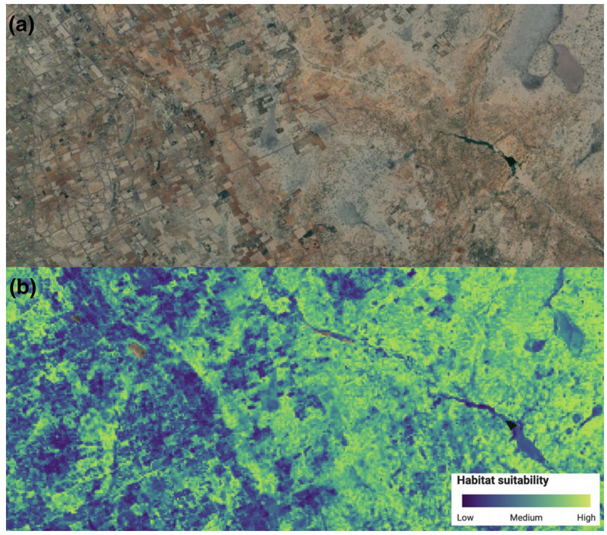

Figure 5 Comparison between the Google Earth Engine satellite base map imagery (a) and predicted suitable habitat for reticulated giraffe (b) across a gradient of anthropogenic disturbance. Fragmented rangelands can clearly be identified on the left side of the image where predicted habitat suitability is low, compared to the right side of the image, where predicted habitat suitability is high. The image captures a subset of Laikipia County, Kenya.

gradient that characterize their broad range. Despite that, we were only able to include 31 reticulated giraffe individuals in the analysis, all of which occurred in a relatively small area compared to the species range (Fig. 1). There is a possibility that the spatial locations of tagged individuals do not reflect the potential variability in space use across differences in habitat conditions, sex, group status, and animal personalities (Bercovitch & Deacon, 2015; Brown & Bolger, 2020). This can limit the predictive power of the model in areas away from the locations of the tagged individuals. It is also possible that giraffes in certain areas are forced to use poor-quality habitats due to anthropogenic pressures. This could explain the average lower suitable index value for the GEC-independent dataset (Fig. 3b) that covers an area larger than the area covered by the tracking data used to train the models. While future tagging outputs could provide further information to improve the models, it is also critical to validate model outcomes in the field (e.g., through surveys; Draper, Marques, & Iriondo, 2019) and to undertake independent site-specific translocation assessments before moving animals (Fennessy *et al*., 2022). Moreover, recent new developments in random forests implementations in SDMs for presence-only datasets show the potential for improving model performance and predictions (Valavi *et al*., 2021, 2022). This development for implementing down-sampling techniques that allow to use thousands of background points while subsampling them at each tree in the random forests to maintain a balanced dataset with the presence data is still not available in GEE. We hope our work with GEE and SDMs will motivate Google developers to implement novel developments in machine learning algorithms.

Our modeling framework combining moderate spatial resolution imagery with telemetry data can be a valuable tool to obtain detailed habitat suitability information. The code and resulting data will be an important tool to complement the complex process of planning future conservation translocations of giraffe and other threatened species. Moreover, the free web application with the 30-m resolution maps can also inform future survey efforts to increase knowledge on isolated populations of undersurveyed species and guide connectivity projects. Indeed, the maps are being used to identify suitable areas to survey giraffe in Ethiopia in a collaboration with the Ethiopian Wildlife Conservation Authority (EWCA). This work is contributing to the development of the first-ever National Giraffe Conservation Strategy of Ethiopia. We hope that this work will promote the continuation of further model developments on the other giraffe species and other threatened species to guide future conservation efforts.

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Author contributions

RDC, JAS and JF conceived the idea. RDC conducted the statistical analysis with assistance from GC. JF, MBB, JSD, SM and JAS collected the data. RDC led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Data availability statement

The Google Earth Engine code and the giraffe tracking data used in this study are freely available at the following Google Earth Engine repository: https://code.earthengine.google.com/?accept_repo=users/gcfspatial/RetGirManuscript. The scripts, data, and outputs from this study are also available in the following Zenodo repository: https://doi.org/10.5281/zenodo.8163921.

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Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure S1. Average bare soil index across different land uses derived from a cloud-free Landsat-8 composite used for modeling reticulated giraffe habitat suitability.

Figure S2. Google Earth Engine screenshots showing: (a) the area defined to create pseudo-absences, (b) an example of a random split of 10 × 10 km blocks – 70% for model fitting (blue) and 30% for model validation (red), (c) an example set of points used for model training (green dots), and a set of points used for model validation (black dots), (d) a zoomed-in section of the block, training, and validation datasets.

Table S1. Mean predicted habitat suitability index (HSI) for the two independent datasets used for model validation and for 100, 250, and 500 random points.