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# Climate and biodiversity change constrain the flow of cultural ecosystem services to people: A case study modeling birding across Africa under future climate scenarios

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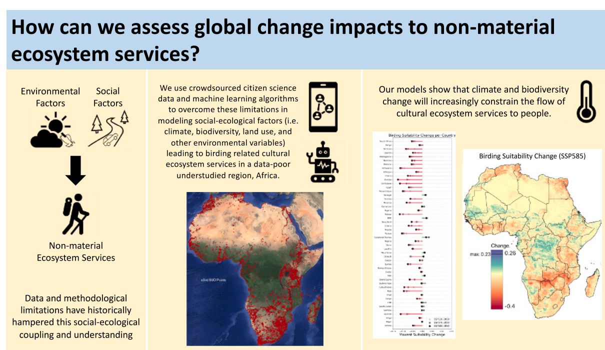
## HIGHLIGHTS

- ML and crowdsourced data help model non-linearities of CES in understudied regions.
- Interactions of climate, biodiversity, environmental, and social factors lead to CES flows.
- Climate and biodiversity changes constrain future CES flows in Africa.
- Regions of high CES use currently tend to be the most vulnerable in the future.
- Our approach can be used in regions across the world to better understand CES.

## GRAPHICAL ABSTRACT

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## ABSTRACT

Global change is currently impacting ecosystems and their contributions to people (i.e. ecosystem services). These impacts have consequences for societies and human well-being, especially in Africa. Historically, efforts have focused on assessing global change from a social or biophysical perspective, treating them as separate entities. Yet, our understanding of impacts to social-ecological systems remains limited, particularly in the Global South, due to a lack of data, tools, and approaches accounting for social and ecological aspects of ecosystem services. This is especially relevant for cultural ecosystem services as they are less tangible. We use a simple indicator and important provider of a multitude of cultural ecosystem services, birding, to understand how climate, biodiversity, and land use change will impact cultural ecosystem services across Africa. We explore how emerging tools and data can overcome limitations in mapping and modeling cultural ecosystem services, particularly in analyzing human preferences and behavior at large spatiotemporal scales and in data-poor regions. Leveraging crowdsourced data from eBird and using machine learning techniques we map and model recreational birding to assess the underlying social-ecological relationships and the impact of future climate and environmental change. We show that bird species richness, protected areas, accessibility, and max temperature contribute most to birding suitability across the continent. Further, we show spatial shifts in the suitability of birding under three future climate scenarios (SSP126, 370, and 585). Models suggest climate and biodiversity change will increasingly constrain the flow of birding related cultural ecosystem services across Africa. This has

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implications for human-nature interactions, development of countries, management of protected areas, and overall human well-being in the future. More generally, we highlight opportunities for crowdsourced datasets and machine learning to integrate non-material ecosystem services in models and thus, enhance the understanding of future impacts to ecosystem services and human well-being.

## 1. Introduction

Climate change, land use change, and the compounding impacts on biodiversity pose major threats to ecosystems, their contributions to people, and social-ecological systems as a whole (Pörtner et al., 2021). Traditionally, ecological and social systems have been treated as separate entities (Biggs et al., 2021; Hossain et al., 2023). This has caused a lack of assessment regarding the coupled social-ecological system, including through the mediating role of ecosystem services and how future impacts on services affect human well-being (Mastrángelo et al., 2019; van der Geest et al., 2019; Pörtner et al., 2021). Insufficient study of social-ecological systems in under-researched regions like Africa poses concerns for conservation, sustainable development, and policy (de Vos et al., 2019). This risk grows as these increasingly populated regions have more reliance on ecosystem services along with significant social, ecological, and economic vulnerability to global change (Pörtner et al., 2021; Tol, 2021). Yet, future impacts of climate, biodiversity, and land use change on ecosystem services are not well understood (Runting et al., 2017).

The lack of attention on global change impacts to ecosystem services is especially pertinent with non-material ecosystem services, or cultural ecosystem services (Millennium Ecosystem Assessment, 2005; Kosanic and Petzold, 2020). Although increasing, the mapping and modeling of cultural ecosystem services is still in its infancy (Manley et al., 2022). Furthermore, lack of data has resulted in a failure to fully account for and safeguard important ecosystem services around the world, especially in Africa (Hoogendoorn and Fitchett, 2016; Snyman et al., 2021; McElwee et al., 2022). Cultural ecosystem services are important as they contribute both directly and indirectly to physical and mental health, as well as to nature conservation, economies, sustainable development, and poverty reduction, particularly in developing countries (Snyman et al., 2021). This is true of avitourism (birdwatching tourism), which is known to garner conservation sentiment and simultaneously aid in human development in low and middle-income countries (Biggs et al., 2011; Steven et al., 2021). Africa's tourism industry currently accounts for ~8.5 % of the continent's GDP and generates over 24 million jobs (Steven et al., 2021), growing faster than the overall economy with projections of doubling by 2030 (Conservation Capital, 2019; Snyman et al., 2021). Many tourists visit sites across Africa to view the unique and rich biodiversity (Hoogendoorn and Fitchett, 2016). Such ecotourism greatly contributes to the livelihoods of local communities in Africa (Arbieu et al., 2017) and to the economies of developing countries, oftentimes relied upon as a source of foreign exchange earnings (Rasool et al., 2021).

Of the nature-based activities that lure tourists and recreationists to sites across Africa, birding is the second most popular (UNWTO, 2014) and is considered one of the fastest growing nature-based recreation activities globally (Schwoerer and Dawson, 2022). Avitourism is a huge untapped market in Africa consisting mainly of wealthier individuals that take long trips and spend significant amounts of money (Biggs et al., 2011; Carver, 2019; World Bank, 2021). For reference, birders in an established birding economy like the US are estimated to spend ~$39 billion USD annually on birding related expenses, generating ~$16 billion USD in tax revenue and ~$96 billion USD in total industry output (Carver, 2019). Due to birding's high popularity, it is one of the most effective ways of crowdsourcing data and contributes greatly to biodiversity and conservation research (Sullivan et al., 2014). If effectively considered by land managers and decisionmakers, birding can be a significant tool for sustainable development within Africa enhancing human well-being and conserving biodiversity and ecosystem services. Furthermore, sustainable management of tourism ecosystem services can benefit some of the most vulnerable rural communities by providing jobs, equitable revenue-sharing arrangements, and co-management of natural resources in a sustainable fashion (Twining-Ward et al., 2018). While recognizing the significance of the indirect economic benefits of ecosystem services to local communities, it is crucial to emphasize that a substantial portion of the direct benefits derived from tourism, particularly in the context of cultural ecosystem services in Africa, accrues primarily to the tourists themselves. Notably, these visitors often comprise of affluent individuals from wealthy countries outside of Africa. Ultimately, developing plans to sustainably and equitably manage cultural ecosystem services, including those related to birding, requires a more holistic integration of social- and ecological aspects of ecosystem services (Steven et al., 2015; Monz et al., 2021).

The multidimensional aspects of social-ecological systems requires social data and approaches that are yet to be developed, hampering our understanding and documentation of these systems globally (IPBES, 2018). This limits our ability to know the role that individual features of biodiversity like species richness or species abundance in protected areas play in the delivery of cultural ecosystem services, as well as the role of social aspects like development (GDP) or infrastructure in facilitating the flow of services. Africa's lack of consistent and comprehensive data is especially pertinent and notoriously limits researchers' and stakeholders' ability to fully carry out research throughout much of the continent (UNWTO, 2014; IPBES, 2018; Mwampamba et al., 2022). Further, although recreation/tourism is one of the most mapped cultural services, proxies are mostly simplistic, error-prone, and biased towards biophysical aspects (Manley et al., 2022). Fortunately, crowdsourced big datasets are increasingly being used throughout the field of ecology to address major limitations in data availability (Havinga et al., 2020; Manley et al., 2022). For example, eBird, an online citizen science platform, has been used for a wealth of information on avian biodiversity (Sullivan et al., 2014), but rarely for the insights it contains on birders themselves. Birders commonly use eBird for contributions to citizen science and as a useful and entertaining tool to keep track of sightings, view bird lists, and to compare, compete, and interact with other birders (Wood et al., 2011). This approach has been so successful that as of 2022, eBird has logged over 1.3 billion observations and has a user base of over 820,000 birders from every country in the world. Along with the emergence of social-ecologically relevant crowdsourced big data, machine learning (ML) has emerged as an effective tool for handling large amounts of complex multidimensional data and analyzing the underlying nonlinear social-ecological dynamics (Willcock et al., 2018; Manley and Egoh, 2022). This large amount of newly relevant data, along with the multitude of useful ML algorithms, creates opportunities to gain novel insights on cultural ecosystem services and future impacts to them, especially in data-poor regions such as Africa.

Novel tools and data, or unconventional use of conventional tools and data are crucial for addressing gaps in the understanding of long-term sustainability of cultural ecosystem services in a rapidly changing world (Espiner et al., 2017). The United Nations has identified climate change as the foremost challenge to global tourism sustainability in the 21st century (UNWTO, 2008). Additionally, land use change significantly drives biodiversity declines and subsequent impacts on ecosystem services (Pörtner et al., 2021). This vulnerability is heightened in nature-based tourism and recreation due to compounding impacts of climate and land use change on biodiversity (Gosling, 2013; Rogerson, 2016; IPBES, 2018). While impacts on biodiversity are well documented, the compounding impacts on cultural ecosystem services are absent, especially in Africa (Hambira and Mbaiwa, 2020; Pörtner et al., 2021). The plausible effects of global change on tourism and recreational ecosystem services include shifts in seasonal visitation patterns, changes in the willingness and ability for visitation, alterations in the availability and quality of ecosystem services, and modifications in the interactions between wildlife and recreationists (Chan and Wichman, 2018; Jamaliah and Powell, 2018; Monz et al., 2021). This theoretical understanding of recreationist behavior has been shown to apply to shorter temporal scales, for example daily and annually due to changes in weather and other site characteristics (Wood et al., 2020; Jaung and Carrasco, 2021) or impacts from disturbance (White et al., 2023) and depend on factors like demographics (Martinez-Harms et al., 2018), recreation activity (Rice et al., 2020), and place connection (Hammitt et al., 2004). However, understanding impacts on longer timescales and across large spatial scales, particularly in the Global South, remains underdeveloped.

The objective of this study is multifaceted and uses birding cultural ecosystem services and Africa as a case study to: 1) develop an approach that can more holistically map and model cultural ecosystem services, particularly at large spatiotemporal scales and in data-poor regions, 2) analyze the underlying biophysical and social drivers of cultural ecosystem services provided by birds in Africa, and 3) assess large-scale spatial and temporal shifts of cultural ecosystem service suitability caused by climate, land use, and biodiversity change.

## 2. Methods

### 2.1. eBird data

To assess and map birding across natural areas of Africa we queried billions of crowdsourced datapoints from the platform eBird (Sullivan et al., 2014). Data from eBird was retrieved from the Global Biodiversity Information Facility eBird Observation Dataset for the timeframe of 2010–2019 (GBIF, 2022). This timeframe represents large growth in the use of eBird giving us an abundance of data but does not include any influence from the global COVID pandemic and associated changes in birding. Uploads to eBird are individually verified in a two-stage system, with automated filters and subsequently local experts, leading to the data being widely considered as highly accurate (Sullivan et al., 2014; Koylu et al., 2019). The initial data contained 10,472,514 records from 13,689 unique users who recorded 2535 unique species. We use a database of urban areas across Africa that cross-references satellite and demographic data (Heinrigs, 2020) to delete entries within urban areas, keeping only data relevant to non-urban nature-based birding. The urban data identifies agglomerations that exceed a population of 10,000 and contain a continuous built environment, accounting for ~140,000 $km^2$ of total area across Africa. This allows us to minimize noise from heavily populated developed regions where most eBird uploads are likely from backyard birders that are more likely to be residents of the area. These backyard residential birders aren't necessarily influenced by environmental and climatic factors like birders visiting non-urban areas. This is because urban areas possess significant infrastructure and other non-natural elements that aid individuals in adapting to and mitigating environmental influences while engaging in recreational activities. While this cuts some of the available data (~19 %), it allows the model to better determine the relationship between birders and the social and biophysical factors that influence birders outside of built urban environments.

From this dataset, we calculated birding-user-days (BUD). Similar to calculating photo-user-days (Wood et al., 2013; Nyelele et al., 2023b), our BUD calculations sum the number of unique eBird users who uploaded at least one eBird checklist per day within each cell of a 25$km^2$ grid across Africa. We then calculate an annual average BUD for each cell across Africa, giving us the average amount of birders uploading to eBird within each grid cell. This allows us to estimate the spatial patterns of birding with eBird data while avoiding biases from users who upload many checklists per day in the same area. Our final BUD filtered dataset consisted of~151,000 unique geolocated BUD points from over 9000 eBird users who recorded 168 unique species on average (std = 204), the largest list recording 1845 unique species.

### 2.2. Covariate data

To create an effective social-ecological model of birding related cultural ecosystem services we needed to identify and collect data on influential covariates driving BUD patterns. Thus, we needed to account for factors related to both the supply of birding cultural ecosystem services (i.e. the birds themselves) and the use of the service (i.e. birders). Thus, we collected data on variables related to both bird presence and tourism/recreation. Climatic covariates within the model include max temperature of the warmest month, mean monthly precipitation, mean monthly near surface wind speed, and cloud cover. Social covariates include GDP and accessibility (i.e. travel time to the closest city, accounting for road networks and urban areas with >50,000 people). Biodiversity covariates include bird species richness and the biodiversity intactness index (i.e. estimates of native species abundance post-anthropogenic impacts compared to pre-anthropogenic impacts). Finally, we include other social-ecologically relevant variables including distance to protected areas and distance to water bodies, as well as land use (i.e. the most dominant land use class for each pixel).

Historical climate data (Table S1) including mean monthly total precipitation (mm) and mean monthly wind speed (m/s), are from the ERA5 reanalysis dataset (Hersbach et al., 2019), mean max temperature of warmest month (K), and mean annual cloud cover (%) were acquired from the global bioclimatic indicators derived from ERA5 dataset (Wouters et al., 2021). All were downloaded from the Copernicus Climate Change Service (https://climate.copernicus.eu) and averaged for the same historical period as the BUD calculations (2010–2019). Land use from the Land Use Harmonization Project standardized dataset is represented as the land use class with the highest percent cover per pixel in 2015 (Chen et al., 2020). Each class is one-hot encoded to represent categories within the models and to test multicollinearity (Table S2). Water body data is from the Esri World Water Bodies dataset and protected area data was acquired from the World Database on Protected Areas (UNEP-WCMC, 2022), both were used in the distance accumulation tool within ArcGIS Pro, along with GTOPO30 elevation data (USGS.gov), to calculate true surface distance. Accessibility data, which essentially measures the travel time to the closest city, was acquired from the Global Accessibility dataset (Weiss et al., 2018). Global gridded GDP data for the year 2015 was acquired from Kummu et al. (2018). Bird species richness data was acquired from the Red List species richness dataset (Jenkins et al., 2013) and biodiversity intactness was acquired from the Global Trends in Biodiversity and Ecosystem Services dataset (Pereira et al., 2020). All data was clipped to the extent of the study area and resampled using cubic convolution for continuous data and nearest neighbor for categorical data to the same resolution (25$km^2$) within ArcGIS Pro to standardize the resolution and optimize the model (original resolutions in Table S1). Multicollinearity was assessed through bivariate correlation coefficients and showed that of the final variables, almost all had weak correlation (0–0.3), ~18 % had moderate correlation (0.3–0.7), and none had high correlation (> 0.7) (Fig. S1).

Projection data for some of the covariates was required for modeling BUD into the future. We use data from Titley et al. (2021) for future bird species richness, Pereira et al. (2020) for future biodiversity intactness, and Chen et al. (2020) for future land use for all three future scenarios. We acquired projections for climate variables including mean annual temperature, mean precipitation, and max temperature of the warmest month from WorldClim (worldclim.org) and wind speed and cloud cover from the CMIP6 projection dataset available on Copernicus Climate Change Service. For climate projections we use data from IPSL-CM6A-LR due to the model's good performance when simulating historical climate attributes throughout multiple regions of Africa (Ayugi et al., 2021; Babaousmail et al., 2021; Klutse et al., 2021; Ajibola et al., 2022; Babaousmail et al., 2023). We also use data from three different future climate scenarios, SSP126, SSP 370, and SSP585 for 2050 (2041–2060), to assess impacts under a range of scenarios. These scenarios vary from high development focused globalized scenarios to low development focused nationalized scenarios (O'Neill et al., 2014). We asses two of the high development scenarios, one oriented towards a more sustainable development in which greenhouse gas emissions are cut over time (SSP 1) to a more energy-intensive fossil fuel-based development (SSP 5). We also assess a future with low development which results in high inequality and high greenhouse gas emissions (SSP 3). These three scenarios result in a range of future greenhouse gas atmospheric concentrations, climate, land use, and more, allowing us to assess various future scenarios (Fig. S2).

### *2.3. Models*

To create an optimal model of BUD and get more in-depth insights into the social-ecological dynamics driving BUD patterns, we first use Random Forest regression via the automated machine learning (AutoML) workflow in ArcGIS Pro to tune, train, and validate a Random Forest model. AutoML allows us to optimize our random forest model by automating the major steps taken when creating ML models, mainly feature engineering and selection, model training, and hyperparameter tuning, thus making the workflow more efficient, effective, and reproducible as it is more friendly for non-ML experts (Karmaker et al., 2021). Random Forest is a decision tree-based algorithm that tests a random subset of covariates and a random subset of data within those covariates within each decision tree to output the average result of each tree (Breiman, 2001). Random Forest is a great tool for exploratory analysis as it can quantify importance of predictors, can uncover complex interactions between predictors, and can estimate arbitrary functional relationships between predictors and response variables (Jones and Linder, 2015). We used the AutoML trained random forest model as an initial exploratory analysis step to gain insight into the social-ecological drivers of BUD and to select the most relevant covariates for birding in Africa. We use variable importance calculations, partial dependence plots, and model uncertainty and validation metrics, such as prediction intervals, $R^2$, and root mean squared error, to assess the best covariates for birding across Africa. Ultimately, the final 11 covariates were chosen based on model performance ($r^2 = 0.299$, MAE = 0.465, and RMSE = 3.126) and multicollinearity when testing a total of 28 variables (Table S1). The final covariates had the greatest variable importance, while trying to minimize collinearity and maximizing the model performance metrics.

We used Maximum Entropy (Maxent) to train a final model and map social-ecological suitability of birding across Africa for a baseline scenario (2010–2019) and future scenarios (2050 SSP126, SSP370, and SSP585) (Phillips et al., 2006). Maxent is an ML algorithm that predicts the probability distribution of a target variable's presence by finding the most uniform distribution (i.e. maximizing the entropy) or in other words, minimizing the entropy of the probability densities of covariates within locations of the target variable relative to covariates across the whole study area (Elith et al., 2011). We refer to this prediction as “suitability” throughout the manuscript as our model essentially predicts the probability of similarity of environmental variables at presence points as compared to each grid cell across the area of interest. A major advantage of Maxent is it only requires presence points and is a robust, heavily used, and proven algorithm in ecology (Lissovsky and Dudov, 2021). We choose to use Maxent over the AutoML Random Forest model because Maxent provides a projection of suitability rather than making specific predictions of the response variable. This was an important detail for us considering we are dealing with qualitative and nuanced aspects of cultural ecosystem services that may lack precise quantitative measurements, especially in the future. Suitability output can be more informative and relevant in the context of cultural ecosystem service supply, use, and flows that may not have clear-cut boundaries or measurable metrics. Moreover, Maxent has demonstrated comparable, and at time greater, accuracy compared to Random Forest, particularly in predictive applications (Fitzgibbon et al., 2022). Additionally, Maxent excels in identifying suitable areas even in instances where presence is not documented in the training data (Fitzgibbon et al., 2022).

To create the Maxent model, we use the Maxent tool within ArcGIS Pro. Individual BUD points were used to represent the presence of birding and covariate data was extracted for each presence point. Along with the presence points Maxent uses unknown presence points, or background points, to contrast the conditions between the areas of presence and the rest of the study region. We generate 50,000 random points throughout Africa and extract the covariate data for each point to use as background points. The Maxent model is then trained on the presence and background data with a cutoff value of 0.5 and used to predict the suitability of birding for a 25km$^2$ resolution grid across the entirety of Africa. The cutoff value of 0.5 is chosen by calculating the optimal Youden's Index, which maximizes both the sensitivity (true positive rate) and specificity (true negative rate). A Youden's Index of 0.55 was calculated for our Maxent model (Fig. S4). However, to enhance interpretability and for practical considerations, we rounded the threshold to 0.5. This decision was driven by the goal of minimizing the omission rate while ensuring that the impact on background points predicted as possible presence was not significantly affected. Ultimately, we use Maxent predictions not as a presence/absence classifier, but as a continuous measure of suitability of birding. We use three-fold cross validation to validate the model and assess the ROC, the classification results, and BUD versus suitability comparisons to assess the trained model.

We use the trained and validated model to predict BUD suitability by extracting projection data for the study area under future climate scenarios. We model future suitability changes using projections for only environmental (bird species richness, biodiversity intactness, and land use) and climatic (max temperature of warmest month, mean monthly precipitation, mean monthly near surface wind speed, and cloud cover) variables and keep all other variables constant (distance to protected areas, distance from water bodies, GDP, and accessibility). This allows us to isolate and assess the impact of climate and environmental change. Future studies could include future projections of variables like protected area, accessibility, and/or GDP to assess the impact of different management, socioeconomic, or political scenarios. To further isolate the impact of climate, biodiversity and land use change, we run separate future Maxent models holding all variables constant except for factors related to each respective model under all three future scenarios (e.g. only climate variables change for the climate model). Thus, for each future scenario (SSP126, SSP370, and SSP585) we create 4 different models (climate change only, biodiversity change only, land use change only, and all change) resulting in 12 total future models. Since many decisions relevant to tourism and natural resources are made at the national level, we aggregated model results by the mean change in suitability for each country in Africa. We then calculate the difference from the baseline mean suitability and the future suitability for each scenario within each country. We leave out small island nations and disputed territories due to data availability, resolution, and other issues. We also calculate the vulnerability of each country's birding related cultural ecosystem services as the amount of area that currently has BUD that loses high suitability (0.5) in the future.

To resolve the smaller scale dynamics within our Maxent model, we use random forest (python sklearn package) to train models for the 10 major biomes of Africa (grasslands, savannas and shrublands; deserts and xeric shrublands; moist broadleaf forests; Mediterranean forests, woodlands, and scrub; montane grasslands and shrublands; flooded grasslands and savannas; dry broadleaf forests; lakes; mangroves; and temperate coniferous forests) (Fig. S5). Our modeled Maxent suitability across Africa was extracted for each biome and used as the dependent variable for the biome model to assess the relative contribution of each of the 11 covariates in explaining the variation in suitability within each biome.

## 3. Results

Mapped BUD revealed clustered regions of birding mostly in countries along the coast of Africa (Fig. 1 and S5). Specifically, South Africa stands out with ~31 % of BUD, most of which is in and around Kruger National Park (Fig. 1b). Beyond South Africa, regions surrounding Lake Victoria were also a hotspot for birders (i.e. Tanzania, Kenya, and Uganda) (Fig. 1a). Another major hotspot is the convergent border region of Angola, Botswana, Namibia, Zambia, and Zimbabwe which makeup the Kavango Zambezi Transfrontier Conservation Area, containing the highly visited Okavango Delta (Fig. 1c).

One of our key questions was to understand what social-ecological aspects drive the patterns of birding we see across Africa. Bird species richness is the most important variable for predicting BUD, demonstrating the importance of healthy ecosystems and biodiversity conservation (Fig. 2). Of species related variables tested, bird species richness showed higher importance than rarity-weighted richness and threatened species richness (which were not included in the final model). The next three most important variables, distance from protected areas, accessibility, and max temperature of the warmest month, show considerably higher importance than the rest of the variables.

Social-ecological dynamics leading to cultural ecosystem service use vary under different contexts, which can be seen in the biome-level variable importance (Fig. 3 and S6). Major drivers of birding, like bird species richness, distance from protected areas, accessibility, and max temperature, stay high in importance throughout most biomes. Conversely, some less important variables at the continental scale become highly important within the context of a specific biome. For example, biodiversity intactness and wind speed in moist broadleaf forests, cloud cover in dry broadleaf and temperate coniferous forests, and precipitation in lake biomes become relatively important.

Three-fold cross validation resulted in correct classification of 92.5 %, 92.9 %, and 92.6 % for each testing fold. Overlay of Maxent response curves onto the Random Forest partial dependence plots, reveals notable agreement between the models of the marginal effect of the covariates on birding (Fig. 2). The observed consistency instills greater confidence in the validity of the identified relationships between predictor and response variables, reassuring us that these associations are not merely internal artifacts specific to a single model but likely reflect genuine patterns in the underlying data. Our Maxent model exhibited good performance with an omission rate of 0.07, an AUC of 0.92 (Fig. 4a) and correct classification of ~92 % of the ~151,000 presence points (with a defined cutoff value of presence at 0.5) (Fig. 4a). When comparing grid level Maxent suitability scores and BUD we see successful identification of high suitability areas in areas with high BUD. Approximately 93 % of birding occurs in pixels with a Maxent suitability score of 0.5 or higher and ~79 % at 0.6 or higher (Fig. 4b). Most of that highly suitable (suitability ≥0.5) land area lies within South Africa, Tanzania, Zambia, Namibia, Madagascar, and Mozambique, accounting for ~52 % (~4.8 million km$^2$) of the highly suitable land area throughout Africa (Fig. 4c). Although suitability matches relatively well with current BUD patterns, it also shows areas of mismatch in which there is high suitability but little or no BUD. For example, the Democratic Republic of Congo (DRC), Algeria, Cote d'Ivoire, Nigeria, and Angola all have significant amounts of highly suitable area, but relatively lower BUD.

Under the three future SSP scenarios, birding cultural ecosystem service suitability patterns show high suitability remaining mainly across the East African Rift and throughout Southern Africa (Fig. 5). Yet, most negative changes to suitability under the three SSP scenarios occur in these same regions, as well as within portions of coastal Northern and

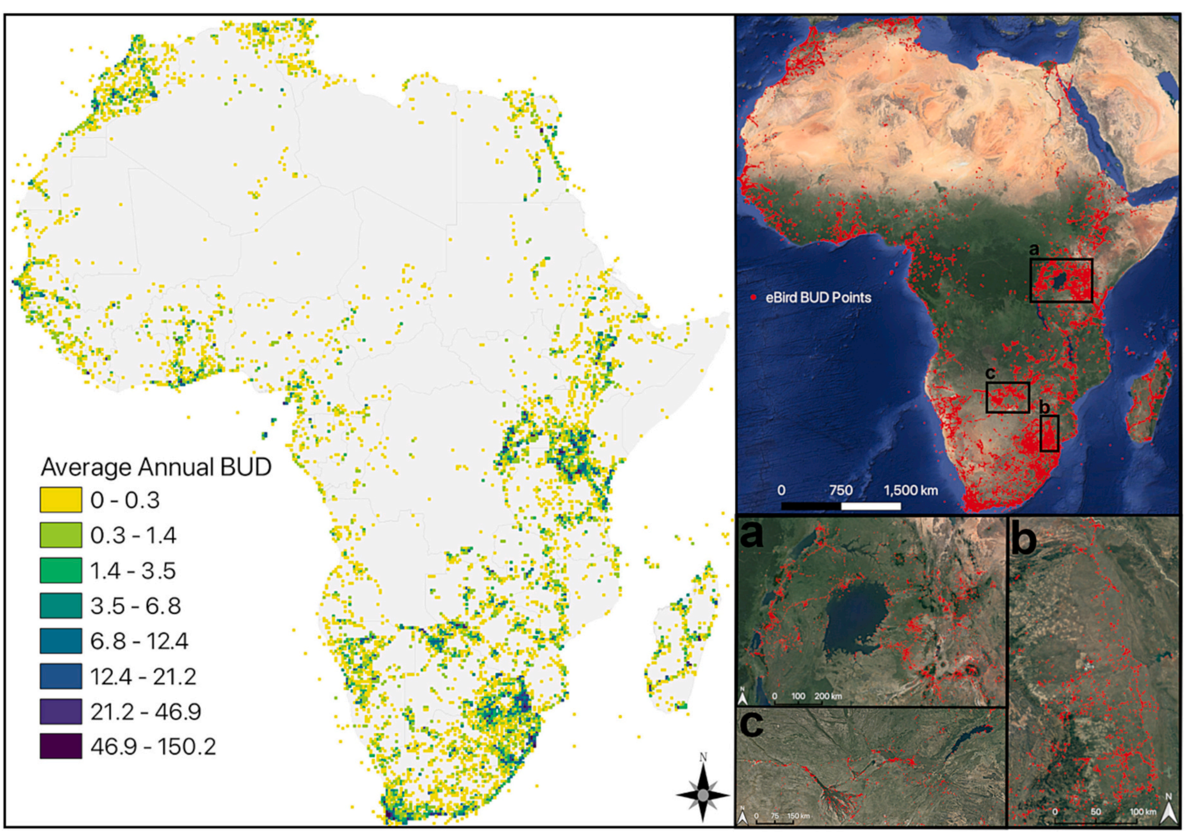


**Fig. 1.** Left: Spatial BUD patterns across Africa (2010–2019). Right: eBird points filtered for user-days across Africa, highlighting high BUD areas around Lake Victoria (a), Kruger National Park (b), and the Kavango-Zambezi Transfrontier Conservation Area (c).

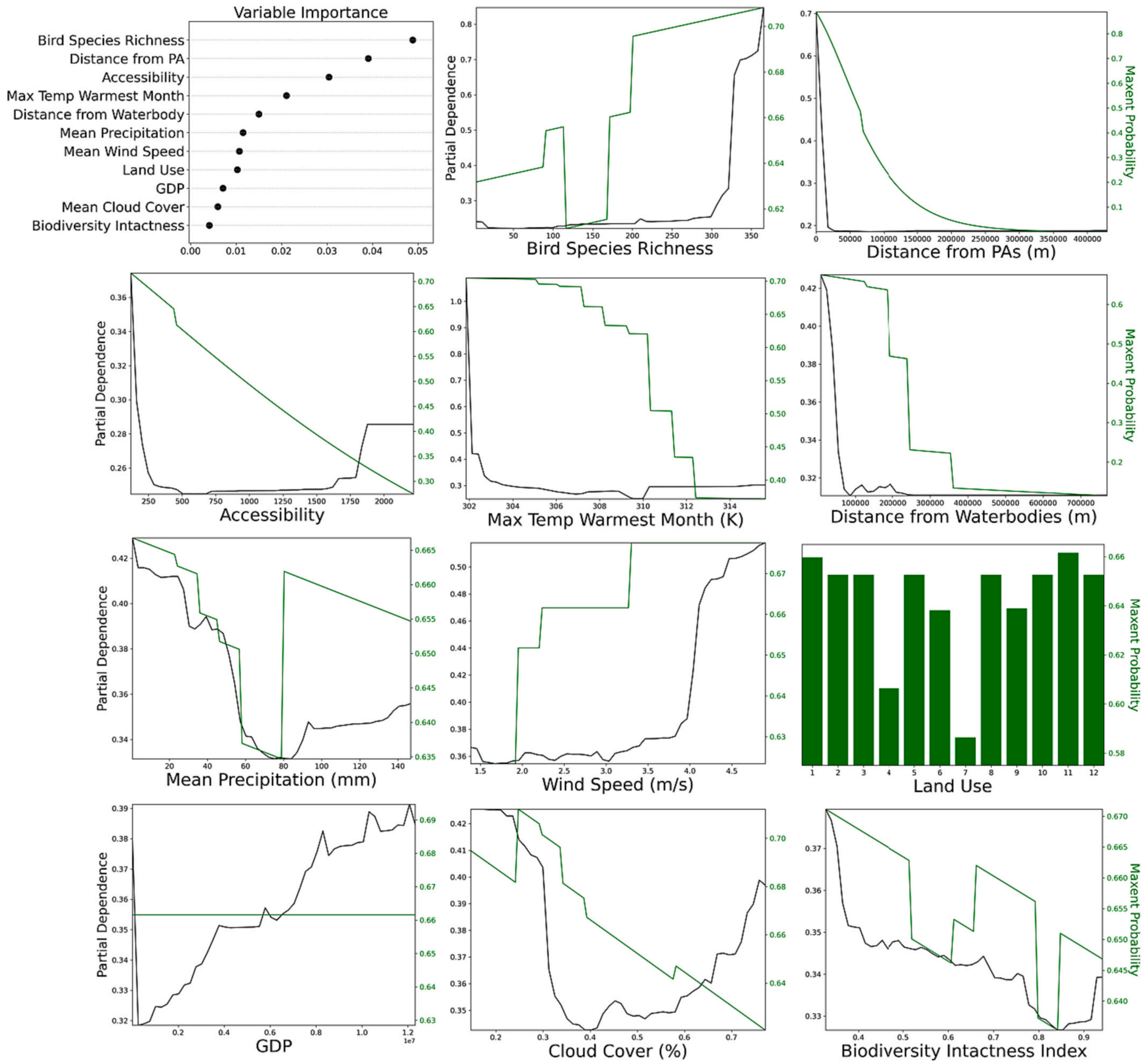


**Fig. 2.** Importance of each variable for birding (top left). Random Forest partial dependence (black) and Maxent response curves (green) for each variable (land use classes defined in Table S2).

Western Africa, increasing in magnitude under higher end warming scenarios. There is an especially pronounced decrease in future suitability in the previously mentioned Kavango-Zambezi Transfrontier Conservation Area and surrounding regions. Overall, suitability is increasingly impacted throughout the continent with higher warming scenarios, suggesting greater constraints to cultural ecosystem services as global temperatures increase (Fig. S6).

Most positive changes in suitability occur in Central Africa, as well as portions of central-eastern and northwestern Africa. Under higher end warming scenarios, suitability increases are negatively impacted as less suitable conditions encroach further into areas that would otherwise see positive impacts under lower end warming scenarios. For instance, there is a loss of ~2.1 million km$^2$ of highly suitable area throughout Africa under SSP126, whereas under SSP585 there is a loss of ~3.6 million km$^2$ (Fig. S7). Negative impacts to birding related cultural ecosystem services are compounded under higher end warming scenarios as there is a near doubling in lost highly suitable land area under SSP585 compared to SSP126.

The decline in future suitability across African countries is primarily attributed to climate change (Figs. 6 and S8). Biodiversity change also contributes significantly to the projected shifts in suitability, albeit to a lesser degree compared to the impact of climate change. Conversely, land use has a minimal influence on the observed changes in suitability.

In general, model results reveal a decline in the extent of suitable area in most countries across all projections, (Figs. 7 and S5). Most countries with high birding will see decreases in countrywide mean suitability, mainly driven by the changing climate. For example, South Africa is estimated to have by far the highest birding levels at ~45,000 BUD but countrywide suitability is projected to decrease (~−0.03 – −0.05) under future scenarios and lose up to ~171,000 km$^2$ of highly suitable area (Fig. 7). Despite these negative impacts, South Africa is still slated to be one of the most suitable for birding cultural ecosystem


**Fig. 3.** Heatmap showing the normalized variable importance (0–1 scale), representing the contribution of each independent variable from the Maxent model in explaining the variation in the suitability within each biome, biomes are organized from highest to lowest total BUD.

services in the future. Conversely, Kenya is estimated to have the second highest birding levels currently at ~14,000 BUD but is projected to see little impact to countrywide suitability (~ −0.01 – +0.003).

Vulnerability, or the total area with birding that loses high suitability in the future (decreases below 0.5 Maxent suitability), differs from total impact to suitability. Because BUD mainly occurs in regions of high suitability, vulnerability shows where current birding could be most impacted (Fig. 7). Although countries such as Uganda, Ghana, and Rwanda are projected to have overall reduced mean nationwide suitability, their vulnerability is comparatively lower as climate and biodiversity change mainly impact areas without any current BUD. The highest vulnerability is projected in the Zambia, Tanzania, Mozambique, Botswana, Egypt, and Madagascar.

## 4. Discussion

### 4.1. BUD and social-ecological drivers

Our BUD estimates per country tend to correlate with high nature-based tourism and associated tourism spending. For example, South Africa, which had the highest BUD, has emerged as a preferred tourist destination in part due to its high biodiversity, mostly in national parks, along with a plethora of other more difficult to measure factors like the abundance of human and physical infrastructure for tourism. In 2015, South African tourism related to biodiversity generated ~$2.4 billion USD of direct spending (Joubert and Poole, 2018), of which in 2010 it was estimated avitourism contributed up to ~$200 million USD and has

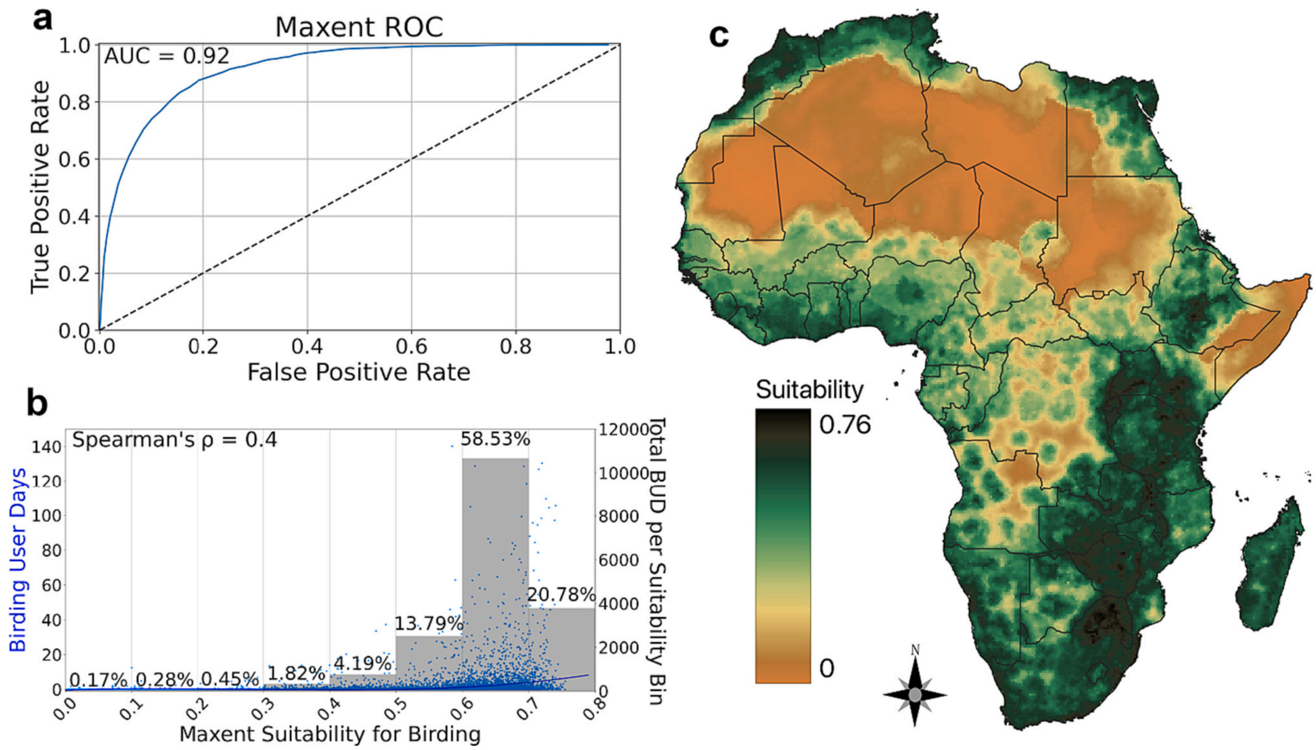


**Fig. 4.** a) ROC curve for Maxent model. b) Scatter plot of Maxent suitability and BUD with bars showing total BUD per 0.1 suitability bin (with percentages). c) Maxent modeled birding suitability across Africa (2010–2019).

only grown since (Department of Trade and Industry, 2010; Joubert and Poole, 2018). The large economic contribution of birding in these regions is indicative of the significant value people place on nature, including birds, across Africa and their potential to contribute to people's well-being. Other countries with high BUD, including Kenya, Uganda, and Tanzania, tend to be among the highest in total leisure tourism spending associated with natural resources (Snyman et al., 2021). Such economic activity from and investment in the wildlife economy can help reduce inequalities (SDG 10) through income generation and sustainable development (Snyman et al., 2021). This suggests that birding related cultural ecosystem services can attract large amounts of tourists, play a role in development, and further build people's connection with the globally less visited natural areas of Africa for years to come. The Kavango-Zambezi Transfrontier Conservation Area, which was established with ecological functioning and tourism in mind (Cumming, 2008), is shown by our analysis as another example of the synergies between ecosystem health and tourism. This is demonstrative of managers and decisionmakers ability to develop people's relational values with nature through protection and improved accessibility of suitable regions along with the effectiveness of crowdsourced data in monitoring these efforts.

The higher importance of overall species richness over rarity within our model is consistent with past literature (Cumming and Maciejewski, 2017), but over threatened species richness differs from previous results (Echeverri et al., 2022). This is likely due to recreation and ecotourism being context and scale dependent. Thus, birding at a continental scale in Africa is driven mainly by species richness in general, rather than by rarity or threatened status as it may be in specific regions of Africa and the world. Species richness is often used as a proxy for the supply of biodiversity-based ecosystem services, but the supply must connect to a beneficiary for it to be identified as an actual ecosystem service (Landers et al., 2016). Bird species richness and BUD across Africa are positively correlated (Spearman's $\rho = 0.21$) but also have areas of mismatch mainly along the central western coast of Africa, spanning from Angola up to Sierra Leone (Fig. S9). This modest correlation underscores the limitation of relying on simplistic supply-based indicators to gain meaningful insights into human-nature relations of cultural ecosystem services. Thus, ML emerges as a valuable tool, enabling us to encompass the complex nonlinear dynamics inherent in the multitude of influential factors, and interactions among factors, that drive cultural ecosystem service flows to people. While richness of biodiversity is important for birding, other factors, especially protected areas, accessibility, and climate, impact human behavior leading to service use (Fig. 2). This finding is consistent with past work showing conservation of species is important for recreation and tourism but is also paired with investment in infrastructure (Echeverri et al., 2022). Our results further this understanding and demonstrate that climatic factors also play a significant role in driving recreation and tourism ecosystem service use across large spatial scales. Importantly, our results show that cultural ecosystem service supply alone is insufficient for explaining ecosystem service flows to people (Fig. 2).

The positive impact of the three most important variables in the system (bird species richness, distance from protected area, and accessibility) demonstrates the need for rich and intact biodiversity, conservation of ecologically important regions, and increasing all people's access to cultural ecosystem services. Protected areas often serve as social-ecological hubs for not only biodiversity, but also cultural interactions and values (Palomo et al., 2014), which is demonstrated by ~84 % of all BUD being within protected areas (~70 % with the total dataset prior to urban masking). Beyond protected area's contributions to ecological health, they also contribute to local economic development, especially in poorer regions (Ferraro et al., 2011), and preservation of important relational values that underpin cultural ecosystem services (Mulongoy and Babu Gidda, 2008). Furthermore, cultural ecosystem services are catalysts for conservation support among the public and thus create a social-ecological feedback loop of conservation providing cultural services, which then increases protected area support (Daniel et al., 2012). In contrast, one of the major climatic influences, max temperature of the warmest month, is negatively correlated with BUD. This suggests that areas tending to reach extreme temperatures

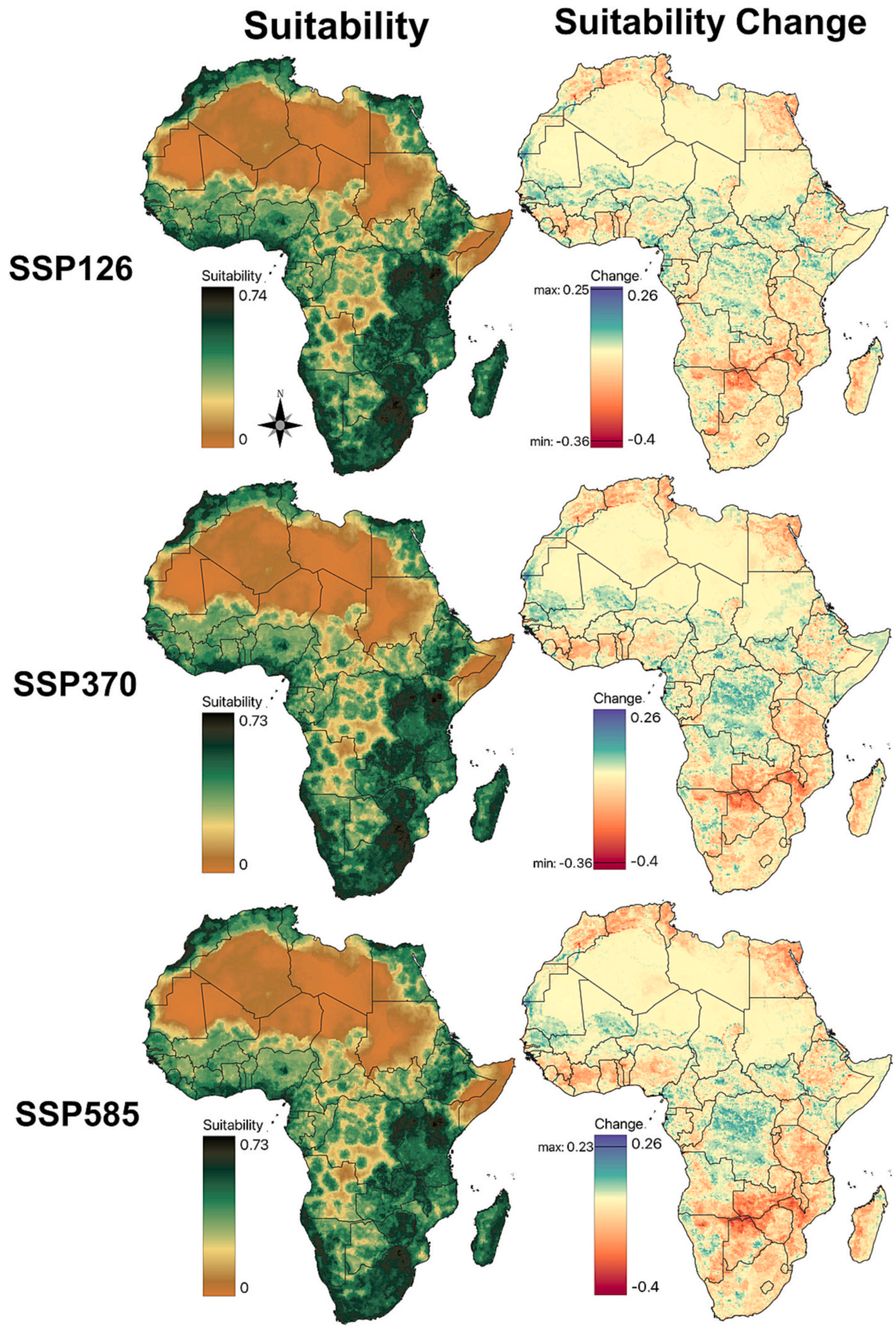


**Fig. 5.** Maps of Maxent suitability predictions under all three scenarios throughout Africa (left) and suitability change from baseline (right).

have less visitation and consequently, that increasing global temperatures will likely directly impact recreation and tourism and constrain cultural ecosystem service flows across the landscape.

The biome-level analysis of our model results not only illustrates the robustness of the most significant variables influencing cultural ecosystem service use across the landscape but also reveals drivers of cultural service use within the specific context of distinct biomes (Fig. S10). One interesting example of this is biodiversity intactness showing exceptionally high importance in moist broadleaf forests. This is a great example of the decision relevant social-ecological dynamics that can be revealed through differing cultural service contexts, as current and future land use changes linked to intensified agriculture are impacting biodiversity intactness in moist broadleaf forests throughout Africa (Tyukavina et al., 2023). Most of Africa's moist broadleaf forests are located within the Congo Basin, where little birding occurs. This region has significant unrealized potential for the provision of cultural ecosystem services, but a multitude of barriers remain, including, but not limited to, the lack of investment in physical and human infrastructure (Telfer and Reed, 2021), corruption and governance issues, and safety and security issues (Snyman et al., 2021). This is evident through low observed BUD and the high importance, but low values, of accessibility and area protected (~17 %), both of which positively affect birding. This inherent contextual variability in cultural ecosystem services underscores the need for sophisticated tools, such as ML, capable of discerning and modeling these nuanced and subjective relationships leading to ecosystem service flows. This becomes especially crucial in modeling human-nature relationships, where a universally applicable theoretical framework is lacking (de Vos et al., 2021).

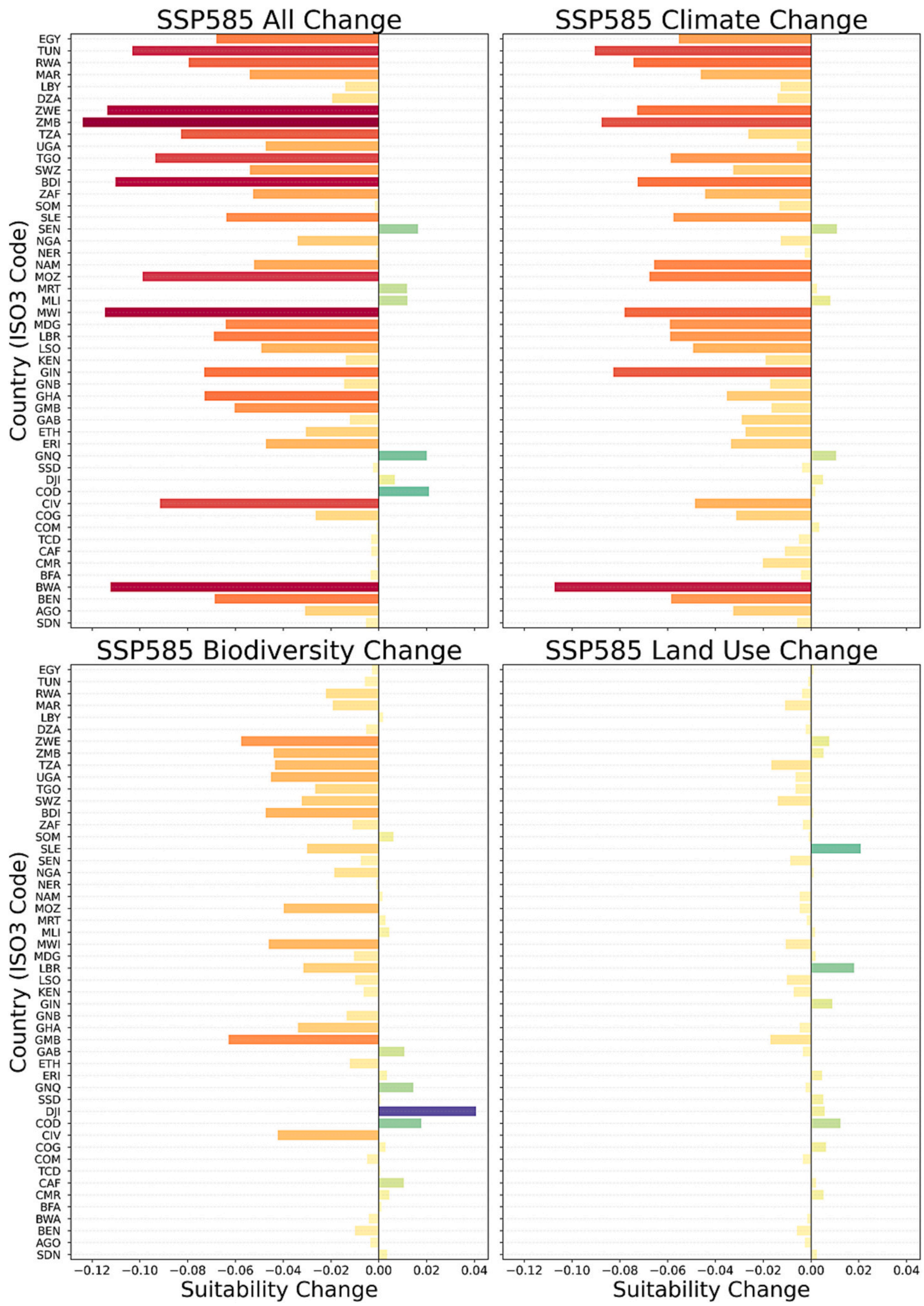


**Fig. 6.** Marginal impact of climate change, biodiversity change, land use change, and all on mean suitability of each African country (represented by ISO3 codes) for SSP585 (other scenarios shown in Fig. S8).

### 4.2. *Birding suitability and future impacts*

The disparity between the suitability of an area and its current BUD uncovers untapped potential for enhanced cultural ecosystem services related to birds. For instance, although Uganda already has the 4th highest BUD, suitability shows much of the country's birding cultural service potential is still underutilized (Fig. S11). In Uganda's case though, the government has taken notice of this opportunity and is investing ~$2 million USD in infrastructure to triple avitourism visitation by 2026 (World Bank, 2021). Investments to increase accessibility can aid in making sure areas of high cultural ecosystem service supply flow to beneficiaries. Importantly, such investments need to be sustainably and equitably implemented, integrating local and indigenous people (Sangha et al., 2019). Other similar regions could increase the flow of cultural ecosystem services to people by investigating what is driving this mismatch, for example conflicts, lack of recognition of ecosystem service supply, or poor tourist perception of the region (Snyman et al., 2021). By leveraging more holistic modeling studies such as this, managers and decisionmakers, like those in Uganda, can effectively pinpoint where infrastructure can be implemented, identify critical needs based on regionally modeled relationships between people and the environment, and anticipate the repercussions of forthcoming environmental shifts like climate, biodiversity, and land use change. Notably, the integration of a modeling study to enhance the flow of cultural ecosystem services to beneficiaries is not always straightforward, owing to a myriad of political, economic, and other influential factors. Our study, while in-depth, does not encompass all the intricate interacting elements that hinder tourism. Decision-makers and land

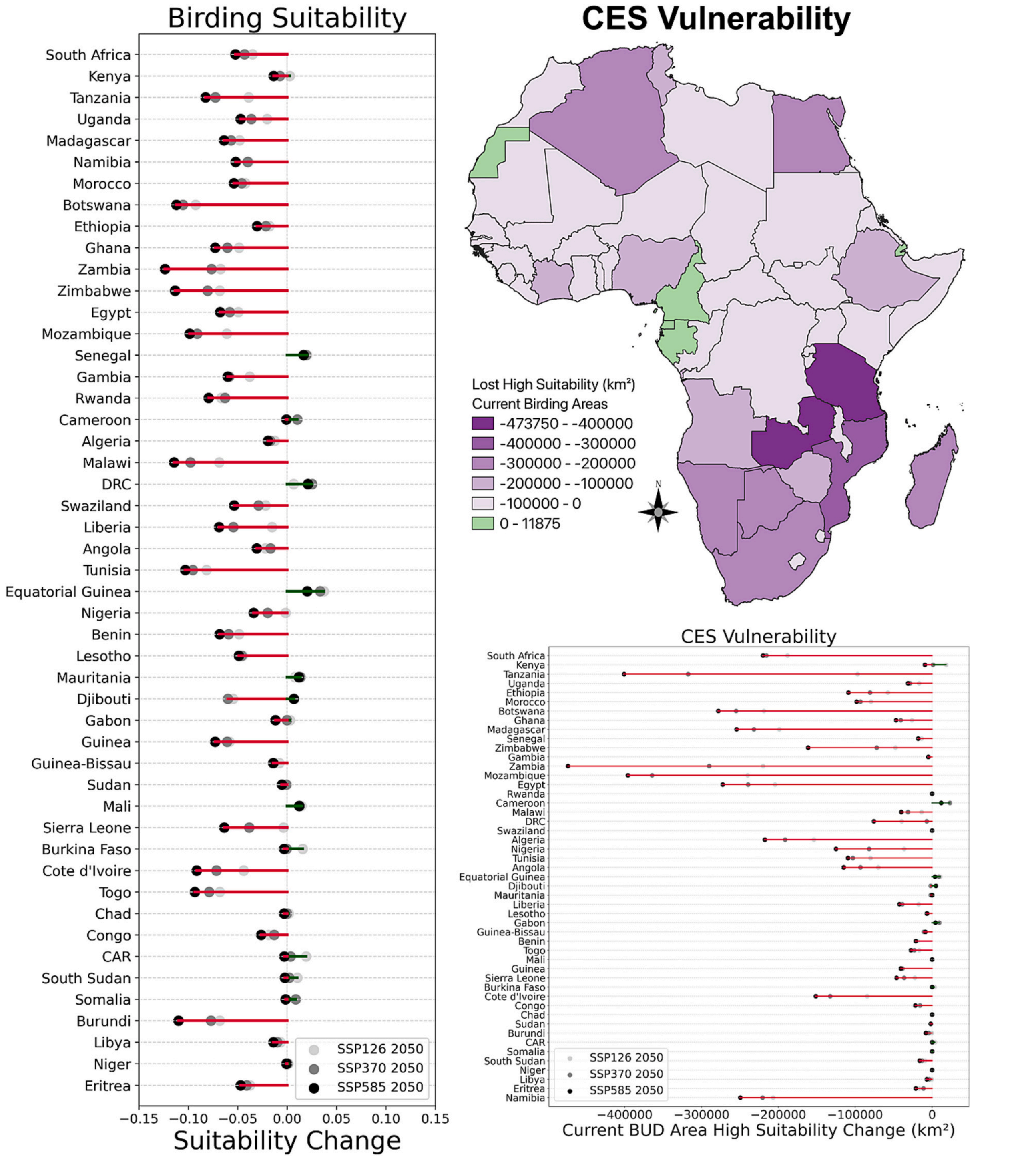


**Fig. 7.** left) Mean nationwide suitability change for each scenario sorted highest to lowest BUD. top right) Birding vulnerability calculated as the total area with current birding losing high suitability in the future (SSP585). bottom right) Birding cultural ecosystem service vulnerability per country under all scenarios.

managers must acknowledge and address these complex factors beyond the scope of our assessment.

Many regions in which our model shows high negative impacts to suitability, contain some of the most tourism dependent countries and areas with the highest current BUD (e.g. Tanzania, Madagascar, and Botswana) (Snyman et al., 2021). This indicates that regions that would expect to see increases in recreation and other cultural ecosystem services, due to increasing global and regional populations and increasing African ecotourism, may be hampered in the future, mainly due to climate and biodiversity change. Furthermore, high visitation in these regions (as measured by BUD) indicates an established connection of people to the local environment, thus future impacts have a greater effect beyond just lost utility. Some of the modeled future increases in suitability match with areas already identified as climatic refugia, like portions of the equatorial rainforests, mountainous regions in Eastern Africa, and regions within the Maghreb, indicating they may also be refugia for biodiversity-based cultural ecosystem services (Cooper et al., 2022).

Ultimately, our results suggest that climate and biodiversity change will influence birding and the substitution behavior of birders. For example, the quality of recreation experiences would decrease as climatically suitable area and biodiversity decreases. This could also increase crowding as suitable land area decreases and the recreation season is constrained by climate change (Shelby and Vaske, 1991). Such substitution behavior of birders has been observed during the COVID-19 pandemic, demonstrating the impact global crises have on human-nature relations (Randler et al., 2023). Further, future shifts in birding suitability, like the modeled increases in the DRC, Equatorial Guinea, Cameroon, Senegal, and Kenya, will require resources and infrastructure to facilitate flow of cultural services to people in newly suitable regions. This requires large amounts of resources for new development which most countries may not have or want to implement and may have to allocate for other more urgent climate change related challenges like food production or increased natural disasters and diseases.

Countries having a higher vulnerability may indicate a need to manage ecosystems and the tourism/recreational services they provide more strategically in the future. This is especially concerning as 15 of the top 20 most vulnerable countries have high (10–20 %) or medium (5–9 %) dependence on tourism for GDP (Snyman et al., 2021). If decreasing suitability is significant enough within these countries it could result in behavioral changes in which recreationists substitute new sites or new activities and possibly slow growth of, or decrease, ecotourism and recreation. More vulnerable regions can bolster their resilience using social-ecological insights on what, where, and why vulnerabilities exist. For example, many of the countries projected to have the greatest decreases in suitability see these impacts due to decreases in bird species richness and increases in temperatures, among other changing environmental factors. With such insights countries can make strategic adaptive and mitigative decisions, for example protecting and/or restoring ecosystems important for birds or implementing recreational infrastructure in cooler more resilient regions. To harness these benefits of birding, along with other non-market benefits, it is imperative to understand the current and future spatial distribution of birding related cultural ecosystem service supply and use as well as where and what resources will be needed, especially in understudied regions.

Beyond just the material impacts we model and discuss; it must be noted that cultural ecosystem services are tied to our non-material relations with nature. Thus, impacts to cultural ecosystem services will inevitably result in compounding impacts to human well-being beyond the tangible and market related aspects (Chan et al., 2016). Our results, while not directly analyzing these aspects, show that climate change will act as a barrier to accessing culturally important ecosystem services. This is the case for birding in this study but can be further considered as impacts to the cultural significance people place on birds. For example, suitability decreases for birding across a large proportion of Africa would affect other cultural services like the spiritual importance related to birds, sense of place, cultural heritage, and other related relational values of nature. Cultural services are known to be synergistic with ecosystem resilience and subsequently other ecosystem services, thus negative impacts to cultural services could have further downstream effects (Daniel et al., 2012). For instance, given that cultural ecosystem services often serve as the primary means by which people connect with nature (Chan et al., 2016), any hindrance to their flow to people could potentially impact public support for environmental conservation and the subsequent attainment of sustainable development goals. Further, impacts will affect different groups in different ways as cultural services are experienced and provided dynamically across groups such as general recreationists, birders, tourists, and local and indigenous populations (Daniel et al., 2012).

On the contrary, because of the inflated importance of certain regions for recreationists (due to sense of place, experience use history, or site popularity), visitation in some areas may be more resilient to climate and biodiversity change impacts as visitors are willing to put up with changing conditions or unwilling to substitute other sites or activities (De Valck et al., 2016). Future substitution behavior must be better understood as the defining attributes of sites for recreation and other cultural ecosystem services shift due to climate and biodiversity change, as shown in this study. Further, in some regions future shifts in suitability will be positive, thus equitable and increased access should be prioritized to regions providing cultural services as many regions lose suitability and inequalities in cultural ecosystem service access already present issues (Martinez-Harms et al., 2018). For all people (indigenous, local, and visitors), the well-being benefits from cultural ecosystem services are essential for good quality of life and in a future of diminishing services, managers and decisionmakers must make concerted and informed efforts to mitigate and adapt. Thus, it is imperative to bear in mind that the beneficiaries of these ecosystem services are not always within the local communities providing them. This dynamic introduces disparities and underscores the importance of considering nuances in such analyses, acknowledging that the distribution of benefits may not align seamlessly with the locales supplying these services.

### 4.3. ML and crowdsourced data

As highlighted by multiple IPBES reports, developing innovative tools and approaches that enable the integration of social-ecological feedbacks and enhance our understanding of the linkages between social factors and biophysical factors is urgently needed (Mastrángelo et al., 2019; Pörtner et al., 2021; Giupponi et al., 2022). Specifically, integrating social science data and coupling ecosystem service supply with use to better understand service co-production, flows, values, and consequences to human well-being will vastly improve our understanding of human relations with nature (Pascual et al., 2017; Willcock et al., 2019; Manley, 2022). We show that advancements in technology, especially ML and the rapid collection of big data, along with the adaptation of widely used tools such as Maxent and eBird, provide fresh possibilities for modeling ecosystem services and forecasting human-nature interactions. Crowdsourced big data is a massive globally available data source that offers novel opportunities to integrate social-ecological aspects of ecosystem services in a novel fashion and address historic limitations, especially in understudied regions, but has yet to be explored thoroughly (Brown and Rounsevell, 2021; Manley et al., 2022). Datasets like eBird provide a consistent measurement of cultural ecosystem service use across large spatial extents consisting of a multitude of management actors and varying data standards and availability (Nyelele et al., 2023a) (Fig. 1). ML can further help us explore human-nature relationships through data driven exploration of social-ecological interactions and hypothesis generation and testing (Scowen et al., 2021; Nyelele et al., 2023a).

Together, these tools offer a more realistic, although less detailed, way to assess human-nature relations on large spatiotemporal scales than traditional methods like surveys, interviews, and participatory mapping. We demonstrate how novel tools like ML and crowdsourced big data can help with the exploration of process interactions and theory development within cultural ecosystem services (Brown and Rounsevell, 2021; Scowen et al., 2021; Manley et al., 2022). Specifically, we use these tools on a large spatiotemporal scale and in an understudied region to test and demonstrate their use. Furthermore, we show the possibility presented by these tools in revealing previously unknown patterns and dynamics in non-material ecosystem service supply, use, and flows, and for the integration of the many interacting variables that produce cultural services. This is illustrative of the opportunity to better integrate social-ecological dynamics within climate impacts and ecosystem service studies, which is essential for the sustainable management of ecosystem services and achieving the CBD and Sustainable Development Goals (IPBES, 2018; Mastrángelo et al., 2019; Pörtner et al., 2021).

### 4.4. Limitations

Cultural ecosystem services are much more complex than can be analyzed through human behavior across a landscape, thus we acknowledge the limitations of this study and suggest future related work. Social aspects of this study are mainly focused on assessing human behavior that can be derived from social data on birders, data on attributes hypothesized and tested to be relevant to birders, and ML that can identify relationships between the two. This leaves out the less tangible aspects of these relationships, for example what are the perceptions and relational values of these birders or how does this non-monolithic group derive benefits from these services differently. Further, our models do not account for all factors that likely drive birding, like perception of safety of a destination, visitation costs, human and physical infrastructure, availability of guides/experts, among a plethora of other social, economic, and political factors (Dieke, 2020). While it is essential for these factors to be accounted for by decisionmakers and land managers, it is beyond the scope of this analysis to account for all realistic factors affecting cultural ecosystem service use.

Other limitations related to the data source include an underestimate of total birding as not all birders use eBird (although overall patterns are likely captured) and an inability to capture relationships related to casual birders, as most eBird users are serious birders (Koylu et al., 2019). Future work should focus more on teasing out the relational value aspects that are essential for the sustainability of not just cultural, but all ecosystem services and ecosystems in general (Chan et al., 2016). For example, this could be done in conjunction with large-scale crowdsourced data using text analysis (Lee et al., 2020) or analysis of review-based platforms (Wang and Hayashi, 2023) to better integrate ecosystem service beneficiary's perceptions and values. In the context of climate change, understanding how climate fits into people's perception and connection with natural regions is essential to understand how human-nature relations will change in the future.

## 5. Conclusion

Addressing critical knowledge gaps will be essential for designing effective policies and interventions that promote the future sustainability and management of biodiversity and ecosystem services (Pörtner et al., 2021). This is especially the case as benefit flows of ecosystem services, particularly to the poorest in society, is not well understood due to a lack of integration of both potential supply and realized use of services (Cruz-Garcia et al., 2017; Willcock et al., 2019). Interestingly, climatic, social, and environmental variables have rarely been used for mapping and modeling cultural services in tandem, echoing the potential pitfalls of past practices using simplistic and/or supply-based proxies (Eigenbrod et al., 2010; Jones et al., 2021). Thus, addressing these gaps, as we attempted in this study, is crucial for consideration of the disparities of future impacts. This is especially the case in the Global South as there is significant reliance upon ecosystem services for human well-being, future development, and sustainability transformations (Scott et al., 2019; Biggs et al., 2021) and uniquely strong interlinkages and convergences between cultural diversity and biodiversity (McElwee et al., 2022).

Because we are amidst a massive data revolution globally, our approach can be used in regions across the world to better understand cultural ecosystem services, the underlying dynamics that lead to service flows, and the future impacts of climate, land use, and biodiversity change. Insights from this analysis and similar analyses can help equitably address major global sustainability challenges and those faced by land managers and decisionmakers by improving the understanding of key dynamics and interactions within social-ecological systems. This can be important for identifying areas of vulnerability and resilience, assessing future trade-offs from environmental or management changes, and designing national development plans, development assistance programs, and international adaptation financing negotiations (Cumming and Allen, 2017; Scott et al., 2019; Snyman et al., 2021). Ultimately, identifying the complexities, uncertainties, and non-material aspects in social-ecological system and ecosystem service management is essential before impacts materialize in the real-world, especially as climate change intensifies (Brown and Rounsevell, 2021).

## CRediT authorship contribution statement

**Kyle Manley:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Benis N. Egoh:** Writing – review & editing, Supervision, Methodology, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.170872.

## References

Ajibola, F.O., Zhou, B., Shahid, S., Ali, Md.A., 2022. Performance of CMIP6 HighResMIP simulations on west African drought. Front. Earth Sci. 10 https://doi.org/10.3389/feart.2022.925358.

Arbieu, U., Grünewald, C., Martín-López, B., Schleuning, M., Böhning-Gaese, K., 2017. Mismatches between supply and demand in wildlife tourism: insights for assessing cultural ecosystem services. Ecol. Indic. 78, 282–291. https://doi.org/10.1016/j.ecolind.2017.03.035.

Ayugi, B., Ngoma, H., Babaousmail, H., Karim, R., Iyakaremye, V., Lim Kam Sian, K.T.C., Ongoma, V., 2021. Evaluation and projection of mean surface temperature using CMIP6 models over East Africa. J. Afr. Earth Sci. 181, 104226 https://doi.org/10.1016/j. jafrearsci.2021.104226.

Babaousmail, H., Hou, R., Ayugi, B., Ojara, M., Ngoma, H., Karim, R., Rajasekar, A., Ongoma, V., 2021. Evaluation of the performance of CMIP6 models in reproducing rainfall patterns over North Africa. Atmosphere 12, 475. https://doi.org/10.3390/atmos12040475.

Babaousmail, H., Ayugi, B.O., Ojara, M., Ngoma, H., Oduro, C., Mumo, R., Ongoma, V., 2023. Evaluation of CMIP6 models for simulations of diurnal temperature range over Africa. J. Afr. Earth Sci. 202, 104944 https://doi.org/10.1016/j.jafrearsci.2023.104944.

Biggs, D., Turpie, J., Fabricius, C., Spenceley, A., 2011. The value of avitourism for conservation and job creation — an analysis from South Africa. Conserv. Soc. 9 (1), 80–90. http://www.jstor.org/stable/26393127.

Biggs, R., de Vos, A., Preiser, R., Clements, H., Maciejewski, K., Schlüter, M., 2021. The Routledge Handbook of Research Methods for Social-ecological Systems. Taylor & Francis.

Breiman, L., 2001. Random forests. Mach. Learn. 45 (1), 5–32. https://doi.org/10.1023/A:1010933404324.

Brown, C., Rounsevell, M., 2021. How can social–ecological system models simulate the emergence of social–ecological crises? People Nat. 3 (1), 88–103. https://doi.org/10.1002/pan3.10167.

Carver, E., 2019. Birding in the United States: A Demographic and Economic Analysis: Addendum to the 2016 National Survey of Fishing, Hunting, and Wildlife-Associated Recreation. US Fish and Wildlife Service, Division of Economics.

Chan, N.W., Wichman, C.J., 2018. The Effects of Climate on Leisure Demand: Evidence from North America.

Chan, K.M.A., Balvanera, P., Benessaiah, K., Chapman, M., Díaz, S., Gómez-Baggethun, E., Gould, R., Hannahs, N., Jax, K., Klain, S., Luck, G.W., Martín-López, B., Muraca, B., Norton, B., Ott, K., Pascual, U., Satterfield, T., Tadaki, M., Taggart, J., Turner, N., 2016. Why protect nature? Rethinking values and the environment. Proc. Natl. Acad. Sci. 113 (6), 1462–1465. https://doi.org/10.1073/pnas.1525002113.

Chen, M., Vernon, C.R., Graham, N.T., Hejazi, M., Huang, M., Cheng, Y., Calvin, K., 2020. Global land use for 2015–2100 at 0.05° resolution under diverse socioeconomic and

climate scenarios. Sci. Data 7 (1), 320. https://doi.org/10.1038/s41597-020-00669-x.
Conservation Capital, 2019. Building a Wildlife Economy: Developing Nature-Based Tourism in Africa's State Protected Areas.
Cooper, J.C., Crouch, N.M.A., Ferguson, A.W., Bates, J.M., 2022. Climatic refugia and reduced extinction correlate with underdispersion in mammals and birds in Africa. Ecol. Evol. 12 (3), e8752 https://doi.org/10.1002/ece3.8752.
Cruz-Garcia, G.S., Sachet, E., Blundo-Canto, G., Vanegas, M., Quintero, M., 2017. To what extent have the links between ecosystem services and human well-being been researched in Africa, Asia, and Latin America? Ecosyst. Serv. 25, 201–212. https://doi.org/10.1016/j.ecoser.2017.04.005.
Cumming, D.H.M., 2008. Large Scale Conservation Planning and Priorities for the Kavango-Zambezi Transfrontier Conservation Area. Unpublished Report Commissioned by Conservation International.
Cumming, G.S., Allen, C.R., 2017. Protected areas as social-ecological systems: perspectives from resilience and social-ecological systems theory. Ecol. Appl. 27 (6), 1709–1717. https://doi.org/10.1002/eap.1584.
Cumming, G.S., Maciejewski, K., 2017. Reconciling community ecology and ecosystem services: cultural services and benefits from birds in South African National Parks. Ecosyst. Serv. 28, 219–227.
Daniel, T.C., Muhar, A., Arnberger, A., Aznar, O., Boyd, J.W., Chan, K.M.A., Costanza, R., Elmqvist, T., Flint, C.G., Gobster, P.H., Grêt-Regamey, A., Lave, R., Muhar, S., Penker, M., Ribe, R.G., Schauppenlehner, T., Sikor, T., Soloviy, I., Spierenburg, M., von der Dunk, A., 2012. Contributions of cultural services to the ecosystem services agenda. Proc. Natl. Acad. Sci. 109 (23), 8812–8819. https://doi.org/10.1073/pnas.1114773109.
de Valck, J., Broekx, S., Liekens, I., de Nocker, L., van Orshoven, J., Vranken, L., 2016. Contrasting collective preferences for outdoor recreation and substitutability of nature areas using hot spot mapping. Landsc. Urban Plan. 151, 64–78. https://doi.org/10.1016/j.landurbplan.2016.03.008.
de Vos, A., Biggs, R., Preiser, R., 2019. Methods for understanding social-ecological systems: a review of place-based studies. Ecol. Soc. 24 (4).
de Vos, A., Maciejewski, K., Bodin, Ö., Norström, A., Schlüter, M., Tengö, M., 2021. The practice and design of social-ecological systems research. In: The Routledge Handbook of Research Methods for Social-ecological Systems. Routledge, pp. 47–63.
Department of Trade and Industry, 2010. Avitourism in South Africa.
Dieke, P.U.C., 2020. Tourism in Africa: Issues and Prospects. Sustainable Human Resource Management in Tourism, African Perspectives, pp. 9–27.
Echeverri, A., Smith, J.R., MacArthur-Waltz, D., Lauck, K.S., Anderson, C.B., Monge Vargas, R., Alvarado Quesada, I., Wood, S.A., Chaplin-Kramer, R., Daily, G.C., 2022. Biodiversity and infrastructure interact to drive tourism to and within Costa Rica. Proc. Natl. Acad. Sci. 119 (11), e2107662119 https://doi.org/10.1073/pnas.2107662119.
Eigenbrod, F., Armsworth, P.R., Anderson, B.J., Heinemeyer, A., Gillings, S., Roy, D.B., Thomas, C.D., Gaston, K.J., 2010. The impact of proxy-based methods on mapping the distribution of ecosystem services. J. Appl. Ecol. 47 (2), 377–385. https://doi.org/10.1111/j.1365-2664.2010.01777.x.
Elith, J., Phillips, S.J., Hastie, T., Dudík, M., Chee, Y.E., Yates, C.J., 2011. A statistical explanation of MaxEnt for ecologists. Divers. Distrib. 17 (1), 43–57. https://doi.org/10.1111/j.1472-4642.2010.00725.x.
Espiner, S., Orchiston, C., Higham, J., 2017. Resilience and sustainability: a complementary relationship? Towards a practical conceptual model for the sustainability–resilience nexus in tourism. J. Sustain. Tour. 25 (10), 1385–1400. https://doi.org/10.1080/09669582.2017.1281929.
Ferraro, P.J., Hanauer, M.M., Sims, K.R.E., 2011. Conditions associated with protected area success in conservation and poverty reduction. Proc. Natl. Acad. Sci. 108 (34), 13913–13918. https://doi.org/10.1073/pnas.1011529108.
Fitzgibbon, A., Pisut, D., Fleisher, D., 2022. Evaluation of maximum entropy (Maxent) machine learning model to assess relationships between climate and corn suitability. Land 11 (9), 1382.
GBIF.org, 2022. GBIF Occurrence Download: eBird Obserbvation Dataset.
Giupponi, C., Ausseil, A.-G., Balbi, S., Cian, F., Fekete, A., Gain, A.K., Essenfelder, A.H., Martinez-Lopez, J., Mojtahed, V., Norf, C., Relvas, H., Villa, F., 2022. Integrated modelling of social-ecological systems for climate change adaptation. Socio-Environ. Syst. Model. 3, 18161 https://doi.org/10.18174/sesmo.18161.
Gosling, S.N., 2013. The likelihood and potential impact of future change in the large-scale climate-earth system on ecosystem services. Environ. Sci. Policy 27, S15–S31.
Hambira, W.L., Mbaiwa, J.E., 2020. Tourism and climate change in Africa. In: Routledge Handbook of Tourism in Africa, 98.
Hammitt, W.E., Backlund, E.A., Bixler, R.D., 2004. Experience use history, place bonding and resource substitution of trout anglers during recreation engagements. J. Leis. Res. 36 (3), 356–378. https://doi.org/10.1080/00222216.2004.11950028.
Havinga, I., Bogaart, P.W., Hein, L., Tuia, D., 2020. Defining and spatially modelling cultural ecosystem services using crowdsourced data. Ecosyst. Serv. 43, 101091 https://doi.org/10.1016/j.ecoser.2020.101091.
Heinrigs, P., 2020. Africapolis: understanding the dynamics of urbanization in Africa. Field actions science reports. J. Field Actions Special Issue 22, 18–23.
Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., Thépaut, J.-N., 2019. ERA5 monthly averaged data on single levels from 1959 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). (Accessed on < 08-2022 >). https://doi.org/10.24381/cds.f17050d7.
Hoogendoorn, G., Fitchett, J.M., 2016. Tourism and climate change: a review of threats and adaptation strategies for Africa. Curr. Issue Tour. 21 (7), 742–759. https://doi.org/10.1080/13683500.2016.1188893.
Hossain, M.S., Basak, S.M., Amin, M.N., Anderson, C.C., Cremin, E., Renaud, F.G., 2023. Social-ecological systems approach for adaptation to climate change. Sustain. Dev. 1–13 https://doi.org/10.1002/sd.2801.
IPBES, 2018. In: Archer, E., Dziba, L., Mulongoy, K.J., Maoela, M.A., Walters, M. (Eds.), The IPBES Regional Assessment Report on Biodiversity and Ecosystem Services for Africa.
Jamaliah, M.M., Powell, R.B., 2018. Integrated vulnerability assessment of ecotourism to climate change in Dana biosphere reserve, Jordan. Curr. Issues Tour. 22 (14), 1705–1722. https://doi.org/10.1080/13683500.2017.1401982.
Jaung, W., Carrasco, L.R., 2021. Using mobile phone data to examine weather impacts on recreational ecosystem services in an urban protected area. Sci. Rep. 11 (1), 5544. https://doi.org/10.1038/s41598-021-85185-7.
Jenkins, C.N., Pimm, S.L., Joppa, L.N., 2013. Global patterns of terrestrial vertebrate diversity and conservation. Proc. Natl. Acad. Sci. 110 (28), E2602–E2610.
Jones, L., Boeri, M., Christie, M., Durance, I., Evans, K.L., Fletcher, D., Harrison, L., Jorgensen, A., Masante, D., McGinlay, J., Paterson, D.M., Schmucki, R., Short, C., Small, N., Southon, G., Stojanovic, T., Waters, R., 2021. Can we model cultural ecosystem services, and are we measuring the right things? People Nat. 4 (1), 166–179. https://doi.org/10.1002/pan3.10271.
Jones, Z., Linder, F., 2015. Exploratory data analysis using random forests. In: Prepared for the 73rd Annual MPSA Conference.
Biodiversity assets are vital for South Africa's tourism economy. In: Joubert, L., Poole, C. J. (Eds.), 2018. National Biodiversity Assessment 2018 Supplementary Material: Compendium of Benefits of Biodiversity. South African National Biodiversity Institute, Pretoria. Report number. http://hdl.handle.net/20.500.12143/6491.
Karmaker, S.K., Hassan, Md.M., Smith, M.J., Xu, L., Zhai, C., Veeramachaneni, K., 2021. AutoML to date and beyond: challenges and opportunities. ACM Comput. Surv. 54 (8) https://doi.org/10.1145/3470918.
Klutse, N.A.B., Quagraine, K.A., Nkrumah, F., Quagraine, K.T., Berkoh-Oforiwaa, R., Dzrobi, J.F., Sylla, M.B., 2021. The climatic analysis of summer monsoon extreme precipitation events over West Africa in CMIP6 simulations. Earth Syst. Environ. 5 (1), 25–41. https://doi.org/10.1007/s41748-021-00203-y.
Kosanic, A., Petzold, J., 2020. A systematic review of cultural ecosystem services and human wellbeing. Ecosyst. Serv. 45, 101168 https://doi.org/10.1016/j.ecoser.2020.101168.
Koylu, C., Zhao, C., Shao, W., 2019. Deep neural networks and kernel density estimation for detecting human activity patterns from geo-tagged images: a case study of birdwatching on Flickr. ISPRS Int. J. Geo Inf. 8 (1) https://doi.org/10.3390/ijgi8010045.
Kummu, M., Taka, M., Guillaume, J.H.A., 2018. Gridded global datasets for gross domestic product and human development index over 1990–2015. Sci. Data 5 (1), 1–15.
Landers, D.H., Nahlik, A.M., Rhodes, C.R., 2016. The beneficiary perspective: benefits and beyond. In: Routledge Handbook of Ecosystem Services. Routledge, pp. 74–87.
Lee, J., Park, H., Kim, I., Kwon, H., 2020. Analysis of cultural ecosystem services using text mining of residents' opinions. Ecol. Indic. 115, 106368 https://doi.org/10.1016/j.ecolind.2020.106368.
Lissovsky, A.A., Dudov, S. v, 2021. Species-distribution modeling: advantages and limitations of its application. 2. MaxEnt. Biol. Bull. Rev. 11 (3), 265–275. https://doi.org/10.1134/S2079086421030087.
Manley, K., 2022. Understanding social–ecological systems using social media data. Nat. Rev. Earth Environ. 1 https://doi.org/10.1038/s43017-022-00320-w.
Manley, K., Egoh, B.N., 2022. Mapping and modeling the impact of climate change to recreational ecosystem services using machine learning and big data. Environ. Res. Lett. 17 (5), 054025. http://iopscience.iop.org/article/10.1088/1748-9326/ac65a3.
Manley, K., Nyelele, C., Egoh, B.N., 2022. A review of machine learning and big data applications in addressing ecosystem service research gaps. Ecosyst. Serv. 57, 101478 https://doi.org/10.1016/j.ecoser.2022.101478.
Martinez-Harms, M.J., Bryan, B.A., Wood, S.A., Fisher, D.M., Law, E., Rhodes, J.R., Dobbs, C., Biggs, D., Wilson, K.A., 2018. Inequality in access to cultural ecosystem services from protected areas in the Chilean biodiversity hotspot. Sci. Total Environ. 636, 1128–1138. https://doi.org/10.1016/j.scitotenv.2018.04.353.
Mastrángelo, M.E., Pérez-Harguindeguy, N., Enrico, L., Bennett, E., Lavorel, S., Cumming, G.S., Abeygunawardane, D., Amarilla, L.D., Burkhard, B., Egoh, B.N., Frishkoff, L., Galetto, L., Huber, S., Karp, D.S., Ke, A., Kowaljow, E., Kronenburg-García, A., Locatelli, B., Martín-López, B., Zoeller, K., 2019. Key knowledge gaps to achieve global sustainability goals. Nat. Sustain. 2 (12), 1115–1121. https://doi.org/10.1038/s41893-019-0412-1.
McElwee, P., He, J., Hsu, M., 2022. Challenges to understanding and managing cultural ecosystem services in the global South. Ecol. Soc. 27 (3) https://doi.org/10.5751/ES-13427-270323.
Millennium Ecosystem Assessment, 2005. Ecosystems and Human Well-being: Synthesis. Island Press, Washington, DC.
Monz, C.A., Gutzwiller, K.J., Hausner, V.H., Brunson, M.W., Buckley, R., Pickering, C.M., 2021. Understanding and managing the interactions of impacts from nature-based recreation and climate change. Ambio 50 (3), 631–643.
Mulongoy, K.J., Babu Gidda, S., 2008. The Value of Nature: Ecological, Economic, Cultural and Social Benefits of Protected Areas.
Mwampamba, T.H., Egoh, B.N., Borokini, I., Njabo, K., 2022. Challenges encountered when doing research back home: perspectives from African conservation scientists in the diaspora. Conserv. Sci. Pract. 4 (5), e564.
Nyelele, C., Keske, C., Gon Chung, M., Guo, H., Egoh, B.N., 2023a. Using social media data to estimate recreational travel costs: a case study from California. Ecol. Indic. 154, 110638 https://doi.org/10.1016/j.ecolind.2023.110638.

Nyelele, C., Keske, C., Chung, M.G., Guo, H., Egoh, B.N., 2023b. Using social media data and machine learning to map recreational ecosystem services. Ecol. Indic. 154, 110606 https://doi.org/10.1016/j.ecolind.2023.110606.

O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Clim. Change 122 (3), 387–400. https://doi.org/10.1007/s10584-013-0905-2.

Palomo, I., Montes, C., Martín-López, B., González, J.A., García-Llorente, M., Alcorlo, P., Mora, M.R.G., 2014. Incorporating the social–ecological approach in protected areas in the anthropocene. BioScience 64 (3), 181–191. https://doi.org/10.1093/biosci/bit033.

Pascual, U., Balvanera, P., Díaz, S., Pataki, G., Roth, E., Stenseke, M., Watson, R.T., Başak Dessane, E., Islar, M., Kelemen, E., Maris, V., Quaas, M., Subramanian, S.M., Wittmer, H., Adlan, A., Ahn, S., Al-Hafedh, Y.S., Amankwah, E., Asah, S.T., Yagi, N., 2017. Valuing nature's contributions to people: the IPBES approach. Curr. Opin. Environ. Sustain. 26–27, 7–16. https://doi.org/10.1016/j.cosust.2016.12.006.

Pereira, H.M., Rosa, I.M.D., Martins, I.S., Kim, H., Leadley, P., Popp, A., van Vuuren, D. P., Hurtt, G., Anthoni, P., Arneth, A., 2020. Global trends in biodiversity and ecosystem services from 1900 to 2050. BioRxiv.

Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecol. Model. 190 (3), 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026.

Pörtner, H.O., Scholes, R.J., Agard, J., Archer, E., Arneth, A., Bai, X., Barnes, D., Burrows, M., Chan, L., Cheung, W.L., 2021. IPBES-IPCC co-sponsored workshop report on biodiversity and climate change. & others.

Randler, C., Jokimäki, J., de Salvo, M., de Almeida Barbosa, R., Staller, N., Tryjanowski, P., Kaisanlahti-Jokimäki, M.-L., Tsai, J.-S., Ortiz-Pulido, R., Rahafar, A., 2023. Spatial, temporal, and motivational changes due to the COVID-19 pandemic in a nature-based leisure activity-a global survey of birders. Iscience 26 (8).

Rasool, H., Maqbool, S., Tarique, Md., 2021. The relationship between tourism and economic growth among BRICS countries: a panel cointegration analysis. Futur. Bus. J. 7 (1), 1. https://doi.org/10.1186/s43093-020-00048-3.

Rice, W.L., Meyer, C., Lawhon, B., Taff, B.D., Mateer, T., Reigner, N., Newman, P., 2020. The COVID-19 Pandemic is Changing the Way People Recreate Outdoors: Preliminary Report on a National Survey of Outdoor Enthusiasts amid the COVID-19 Pandemic.

Rogerson, C.M., 2016. Climate change, tourism and local economic development in South Africa. Local Econ. 31 (1–2), 322–331.

Runting, R.K., Bryan, B.A., Dee, L.E., Maseyk, F.J., Mandle, L., Hamel, P., Rhodes, J.R., 2017. Incorporating climate change into ecosystem service assessments and decisions: a review. Glob. Chang. Biol. 23 (1), 28–41.

Sangha, K.K., Russell-Smith, J., Costanza, R., 2019. Mainstreaming indigenous and local communities' connections with nature for policy decision-making. Glob. Ecol. Conserv. 19, e00668 https://doi.org/10.1016/j.gecco.2019.e00668.

Schwoerer, T., Dawson, N.G., 2022. Small sight—big might: economic impact of bird tourism shows opportunities for rural communities and biodiversity conservation. PloS One 17 (7), e0268594.

Scott, D., Hall, C.M., Gössling, S., 2019. Global tourism vulnerability to climate change. Ann. Tour. Res. 77, 49–61. https://doi.org/10.1016/j.annals.2019.05.007.

Scowen, M., Athanasiadis, I.N., Bullock, J.M., Eigenbrod, F., Willcock, S., 2021. The current and future uses of machine learning in ecosystem service research. Sci. Total Environ. 799, 149263 https://doi.org/10.1016/j.scitotenv.2021.149263.

Shelby, B., Vaske, J.J., 1991. Resource and activity substitutes for recreational salmon fishing in New Zealand. Leis. Sci. 13 (1), 21–32. https://doi.org/10.1080/01490409109513122.

Snyman, S., Sumba, D., Vorhies, F., Gitari, E., Ender, C., Ahenkan, A., Pambo, A.F.K., Natacha, O.A., 2021. State of the Wildlife Economy in Africa.

Steven, R., Morrison, C., Castley, J.G., 2015. Birdwatching and avitourism: a global review of research into its participant markets, distribution and impacts, highlighting future research priorities to inform sustainable avitourism management. J. Sustain. Tour. 23 (8–9), 1257–1276. https://doi.org/10.1080/09669582.2014.924955.

Steven, R., Rakotopare, N., Newsome, D., 2021. Avitourism tribes: as diverse as the birds they watch. In: Pforr, C., Dowling, R., Volgger, M. (Eds.), Consumer Tribes in Tourism: Contemporary Perspectives on Special-Interest Tourism. Springer Singapore, pp. 101–118. https://doi.org/10.1007/978-981-15-7150-3_8.

Sullivan, B.L., Aycrigg, J.L., Barry, J.H., Bonney, R.E., Bruns, N., Cooper, C.B., Damoulas, T., Dhondt, A.A., Dietterich, T., Farnsworth, A., Fink, D., Fitzpatrick, J. W., Fredericks, T., Gerbracht, J., Gomes, C., Hochachka, W.M., Iliff, M.J., Lagoze, C., la Sorte, F.A., Kelling, S., 2014. The eBird enterprise: an integrated approach to development and application of citizen science. Biol. Conserv. 169, 31–40. https://doi.org/10.1016/j.biocon.2013.11.003.

Telfer, P.T., Reed, P.E., 2021. Tourism in the Congo Basin Rainforests: How to Accelerate Tourism and Make it Regionally Sustainable.

Titley, M.A., Butchart, S.H.M., Jones, V.R., Whittingham, M.J., Willis, S.G., 2021. Global inequities and political borders challenge nature conservation under climate change. Proc. Natl. Acad. Sci. 118 (7), e2011204118 https://doi.org/10.1073/pnas.2011204118.

Tol, R.S.J., 2021. The distributional impact of climate change. Ann. N. Y. Acad. Sci. 1504 (1), 63–75. https://doi.org/10.1111/nyas.14497.

Twining-Ward, L., Li, W., Bhammar, H., Wright, E., 2018. Supporting Sustainable Livelihoods through Wildlife Tourism.

Tyukavina, A., Hansen, M.C., Potapov, P., Parker, D., Okpa, C., Stehman, S. v, Kommareddy, I., Turubanova, S., 2023. Congo Basin forest loss dominated by increasing smallholder clearing. Sci. Adv. 4 (11), eaat2993 https://doi.org/10.1126/sciadv.aat2993.

UNEP-WCMC, 2022. Protected Area Profile for Africa from the World Database on Protected Areas.

UNWTO, 2008. Climate Change and Tourism Responding to Global Challenges. World Tourism Organization. https://doi.org/10.18111/9789284412341.

UNWTO, 2014. Towards Measuring the Economic Value of Wildlife Watching Tourism in Africa.

van der Geest, K., de Sherbinin, A., Kienberger, S., Zommers, Z., Sitati, A., Roberts, E., James, R., 2019. The Impacts of Climate Change on Ecosystem Services and Resulting Losses and Damages to People and Society. Springer, Cham, pp. 221–236 (Loss and damage from climate change).

Wang, Y., Hayashi, K., 2023. Methodological development of cultural ecosystem services evaluation using location data. J. Clean. Prod. 396, 136523 https://doi.org/10.1016/j.jclepro.2023.136523.

Weiss, D.J., Nelson, A., Gibson, H.S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., Dalrymple, U., Rozier, J., Lucas, T. C.D., Howes, R.E., Tusting, L.S., Kang, S.Y., Cameron, E., Bisanzio, D., Gething, P.W., 2018. A global map of travel time to cities to assess inequalities in accessibility in 2015. Nature 553 (7688), 333–336. https://doi.org/10.1038/nature25181.

White, E.M., Winder, S.G., Wood, S.A., 2023. Applying novel visitation models using diverse social media to understand recreation change after wildfire and site closure. Soc. Nat. Resour. 36 (1), 58–75.

Willcock, S., Martínez-López, J., Hooftman, D.A.P., Bagstad, K.J., Balbi, S., Marzo, A., Prato, C., Sciandrello, S., Signorello, G., Voigt, B., Villa, F., Bullock, J.M., Athanasiadis, I.N., 2018. Machine learning for ecosystem services. Ecosyst. Serv. 33, 165–174. https://doi.org/10.1016/j.ecoser.2018.04.004.

Willcock, S., Hooftman, D.A.P., Balbi, S., Blanchard, R., Dawson, T.P., O'Farrell, P.J., Hickler, T., Hudson, M.D., Lindeskog, M., Martinez-Lopez, J., Mulligan, M., Reyers, B., Shackleton, C., Sitas, N., Villa, F., Watts, S.M., Eigenbrod, F., Bullock, J. M., 2019. A continental-scale validation of ecosystem service models. Ecosystems 22 (8), 1902–1917. https://doi.org/10.1007/s10021-019-00380-y.

Wood, C., Sullivan, B., Iliff, M., Fink, D., Kelling, S., 2011. eBird: engaging birders in science and conservation. PLoS Biol. 9 (12), e1001220 https://doi.org/10.1371/journal.pbio.1001220.

Wood, S.A., Guerry, A.D., Silver, J.M., Lacayo, M., 2013. Using social media to quantify nature-based tourism and recreation. Sci. Rep. 3 (1), 2976. https://doi.org/10.1038/srep02976.

Wood, S.A., Winder, S.G., Lia, E.H., White, E.M., Crowley, C.S.L., Milnor, A.A., 2020. Next-generation visitation models using social media to estimate recreation on public lands. Sci. Rep. 10 (1), 15419 https://doi.org/10.1038/s41598-020-70829-x.

World Bank, 2021. Opportunities for the Development of Birdwatching Tourism in Uganda.

Wouters, H., Berckmans, J., Maes, R., Vanuytrecht, E., De Ridder, K., 2021. Global bioclimatic indicators from 1950 to 2100 derived from climate projections, version 1.0, (for [extracted period], [model], [ensemble member], [experiment] etc). In: Copernicus Climate Change Service (C3S) Climate Data Store (CDS), (Accessed on 08-2022). https://doi.org/10.24381/cds.a37fecb7.