Explainable artificial intelligence to interpret spatially-explicit impacts of future climate change on species distribution

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***Abstract*— Biodiversity is essential for maintaining ecosystem balance and functionality, providing vital services such as climate regulation. The rapid decline in biodiversity, driven by habitat loss, habitat fragmentation, and climate change, poses significant threats to ecosystems. Climate change, in particular, is fundamentally altering habitats, leading to shifts in species distributions. However, existing research often lacks decomposed contribution analyses, particularly spatially, for a changing individual environmental attributes when modeling species distribution as an aggregate result of all factors and their interactions. Such analyses are crucial for identifying climate refugia and prioritizing conservation efforts. Taking endangered mammal species as an example, this study addresses this gap by employing species distribution modeling (SDM) and the post-hoc interpretability method, Shapley values, to analyze how future environmental variables are likely to reshape habitat suitability spatially. Our findings indicate that by 2070, some regions in North America, Europe, and Australia will become suitable for many species due to changes in annual mean temperature, while extensive areas in the Amazon and Congo rainforests will become less suitable. Annual mean precipitation is also projected to drive worsening conditions for local species, particularly in South America and central Africa. Our analysis demonstrates the effectiveness of explainable AI (xAI) techniques, such as Shapley values, in elucidating the future impacts of climate change by accounting for the interactions between environmental attributes. We identify a spatial analysis tool to develop conservation strategies targeted at the environmental attribute level, aimed at mitigating the diverse impacts of climate change on global biodiversity.**

Keywords*— *Explainable machine learning, Shapley values, SHAP, SDM, climate change

I. INTRODUCTION

Species conservation plays a crucial role in maintaining the balance and functionality of ecosystems[1]. Biodiversity is vital for conservation as it ensures the resilience and adaptability of ecosystems, supporting essential services such as nutrient cycling[2], [3]. In recent decades, biodiversity has declined at an alarming rate due to habitat loss and fragmentation, overexploitation of natural resources, and climate change[4]. In fact, climate change has emerged as one of the most significant threats to global biodiversity[5]. Rising temperatures, changing precipitation patterns, and the increasing frequency and intensity of extreme weather events are fundamentally altering habitats and ecosystems worldwide[6]. Understanding the impacts of climate change on species distribution is critical for developing effective conservation strategies and mitigating biodiversity loss and the degradation of ecosystem services.

Despite numerous studies on climate change and species distribution, the scientific community has yet to develop methods for spatially decomposing the contributions of changing individual environmental factors in species distribution models (SDMs). The absence of these studies from the literature represents a critical gap in our collective understanding of both species conservation and climate change impacts. Greater spatial-, species-, and attribute-level detail is needed to identify climate refugia—areas that remain suitable for species despite changing climate conditions—and for planning conservation actions that can enhance the resilience of ecosystems[7]. Detailed, spatially explicit analyses are also necessary for landscape features, such as land cover, to be incorporated into forward-facing models to create a more comprehensive picture of how species distributions might shift[8]. Once developed, these analyses can help identify areas where conservation efforts should be prioritized, ensuring that resources are allocated efficiently to protect the most vulnerable species and habitats[9].

Species distribution modeling (SDM) is a widely used technique for studying the interactions between species and climate. However, many advanced models rely on ecologically uninterpretable machine learning algorithms, making it challenging to translate SDM results into actionable policies and conservation strategies. Recently, post-hoc interpretability methods, such as Shapley values[10] and Local Interpretable Model-agnostic Explanations (LIME)[11], have been proposed to enhance understanding of the contributions of different predictors in these models[12]. However, they have seen limited use in SDMs and have never been applied to future projections. We aim to fill this critical gap by integrating SDM and the Shapley value technique[10]. Integrating these methods is an important step toward developing a comprehensive understanding of how future environmental conditions are likely to reshape biodiversity patterns spatially.

II. Methods

We model the effects of climate change on the future distribution of 145 endangered[13] mammal species using species occurrence data available in the Global Biodiversity Information Facility (GBIF). The focus of our analysis is mammals due to their well-documented studies, the availability of sufficient occurrence records, and well-documented habitat requirements, such as those provided by the IUCN[13]. The analysis consists of two major steps (Figure 1). First, we develop a random forest-based species distribution model (SDM) that is tailored to each species using occurrence data and current environmental variables (e.g., bioclimatic, land cover, topography, etc.). Second, post-hoc analysis is completed using the Shapely value method to analyze the impact of climate change on the current and future geographic distribution of species. The Shapley method uses current and projected future environmental variables to assess the spatial contribution of each variable to each species' distribution. Differences in contributions between current and future scenarios provide an indication of the potential impact of changes in specific environmental variables.

A. Data processing

Species occurrences. SDMs are based on species occurrence data, which include taxonomic observations recorded at specific times and locations[14]. These data are used to quantify patterns and determinants of biodiversity and for predicting the responses of ecological systems to global change. Various platforms host species occurrence data, including the Global Biodiversity Information Facility (GBIF), iNaturalist, eBird, and the Botanical Information and Ecology Network (BIEN). We retrieved occurrence data for global endangered[13] mammals from GBIF using the R package rgbif[15] from the year 1981 onwards[16]. To improve model accuracy and reliability, we used R package occTest[17] to retain only those records that had valid geographic coordinates by removing records with incomplete or invalid coordinates, such as those with longitude values exceeding 180 in a geographic coordinate system. We also excluded records with

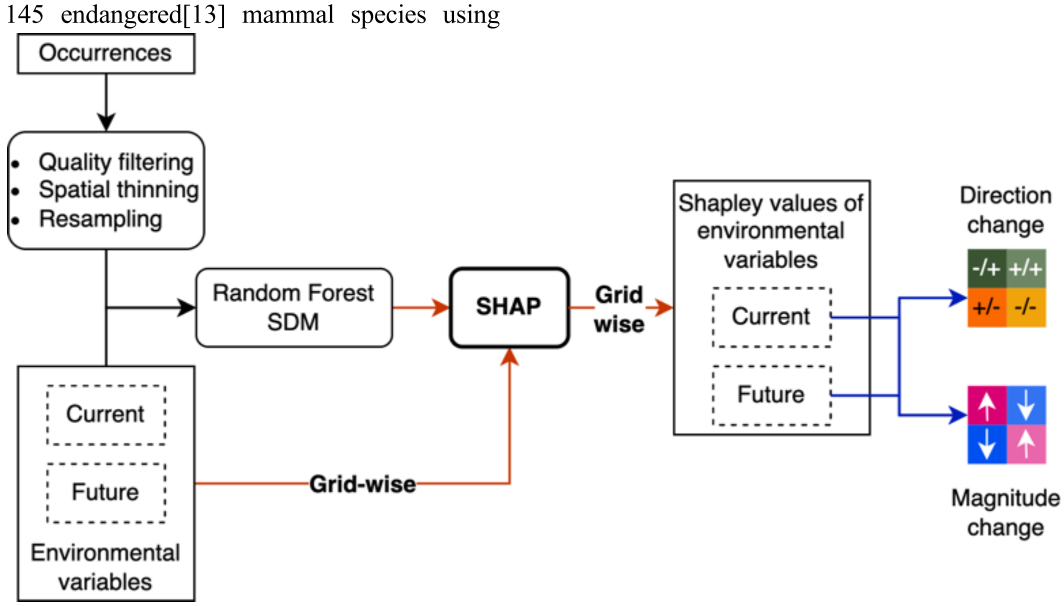

Fig. 1 Conceptual workflow of the climate change impact analysis. Black arrows indicate species distribution modeling (SDM), red arrows indicate model explanation, and blue arrows indicate climate change impact analysis. SHAP (SHapley Additive exPlanations) is the method to use Shapley values to interpret models.

suspicious coordinates, like exactly zero latitude or longitude, as well as coordinates located at political centroids.

Environmental variables. Environmental covariates included climate and land cover variables. We used climate variables from CHELSA-BIOCLIM+ (climatologies at high resolution for the Earth's land surface areas – bioclimatic variables plus) due to its higher performance compared to WorldClim data[18], [19]. CHELSA-BIOCLIM+ offers global climate-related variables at 10km resolution, covering both historical (1981–2010) and future projections (up to 2100). Variables include temperature and precipitation, which are crucial for ecological studies. The dataset is based on a combination of downscaled climate data and state-of-the-art modeling approaches, providing valuable insights into climate-driven changes in ecosystems[19].

We selected CHELSA-BIOCLIM+ variables with low Pearson correlations (< 0.7), including mean annual temperature (BIO1), mean diurnal temperature range (BIO2), annual precipitation (BIO12), precipitation seasonality (BIO15), and precipitation in warmest quarter (BIO10) / (precipitation in coldest quarter (BIO11) + precipitation in warmest quarter). We used data from 1981 to 2010 to represent current environmental conditions and projections for 2041 to 2070, simulated by the GFDL-ESM4 model under the SSP370 scenario, to represent near-future conditions[18].

To assess potential human impacts, we used current and projected future land cover maps created by Chen et al.[20]. The current land cover map, referencing the year 2015, served as the current condition. For near-future conditions, we selected the land cover map for the year 2070, simulated under the SSP370 scenario, to match with climatic variables. The layers were resampled from a resolution of 1 km to 10 km using the nearest neighbor interpolation method.

B. *Species distribution modeling (SDM)*

Domain selection. To fit and project the SDM for each species, we modeled their possible distribution domain, accounting for the limited dispersal abilities of mammals. For each species, we extracted TNC terrestrial ecoregions[21] overlapping with their native ranges defined by IUCN[13] and also included neighboring ecoregions. All model fitting and projections were conducted within the defined domain of each species, assuming that the species can only disperse to suitable climates in adjacent ecoregions.

Processing occurrence data. After cleaning the occurrence data for geographic irregularities (as detailed above), we removed occurrences outside of the defined domain and filtered out those not covered by all environmental layers to ensure consistency. If multiple records existed within the same 10km grid cell, only one record was retained. To minimize spatial autocorrelation, we applied spatial thinning to the occurrences using the R package spThin[22], ensuring that all retained records were at least 20km apart. However, in cases where fewer than 20 records were available, we did not apply spatial thinning to avoid excessively reducing the sample size. To reduce extrapolation in model evaluation and address spatial autocorrelation, we then spatially stratified occurrences into five folds for cross-validation. This process involved computing k-means clusters on the occurrence coordinates to create 25 clusters. These clusters were then randomly assigned into five folds. This process helps to reduce the impact of spatial autocorrelation and ensures that no significant portion of the environmental space is excluded from model fitting.

Model fitting. We employed the Random Forest algorithm[23] to construct all SDMs using the R package biomod2[24]. Pseudo-absences were randomly selected within the defined domain, matching the number of processed occurrences. The model's performance was evaluated using overall accuracy, True Skill Statistic (TSS), and Area under Receiver Operating Characteristic curves (AUC), with cross-validation[25]. Subsequently, all available occurrences were used to build a full model for projecting both current and future conditions.

C. *Shapley value and variable contribution*

The Shapley value[10], derived from cooperative game theory, is used to fairly allocate the payouts among players in a game. In the context of SDM, the 'payout' is the species distribution and the 'players' are the environmental variables. Shapley values illustrate how each explanatory feature affects the model's output by comparing it to the base value, which is the average output over the training dataset[26]. Positive Shapley values indicate a contribution toward presence, while negative values indicate a contribution toward absence. The magnitude of the Shapley value reflects the importance of the feature. By calculating Shapley values for current environmental variables across all grid cells, we can assess the spatially explicit contribution of each variable to species distribution. Similarly, using future environmental variables allows us to estimate the contribution of future variables to future distributions, assuming the species-environment relationships remain unchanged.

An extension to Shapley has been developed to explain individual predictions using Shapley values called SHapley Additive exPlanations, or SHAP[27]. For a given $f(x)$ for a single input x, the SHAP method explains the prediction as the sum of the contributions from each feature value[27]:

$$g(x') = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i x_i' \tag{1}$$

where g is the explanation model. x' is the simplified x that maps to the original x by function $x = h_x(x')$. M is the number of input features. $\emptyset_0$ is the constant value when all inputs are missing, and $\emptyset_i \in \mathbb{R}$ is the feature attribution for feature i. Shapley values are the unique solution to Eq.1, satisfying three key properties: local accuracy, missingness, and consistency.[27]:

$$\emptyset_i = \sum_{Q \subseteq S \setminus \{i\}} \frac{|Q|!\,(|S| - |Q| - 1)!}{|S|!} [f_{Q\cup\{i\}}(x_{Q\cup\{i\}}) - f_Q(x_Q)] \tag{2}$$

where S is the set of all features in the model. Q is a subset of S. $f_{Q\cup\{i\}}$ is a model trained with feature i present and f_Q is a model trained with feature i withheld. Thus, $f_{Q\cup\{i\}}(x_{Q\cup\{i\}}) - f_Q(x_Q)$ represents the effects of including feature i on the model. Because the effect of withholding a feature relies on other features, $\emptyset_i$ calculates the weighted average of $f_{Q\cup\{i\}}(x_{Q\cup\{i\}}) - f_Q(x_Q)$ of all possible subsets $Q \subseteq S\backslash\{i\}$.

Several methods, such as Kernel SHAP and Linear SHAP[26], [28], have been developed to approximate Shapley values (Eq. 2). We used the fastshap package[29] to estimate Shapley values, which efficiently implements a Monte Carlo sampling approach[28]. This approach provides an efficient way to compute the Shapley values, ensuring accurate and consistent attribution of feature contributions in our models.

D. *Climate change impact analysis*

We retained only those SDMs with an average AUC above 0.7, ensuring the reliability of our climate change analysis. For each environmental variable, we created spatial contribution maps for both current and future conditions. The impact of climate change was assessed by analyzing the direction and magnitude of changes in each climate-related variable contribution. As described above, Shapley values are signed, with negative values indicating contributions to species absence and positive values indicating contributions to presence. The changes in direction over time can be categorized as negative to negative, negative to positive, positive to negative, and positive to positive. Changes in the direction of contributions can signal significant shifts, such as a potential habitat crisis (from positive to negative) or the emergence of new possible habitats (from negative to positive). Even when the direction remains consistent, the magnitude of the variable's contribution can change, affecting species distribution by making conditions more or less suitable. To capture these variations, we calculated the quantitative differences between the contributions of variables under current and future conditions.

III. RESULTS

Climate change is expected to exert different impacts on various regions and species. Extensive regions of the world are projected to experience annual mean temperatures that will become unsuitable for local species by 2070, particularly in the Amazon and Congo rainforests (Figure 2B). Even more concerning is that the annual mean precipitation in these regions is also expected to become unsuitable for these species by 2070 (Figure 2B). On a positive note, numerous areas where the annual mean temperature is currently unsuitable are projected to become suitable for over half of the local species by 2070, including regions in North America, Europe, and Australia.

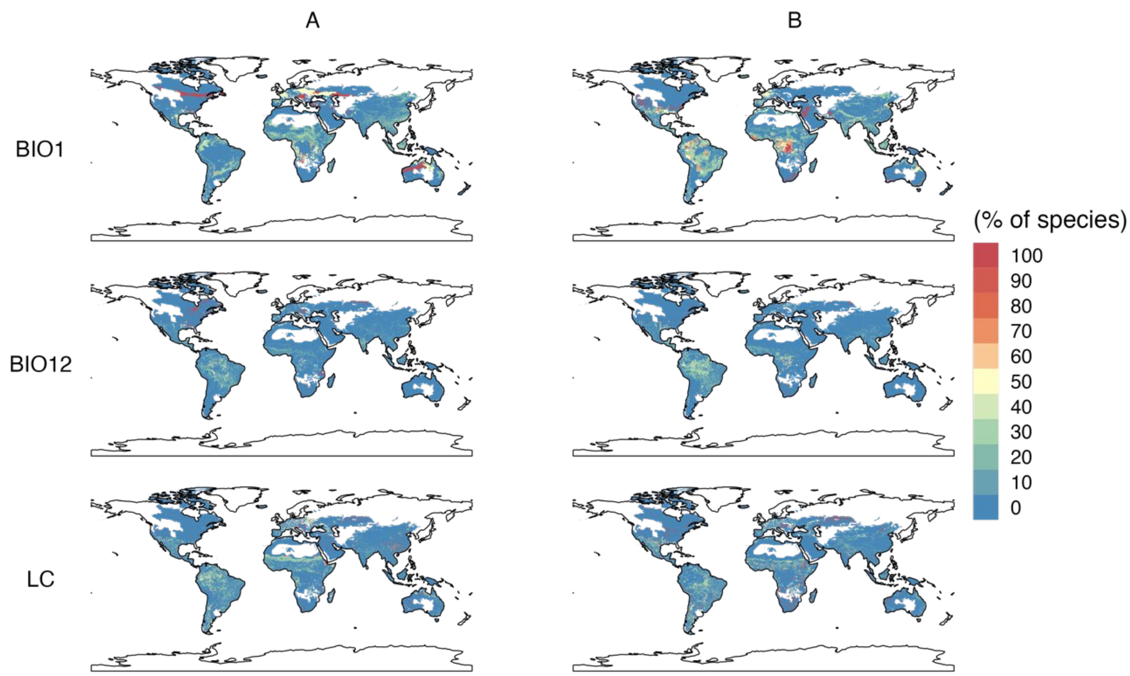

Fig. 2 Number of endangered mammal species experiencing environmental changes from (A) non-suitable to suitable and (B) suitable to non-suitable conditions by 2070. Variables shown include changes in contributions of BIO1 (annual mean temperature), BIO12 (annual mean precipitation), and LC (land cover).

The modeled impacts of land cover change on species distribution are relatively fragmented. Many species' habitats, such as those in African countries and China, are projected to degrade for almost all local species due to deforestation or urbanization (Figure 2B). Notably, the areas south of the Sahara Desert are predicted to become suitable for approximately 30% of associated species by 2070 (Figure 2A). Additionally, South America is also expected to experience habitat recovery, offering improved land cover conditions for species distribution.

Many areas are also expected to experience gradual impacts of climate change. Regions currently characterized by suitable annual mean temperatures are projected to become generally less suitable by 2070, particularly in the Amazon and Congo rainforests (Figure 3A). In contrast, only a few regions are expected to become more suitable for species habitation in terms of annual mean temperature by 2070. However, areas that are currently unsuitable are anticipated to become even more unsuitable for species by 2070, particularly in North America, Europe, and South America (Figure 3B). Annual mean precipitation is predicted to become less suitable for species in South America and central Africa, affecting these regions widely.

IV. Discussion

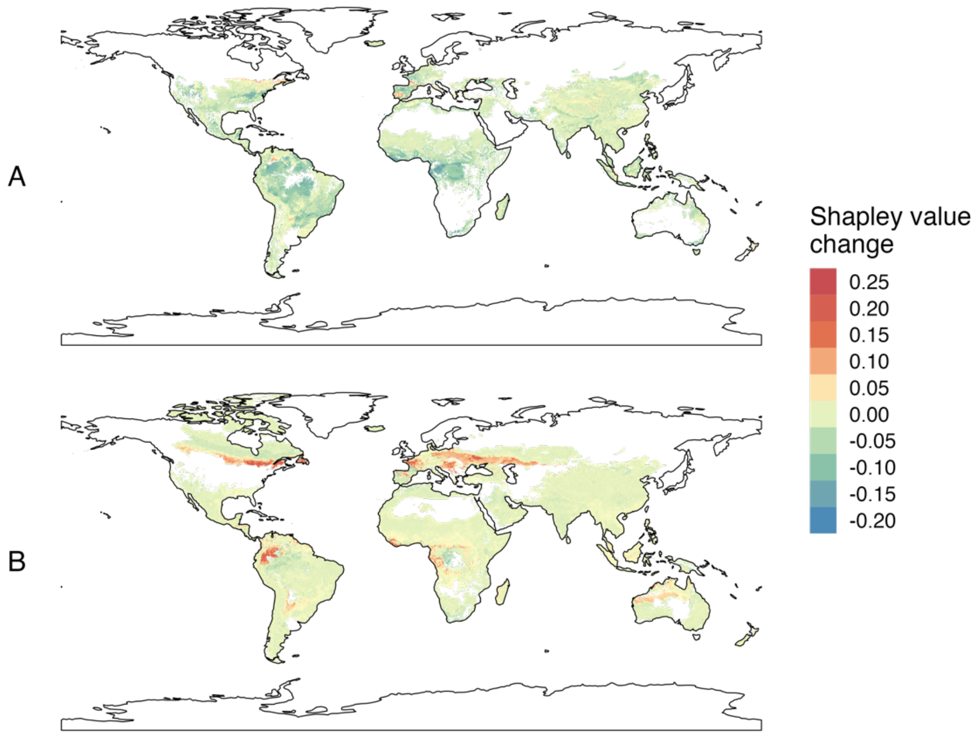

Fig. 3 Magnitude of contribution change of BIO1 (annual mean temperature) on the suitability of an area to support endangered mammal species by 2070 for (A) areas that are currently suitable, and (B) areas that are currently not suitable. Positive Shapley value change indicates the increasing contribution.

The projected climate changes, including shifts in annual mean temperature and precipitation, alongside land cover alterations, pose significant challenges for species distribution. By 2070, regions like the Amazon and Congo rainforests are expected to become less suitable for endangered, local mammal species, with annual precipitation declines exacerbating habitat stress. Conversely, areas south of the Sahara and parts of South America may experience habitat recovery. However, land cover changes due to deforestation and urbanization, particularly in African countries and China, will likely fragment habitats. These findings provide conservative suggestions to mitigate the diverse impacts of climate change on global biodiversity.

By explaining the environmental variables in the SDMs using the Shapley values, we accounted for the interactions between these variables and quantified their changing contributions to species distribution. The results provide spatially explicit insights into how climate and land cover are likely to influence biodiversity now and into the future, highlighting areas of critical concern and potential resilience under future climate scenarios. The application of xAI techniques can help interpret what have previously been black-box SDMs and significantly improve our understanding of what aspects of future climate change will impact species distributions[12]. However, xAI techniques like Shapley values can be computationally intensive and may not always capture the complexities of interactions among predictors, limiting their effectiveness in certain contexts[12]. Given that different species respond variably to climatic conditions, our future work will include an examination of a broader range of species, including plant species. We will also apply various climate scenarios to obtain a comprehensive understanding of the spatially explicit impacts of climate change on biodiversity.

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