

# Chapter 5

## Future impacts of climate change and deforestation on endemic trees of Western Ghats, South India

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### Abstract

The Western Ghats (WG) include a narrow belt of rainforests exposed to the south-west Indian monsoon. They shelter diverse forest types and rare endemic biodiversity, making the WG one of the 25 major biodiversity hotspots on Earth. The WG are also one of the most threatened biodiversity hotspots, as climate change and deforestation are expected to strongly affect rainforest cover and composition. Here we assess the vulnerability of endemic tree species to ongoing and future global changes, with statistical models of environmental changes and Species Distribution Modeling (SDM). In the absence of any action, we expect that the rainforest would disappear from the area by 2070, entailing massive extinction. In addition, climate change should increase species rarity and extinction risk of endemic trees that are specialized to specific rainfall regimes related to monsoon. We discuss the interest and limits of ecological models for guiding future conservation strategies and safeguarding the unique biodiversity in the area. We discuss the advantages and challenges of assessing and predicting threats using SDM techniques, which should be of general significance for the conservation and management of other biodiversity hotspots in South-East Asia.

**Keywords:** Biodiversity hotspot, Climate change, Conservation, Deforestation, Rainforest tree diversity, South India

## 5.1 Introduction

The Western Ghats of India (WG) are one of the 25 most important biodiversity hotspots of the world (Myers et al., 2000). Sharp environmental gradients characterize this mountain range, which have determined past diversification and extant species distributions (Pascal, 1988; Bawa et al., 2007; Ramesh et al., 2010, Bose et al., 2016; Bose et al., 2019). The area is subject to intense and rapid changes in land cover and land use (Kale et al., 2016), resulting in decreasing forest cover and threats to endemic species. In addition, many species occur at low local density and low regional frequency, which increases their vulnerability to habitat destruction (Davidar et al., 2018).

Among the 50,369 plant species globally assessed in the IUCN Red List (accessed on 28 October 2021), more than a quarter are tagged “needs updating”. Around 16% of the total estimated number of plants (Paton et al., 2008) are actually red listed, and biodiversity hotspots likely host most undiscovered species (Joppa et al., 2011). This situation underlines an urgent need to further sample and assess the dynamics of species in biodiversity hotspots such as the WG. Identifying and prioritizing the species most at risk in the WG should guide the efforts of local stakeholders.

We expect that climate change should impact forest ecosystems and endemic tree species adapted to the highly seasonal monsoon regime particular to the WG (Das and Behera, 2019). For instance, dryer and longer dry seasons should negatively affect Myristicaceae trees that live in swamp and humid forests (Priti et al., 2016). In addition, as in other tropical forests of the world, high population density and economic development in the WG would entail continuing reduction in forest cover in the area (Reddy et al., 2013). We thus also expect deforestation to represent a major threat to forest biodiversity in coming decades.

We can anticipate that ongoing threats to ecosystems and biodiversity will continue to increase in the future, but we currently lack quantitative assessments that could inform the debate on conserving the natural heritage and guide further actions. To objectively and quantitatively analyze species distributions, previous works have used statistical, ecological models of species and forest distribution for prioritizing conservation areas in Southeast Asia (Hughes, 2017), as well as in the WG (Prasad et al., 1998; Amarnath et al., 2003; Das et al., 2006; Athira et al., 2017).

Species Distribution Models (SDM) identify potential species distributions and help to detect their changes through time, which allows defining areas of conservation importance and greater sustainability under future environmental changes (Elith and Leathwick, 2009). For instance, Joshi et al. (2017) used SDM to assess hotspots of rattan species in WG, and Giriraj et al. (2008) to identify potential areas of the high-elevation endemic *Rhododendron nilagaricum*. Gaucherel et al. (2016) used SDM based on climate predictors to identify the potential distributions of endemic trees in WG, and

to delineate important areas for conservation. Pelletier et al. (2018) and Stévant et al. (2019) assessed potential population loss and range reduction to estimate the potential conservation status of tropical forests at the global scale in the future. However, there is no recent assessment of the joint impact of climatic changes and deforestation on the future of forest biodiversity in the WG biodiversity hotspot.

We assessed the expected change of suitable habitat area under scenarios of future climate change and anthropogenic deforestation. We used the SDM approach to forecast future threats to endemic tree species, which should help in the design of appropriate conservation strategies.

## 5.2 *Material and methods*

### 5.2.1 *Study area and endemic species data*

We delimited the study area based on the world map of ecoregions (Olson et al., 2001). We selected polygons belonging to the categories "North WG montane rain forests", "North WG moist deciduous forests", "Malabar Coast moist forests", "South WG montane rain forests", "South WG moist deciduous forests", "Malabar Coast moist forests", "South WG montane rain forests", "South WG moist deciduous forests". The resulting area is a 1600 km-long, narrow escarpment facing India's southwestern coast and receiving a broad gradient of rainfall depending on monsoon exposure (Pascal, 1988). The wet and moist forests here are isolated from the evergreen forests of north eastern India and Indochina by the rapid decline in rainfall towards the leeward east and the north, contributing to a unique evolutionary and biogeographic heritage (Bossuyt et al., 2004). We also mapped the administrative limits from Global ADministrative database (<https://gadm.org/>), and the protected areas from the World Database on Protected Areas (<https://www.protectedplanet.net>).

The Atlas of WG endemic trees (Ramesh and Pascal, 1997) reports occurrence data based on three sources: (1) herbarium specimens, (2) published data and (3) results of intensive field surveys conducted in 1970–1990 by botanists from the French Institute of Pondicherry (FIP). We built a dataset from the Atlas including 8,316 occurrences corresponding to 165 taxa with at least 12 occurrences each.

We get up-to-date IUCN status of the selected endemic trees by using the *rredlist* package in R (functions *rl\_threats* and *rl\_status*).

### 5.2.2 *Climatic data*

We used present-day climatic data for modelling species distributions from available occurrence data. We considered 19 bioclimatic variables provided in the CHELSA (Climatologies at High resolution for the Earth's Land Surface Areas) database. We selected four of these variables with less correlation

( $\leq 0.7$ ): mean annual temperature (bio1), temperature seasonality (bio4), annual precipitation (bio12), and rainfall seasonality (bio15). The climatic data from meteorological stations were averaged over several decades (1973-2013), and interpolated to provide raster maps at 1 km x 1 km resolution.

We considered the future climate scenario SSP 5 (Shared Socioeconomic Pathway), representing conventional development, and RCP 8.5 (Representative Concentration Pathway, O'Neill et al., 2014), corresponding to an atmospheric CO<sub>2</sub> concentration increase to 1135 ppm in 2100 (MIROC-ES2L Global Climate Model). This scenario should well represent climate change in next decades under a business-as-usual economic policy (Schwalm et al., 2020). We got the predictions from the CHELSA database for the selected climatic variables for the years 2040, 2060, 2080 and 2100.

### 5.2.3 Forest cover and deforestation data

We classified pixels of Landsat images at 30 m resolution every 5 years from 2000 to 2020 (Vancutsem, 2020) as either including natural moist tropical forest or not. The approach excluded plantation and regrowth from the forest category, but included degraded forests. We classified forested and deforested pixels by comparing forest covers between 2000 and 2010 (Vancutsem et al., 2020). We related the resulting binary deforestation index to 8 predictors, i.e., topography (altitude and slope), accessibility (distances to nearest road, town, and river), forest landscape (distance to forest edge), deforestation history (distance to past deforestation), and land conservation status (presence of a protected area). We obtained elevation (in m) and slope (in degree) at 90 m resolution from the SRTM Digital Elevation Database v4.1 (<http://srtm.csi.cgiar.org/>). We calculated distances (in m) to nearest road, town and river at 150 m resolution based on OpenStreetMap (OSM) (<https://www.openstreetmap.org/>). We calculated the distance to the forest edge at 30 m resolution based on the forest cover map in 2010. Distance to past deforestation in 2010 was computed at 30 m resolution based on the 2000-2010 forest cover change map. Data on protected areas were rasterized at 30 m resolution.

We performed logistic regression of the deforestation index according to the 8 predictors for 10000 pixels randomly drawn in each forest/non-forest category. To account for the residual spatial variation in the deforestation process, we included an additional random effect for 10 km × 10 km spatial cells covering the study area. We chose this grid resolution in order to have a reasonable balance between a good representation of the spatial variability of the deforestation process and a limited number of parameters to estimate. We assumed that random effects were spatially autocorrelated through an intrinsic conditional autoregressive (iCAR) model (Besag, 1991). We performed backward variable selection based on model AIC to select the most influential predictors. We estimated coefficient values in the final parsimonious model by performing hierarchical Bayesian inference (Vieilledent, 2021). We interpolated at 1 km the spatial random effects at 10 km using bicubic interpolation.

We forecasted deforestation trends until 2100, based on the model fitted for the period 2000-2010, by assuming a "business-as-usual" scenario. We calculated the density of forest pixels within 1 km x 1 km cells at all dates. Figure 1 shows the forest cover in 2000 (left) and projected in 2040 (center) and 2060 (right). Although forests are expected to persist in most steep slopes of the WG, deforestation is expected to be considerable in low and mid-elevation areas. When projecting the trend in 2070 and later, the model predicted that no wet tropical forests would persist in the area.

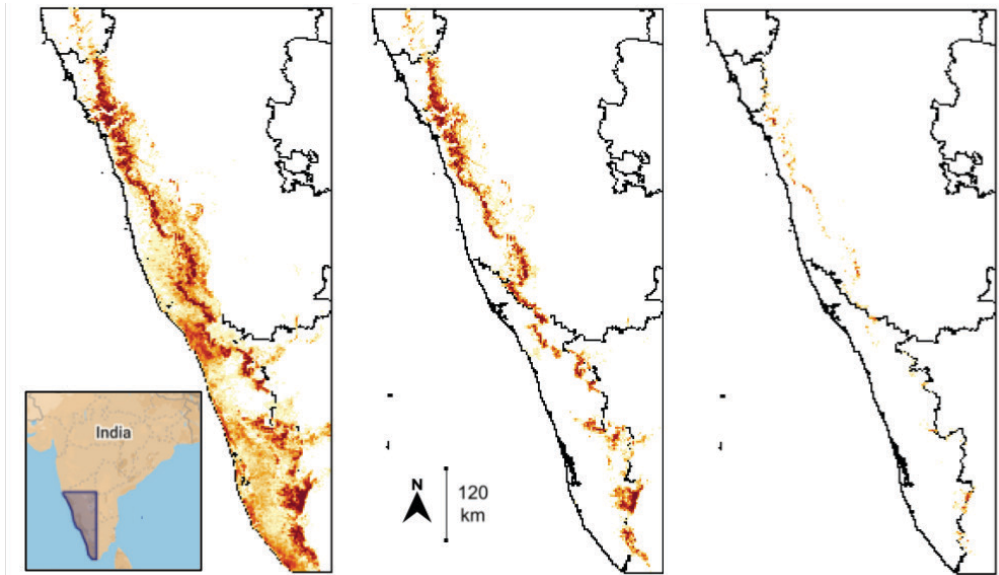


Figure 1. Map of wet and moist tropical forests in Western Ghats of India, derived from Landsat images in 2000 (left), and projected in 2040 (center) and 2060 (right) under a "business-as-usual" scenario of deforestation. 1km x 1km cells with at least 10% forest cover are shown across a gradient of red color (darker = greater forest cover).

#### 5.2.4 Species distribution modelling

We performed Maxent Species Distribution Models (SDM) using the function *maxent* in R package *dismo*. We selected 165 species with at least 12 recorded occurrences, because SDMs need enough information to provide reliable assessment of species ecological niches. The model provided potential habitat suitability maps encoded with normalized probabilities. Our next objective was to obtain a measure of potential habitat loss. We defined binary maps of potential distributions by thresholding the probabilities to the maximum of True Skill Statistic (TSS, the sum of specificity and sensitivity minus one, Allouche et al., 2006), which is recommended for SDMs with presence-only data (Liu et al., 2013). We used the function *AOO.computing* from the *ConR* package (Dauby et al., 2017) to obtain a quantified area reflecting the species potential habitat, with default parameter values (i.e., 2 x 2 km<sup>2</sup> cell size). Finally, we assessed the relative habitat loss for a given species *s* between two

given years  $i$  and  $j$  ( $j > i$ ) as the ratio:

$$\frac{AOO_{s,j} - AOO_{s,i}}{AOO_{s,i}}$$

This prediction can be used for prioritizing sampling and assessment efforts towards species subject to greatest loss of potential habitat in the WG.

We trained the Maxent SDM using the 1998 Atlas occurrence data (randomly split for each species into 80% occurrences for training and 20% for testing), a 2000 forest raster and the four present-day bioclimatic variables. We quantified the permutation importance of each predictor as the loss in model performance (in terms of AUC) when the predictor values were randomly permuted (Altmann et al., 2010).

We projected future species distributions under three distinct scenarios of environmental changes:

- With deforestation only, as it is supposed to be the main threat for tree population persistence over a short term. We projected future species distributions under forecasted deforestation patterns in 2035, while keeping the climatic variables as in 2000.
- With only climate change, under the 2040 projection of bioclim variables for RCP 8.5, (O'Neill et al., 2014), modelled with MIROC-ES2L (Hajima et al., 2020). We kept the forest raster as in 2000, closest to Atlas publication date, thus neglecting any further deforestation.
- With both climate change and deforestation, using the four projected bioclim variables of 2040 along with the 2035 forest cover raster.

Synthetic maps of potential richness loss were eventually created under each hypothesis by summing SDM output probabilities over all species pixel by pixel (Grenié et al., 2020), and we quantified the temporal variations as the ratios between different years.

## 5.3 Results

### 5.3.1 Current conservation status

192 out of the 340 (56%) endemic tree species of the WG are reported in the IUCN Red List, among which 24 are critically endangered, 85 are endangered and 55 are vulnerable (Figure 2). 84% of red listed species were assessed in 1998, just after the publication of the *Atlas* (Ramesh and Pascal, 1997).

### 5.3.2 Forecasted impacts of deforestation and climate change

Based on the Landsat image analyses, we found that forest cover in the study area decreased by 6% between 2000 and 2010, and by 8% between 2010 and 2020. Our deforestation model showed that rainforest cover in the WG should disappear between 2060 and 2070 (Figure 1). Without action for slowing

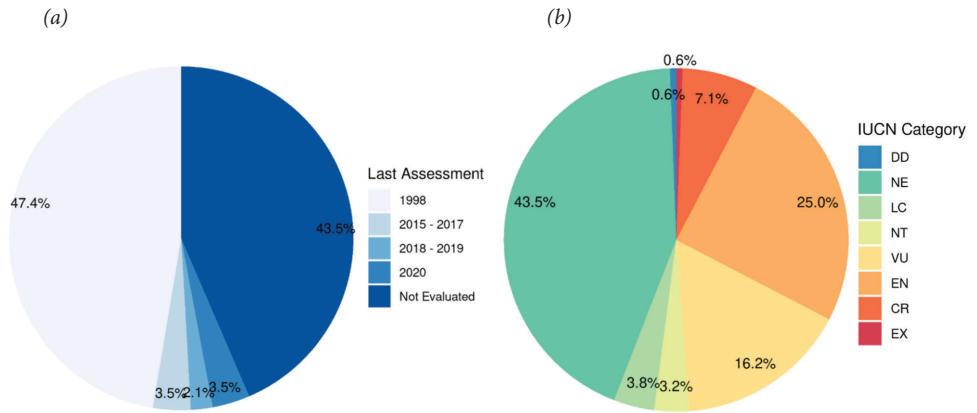


Figure 2. Pie plots giving the percentage of WG endemic tree species per (a) date of last assessment in IUCN Red List, (b) IUCN category at last assessment.

down deforestation and maintaining strict protection in protected areas, this scenario would entail a massive extinction crisis in the WG hotspot within the 21<sup>st</sup> century.

We quantified the mean permutation importance of each predictor for all species (percentage in brackets): BIO1 = Annual Mean Temperature (20.7%), BIO4 = Temperature Seasonality (38.5%), BIO12 = Annual Precipitation (10.0%) and BIO15 = Precipitation Seasonality (13%). The forest predictor had 18% mean permutation importance. Therefore, although deforestation should entail rapid habitat destruction and population extinctions, sensitivity to climate change is also expected to influence future tree species distribution.

Figure 3 shows the potential loss of species richness based on the scenarios of climate and forest cover changes. Deforestation should first heavily impact WG lowlands, especially in the south-western part of the WG. Climate change should drive loss in almost all areas, with the higher elevations being relatively spared and the eastern flanks of the WG being particularly impacted. Protected areas in northern and mid WG would be particularly vulnerable to the effects of climate change. In comparison, southern uplands should be relatively well preserved. The two types of threats are complementary in terms of the areas impacted. Globally, species richness in the WG would hence be highly threatened by both deforestation and climate change combined in the near future. Results concerning potential habitat losses per species are alarming as well.

Figure 5 exemplifies and synthesizes the habitat maps at different years for the species *Nothopegia travancorica*, *Cinnamomum malabattrum* and *Aglaia elaeagnoidea*. Suitable habitat lost due to deforestation in 2035 appears in green, especially in lowlands. The figure also shows in blue the remaining habitat when adding the influence of climate change in 2040. The areas that remain potentially suitable for them are in higher elevation areas of the WG. WG forests to the

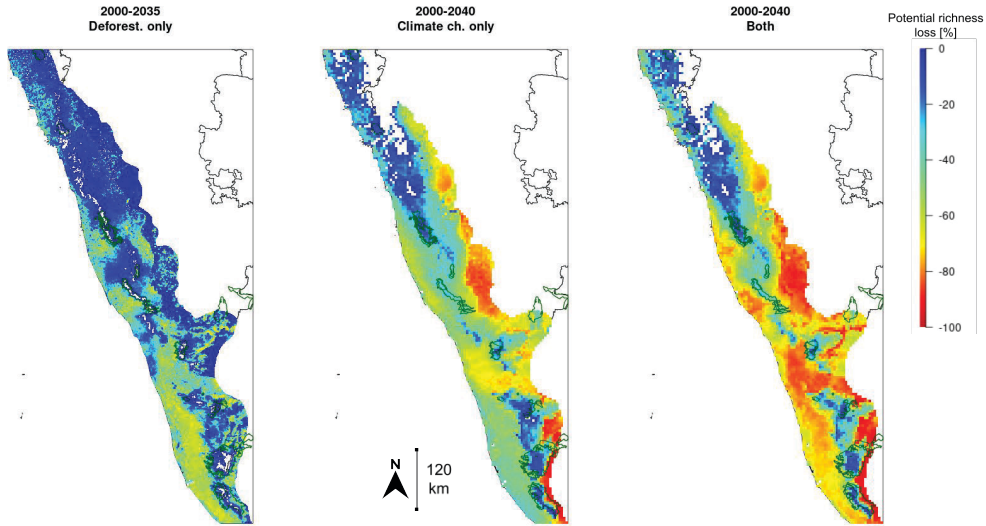


Figure 3. Potential richness losses in 2035 under the influence of deforestation only (left), in 2040, under the influence of climate change only (middle), and in 2040 under both deforestation and climate change (right). The color scale ranges from 0% (dark blue) to 100% (bright red) potential richness loss. Protected areas are overlaid with dark green borders. Potential richness is calculated by summing the SDM probabilities of occurrence over all species.

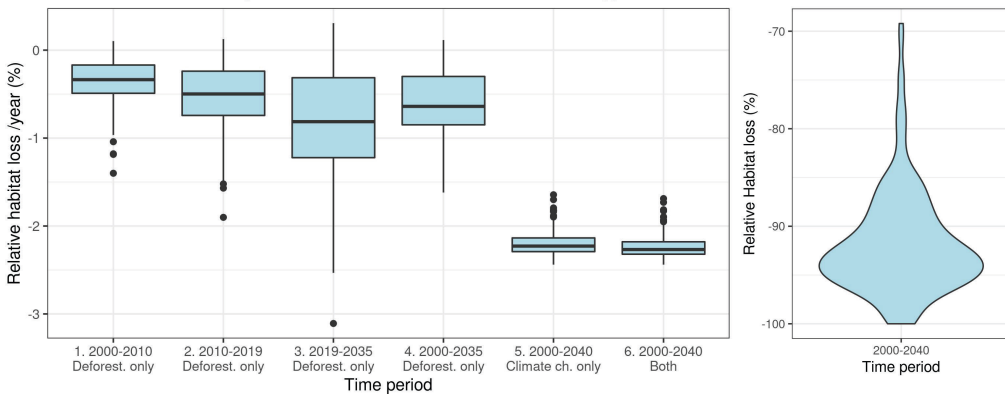


Figure 4. Boxplot of species relative habitat losses per year under different hypotheses (left), and violinplot of the relative habitat loss driven by both deforestation and climate change between 2000 and 2040 (right).

north of Palghat gap would be heavily impacted by the forecasted changes, and would greatly reduce the northern extent of *Cinnamomum malabattrum*, while southern hills of WG should serve as a refuge for both species.

Under our model predictions, two species, *Aglaia elaeagnoidea* and *Actinodaphne campanulata*, should become extinct by 2040 in the WG due to climate change. They are currently listed as LC and EN/VU respectively based



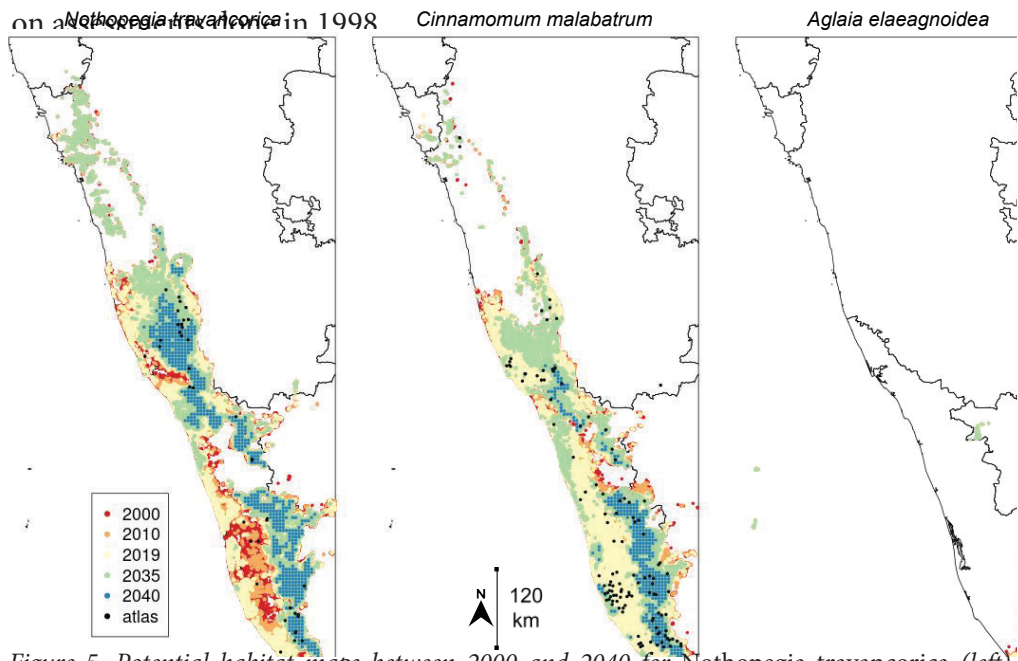


Figure 5. Potential habitat maps between 2000 and 2040 for *Nothopogia travancorica* (left), *Cinnamomum malabatum* (middle) and *Aglaia elaeagnoidea* (right). Colored points represent suitable areas for different years: 2000, 2010, 2019 and 2035 rasters were obtained considering only climate change whereas the 2040 raster results from the consideration of both 2035 deforestation and 2040 climate change models.

## 5.4 Discussion

### 5.4.1 Expected issues and challenges for conservation

The deforestation model highlights major threats to rainforests in Western Ghats over the short term (complete disappearance by 2070). The model is "pessimistic" insofar as it considers that conservation strategies would not be enough to prevent habitat shrinkage within protected areas. The effect of climatic change is also expected to be considerable in the next decades, under a scenario of increased CO<sub>2</sub> concentration following the current trend (Schwalm et al. 2020). Nonetheless, its effect on population extinction should last longer than that of deforestation. While forest cutting entails immediate population extinction, climate change should entail more gradual decrease of population persistence and regeneration. Local topographic refugia can play an important role by allowing species persistence in small relict populations (Zellweger et al., 2020). In addition, ecological and genetic variation within species can allow some more resistant tree populations to persist and even be selected under future climatic conditions (Capblancq et al., 2020).

Since habitat diversity is very high in Western Ghats due to sharp environmental gradients, all the habitats are relatively small and sensitive to the effects of future deforestation and climate change. However, we note that northern WG would face more intense habitat loss, especially due to climate change (Figure 3). This area presents greater rainfall seasonality and should

be greatly sensitive to future alterations of the monsoon regime. Conversely, rainfall is more aseasonal in the South, where habitat loss due to climate change is expected to be less pronounced (e.g., Figure 5). Noticeably, the southern WG area served as a refugia during past drier periods (Bose et al., 2016; 2019), and could thereby serve as a refugia in future as well. Local endemism is high in the area due to this specific biogeographic context, and preserving the biodiversity in the area should be a priority for preserving evolutionary potential both within and between taxa (Bose et al., 2019). In a broader perspective, maps of habitat loss per species (Figure 5) and of species richness loss globally (Figure 3) could help designing a network of protected areas that is adapted to the future expected threats.

Although our models predict great habitat loss in the near future (Figure 4), we still predict that only 2 species over the 165 analyzed with the SDM approach should go extinct by 2040. This phenomenon supports the idea that mass rarity should precede mass extinction events, a pattern found in long-term paleontological surveys (Hull et al., 2015). In addition, our model does not acknowledge inertia in population and metapopulation extinction, which can entail long-term extinction debts (Hylander and Ehrlén 2013). Persistence of endemic species in small habitat remnants should not be deemed sufficient to ensure long-term persistence. Previous surveys in US National Parks (Harris, 1984) and small forest remnants have shown that biodiversity continues to erode due to isolation and small population sizes (Brook et al., 2003), despite strict local conservation policy.

#### 5.4.2 *Advantages and limitations of species distribution modelling*

Species Distribution Models (SDMs) analyze environmental drivers of species distributions, reflecting their ecological niche requirements (Elith and Leathwick, 2009). SDMs are thus suited to forecast changes in species distributions in response to future environment, so that the projected maps can help to identify where, how and when to define priority conservation areas. However, because of the correlative nature of SDM, their use in guiding conservation and management strategies should acknowledge some limitations and thus requires specific precautions (Muscatello et al., 2020).

First, the reliability of SDM, and in particular their predictive ability, critically depends on an appropriate choice of predictors (Fourcade et al., 2018). Here, we integrated bioclimatic variables that are known to be major drivers of forest types in WG, namely rainfall amount, rainfall seasonality, and temperature variables. Even with such relevant predictors, projecting future potential habitat based on current environmental conditions can suffer from extrapolation errors (Colwell and Rangel, 2009), which undermine model transferability (Yates et al., 2018).

Second, a SDM represents a broad envelope of environmental conditions that permit the establishment and persistence of a given species, at the best. It does not acknowledge dispersal and establishment limitations, especially under

rapid environmental changes. Even at an equilibrium of habitat occupancy, any given species cannot occupy all of its suitable habitat, and the ability to more or less occupy the suitable habitat can broadly vary across species (Grenié et al., 2020). Recent works have suggested using additional information on species dispersal abilities (Monsimmet et al., 2020) and/or population densities (Santini et al., 2019) to derive more reliable estimates of species occurrences under future scenarios of habitat changes.

Third, endangered species are rare, and the limited number of occurrences limits the statistical power and validity of SDM. Although more and more efficient regularization techniques can prevent overfitting, new works have suggested integrating information on cooccurrence and biogeographical patterns to increase predictive ability of rare species (Deneu et al., 2021). Recent methodological advances addressing the major challenges mentioned here open new perspectives for using refined SDM models to better predict future species distributions (Kindsvater et al., 2018; Zhang et al., 2020; Deneu et al., 2021).

To overcome the limitations of correlative SDM approaches, recent works have called for more process-based models, which would more explicitly integrate ecophysiological constraints, biotic interactions and dispersal dynamics (e.g., for North American trees, Case and Lawler, 2017). Dynamic Global Vegetation Models (DGVM) are designed to predict ecosystem properties depending on environmental conditions, using ecophysiological and biophysical rules. Although DGVM are not intended to predict distributions of individual species, they can provide insights into the functioning of habitats sheltering threatened species. In addition, DGVM acknowledge the ecological strategies of plant functional groups, and are now going into finer and finer characterization of species-specific responses. A combined use of SDM and DGVM should thus help define relevant strategies for habitat and species conservation. The impact of fragmentation on population extinction and colonization should also be more explicitly integrated in predictive models (Kale et al., 2010; Athira et al., 2017; Thomson et al., 2020).

#### *5.4.3 Perspectives for estimating and predicting IUCN status*

A SDM provides a probability map reflecting potential habitat suitability for a given species. While IUCN criteria and reserve managers need information on the “actual” distribution of populations, SDM cannot predict the actual future of populations, and thus cannot directly be used to assess the conservation status and species occurrences in future. Thresholding SDM probabilities is a way to derive binary presence-absence maps (Liu et al., 2013), which represent potential geographical ranges and can thus inform potential species status regarding IUCN criteria B (geographic ranges). Different methods have been proposed to calculate the threshold depending on prediction accuracy (Liu et al., 2005). Maximizing the True Skill Statistic (TSS, the sum of specificity and sensitivity minus one, Allouche et al., 2006)

is currently a standard approach, with the advantage of being independent of species prevalence. An original thresholding approach has been introduced by Syfert et al. (2014) to specifically estimate IUCN species Extent Of Occurrence (EOO) from SDMs outputs. It maximizes geographical similarity between SDM predictions and the empirical EOs obtained by drawing a minimum convex polygon around species occurrences. Recent tools and packages have been proposed to assess IUCN status from EOO and AOO (Area of Occupancy) assessment, e.g., the R package *ConR* (Dauby et al., 2018). In any case, caution is needed to avoid misvaluation of conservation status from potential instead of actual distribution changes (Walker et al., 2020).

Classic IUCN criteria involve measures of actual population changes, while assessing range and occurrence variation with SDMs represent a sensibly different approach. Because of the caveats in relating habitat suitability maps to existing IUCN criteria, recent works have advocated integrating new geographic range metrics in IUCN criteria (Brooks et al., 2019). The Area Of Habitability (AOH, also known as ESH for Extent of Suitable Habitat) is a measure of species habitat range considering occurrences, habitat type and elevation preferences. AOH can be used as an upper-estimate for AOO when measured at a 2 x 2 km<sup>2</sup> resolution (Santini et al., 2019) and even for EOO when drawing a Minimum Convex Polygon (MCP) around selected areas. However, a unified and consistent calculation for AOH is yet to be defined as stated in Brooks et al. (2019). The use of disparate data sources and habitat type maps for instance are preventing the scientific community from comparing results. How AOH and SDM suitability maps can be related opens interesting perspectives in this regard. Both aim at estimating a spatial distribution of the ecological niche for a given species. Santini et al. (2019) even combined AOH with population density to estimate population size: such practices should be studied and assessed with a view to being standardized and widespread. Finally, when creating habitat models, one should not forget that there are other factors determining conservation planning such as social (Löhmus et al., 2020) and economic aspects. Integrating preservation of ecosystem services and species conservation is a major goal in the current sustainable management agenda. Specifically, tree diversity and carbon storage cobenefits in tropical human-dominated landscape (Osuri et al., 2020).

Interdisciplinary research should help better assess threats and better guide conservation strategies. Computer science and especially Machine Learning (ML) has a great potential to offer to conservation science. Prediction algorithms can be used to directly link species occurrences along with some predictors to IUCN status, thus bypassing the use of SDMs (Zizka et al., 2020). Bland et al. (2015) led a comparative study of seven ML models to predict the status of currently Data Deficient terrestrial mammals. Open data and participatory science projects such as Pl@ntNet (Bonnet et al., 2020) provide access to a huge amount of data, which opens new perspectives for powerful use

of deep learning techniques. New approaches in optimization under constraints should help incorporate numerous and heterogeneous criteria for identifying optimal conservation strategies (Justeau-Allaire et al., 2021). Conservation science has a lot to offer to computer science as well: less tractable problems such as class imbalance (Wang et al., 2017), presence-only data or observation bias (Meyer et al., 2016; Walker et al., 2020) are feeding ML research.

#### *5.4.4 Models complement but do not replace field surveys*

While we noted the benefit of using a modelling approach to predict future threats and guiding decision and management strategies, under multiple and complex constraints, we should still also underline that the modelling approach is complementary and cannot replace empirical and observation data. In this regard, a Long-Term Ecological Research (LTER) framework is needed for long-term monitoring of biodiversity changes in WG (Reddy et al., 2018). The results should validate or conversely infirm the predictions of SDM. In the cases that observed trends differ from SDM predictions, this should allow assessing the importance of processes most often neglected in SDM, such as species dispersal dynamics, and adaptation to new environmental conditions. In addition, knowledge gaps on the diversity of organisms in the WG biodiversity hotspot remain, which require continuing field exploration and taxonomic surveys (e.g., Shigwan et al., 2020). Improving knowledge is pivotal in conservation science, and a tenet of the Rio Declaration on Environment and Development in 1992.

Expert knowledge plays a major role in IUCN risk assessments and could be assisted and not replaced by automatic prediction (Bachman et al., 2011). Automatic pre-assessment can guide observation efforts (sampling strategy and field check of threats). A key research avenue would be to bridge the gap between manual and automatic assessment by working with new data and methods (Zizka et al., 2020). This synthesis shows that further IUCN assessment efforts are urgently needed to update the status of formerly evaluated species, and to provide an assessment of unevaluated species in WG.

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