A National Application of the Species Habitat Index for Ethiopia Reveals Uneven Habitat Change Across Plant Groups and Ecosystems

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ABSTRACT

Accelerating delivery of the Kunming-Montreal Global Biodiversity Framework (GBF) requires indicators that can detect species-level habitat change at policy-relevant scales. The Species Habitat Index (SHI) offers a method to optimise resource allocation and enhance national biodiversity reporting, but its broader utilisation has been constrained by significant data gaps, particularly for taxa that are less well documented than birds and mammals. In this study, we

(i) examine how methodological choices impact the assessment of changes in species' suitable habitat through the SHI, and (ii) develop a national SHI for plants of Ethiopia. We compiled georeferenced occurrence records and IUCN-based habitat preferences for 1,247 plant species (141 families; 340 endemics) and combined these with a 29-year land-cover time series (1992–2020) to quantify SHI. We first compared different geometry-based range-mapping methods with species distribution models (SDMs) to assess their influence on SHI estimates and then applied a combined approach to estimate national SHI trends for Ethiopian plants. SHI trends were broadly robust across methods, with Rapoport's Mean Propinquity polygons showing closest match with SDMs. Nationally, median SHI increased slightly (+0.51%), but declines were common and disproportionately affected endemic and non-woody species. Declines SHI trends were concentrated in species inhabiting shrubland and grassland land-cover classes and were geographically clustered in highland regions corresponding to the Afro-alpine and Dry Evergreen Afromontane Forest and Grassland Complex vegetation types. These findings demonstrate that SHI can be applied to data-limited floras using simplified range-mapping approaches, providing a scalable tool for biodiversity monitoring. At the same time, the results highlight uneven responses to land-cover change and the need to prioritise vulnerable ecosystems in Ethiopia's conservation planning.

KEYWORDS

Biodiversity indicators, Global Biodiversity Framework, Land-cover change, Monitoring, Range-mapping, Plant conservation

1 – INTRODUCTION

Reversing current trends of biodiversity loss and environmental degradation requires a robust monitoring framework supported by clear, precise, and reportable metrics and indicators, as outlined in the Global Biodiversity Framework (GBF; CBD, Secretariat 2022). Metrics that effectively incorporate environmental changes are essential for understanding the impacts of habitat modification and conversion, the primary drivers of biodiversity loss (Díaz et al., 2019). While these drivers have been relatively well-studied at the ecosystem level, particularly in forests (e.g., Hansen et al., 2010; 2013), species-level habitat trends have received comparatively less attention, despite their importance for assessing extinction risk and informing conservation decision-making (IUCN, 2012a).

Developing informative species-level indicators necessitates addressing key challenges in species range mapping, specifically in minimising commission errors—areas incorrectly mapped as part of the species' distribution where the species is absent—and in consistently delineating only the suitable areas for a species, such as those defined by habitat and

elevation preferences (Rondinini et al., 2006; Brooks et al., 2019). The Area of Habitat (AOH), as defined by Brooks et al. (2019), represents the spatial extent of suitable habitat within the geographic range of a species, providing a more ecologically relevant measure of habitat availability by reducing commission errors. While AOH plays a critical role in linking habitat characteristics with species-level assessments and enhancing mapping of at-risk biodiversity (Lumbierres et al., 2021; 2022), it typically represents the best map possible at a single point in time. The lack of a temporal dimension limits AOH's ability to track changes in the habitat coverage and availability, and their consequent impacts on species.

Advancements in remotely-sensed land-cover datasets with long-term time series (e.g., Jung et al., 2020; Harper et al., 2023) offer unprecedented opportunities to quantify changes in species' habitats over time (Rondinini et al., 2011; Bird et al., 2012; Pettorelli et al., 2014; Visconti et al., 2016). The Species Habitat Index (SHI), developed as part of the indicator framework of the Group on Earth Observations Biodiversity Observation Network (GEO BON) (https://geobon.org/; GEO BON 2015), integrates these data to estimate AOH over time, facilitating temporal assessments of species' habitat coverage (Jetz et al., 2019; Powers & Jetz, 2019; Simkin et al., 2022). As part of the suite of indicators supporting the GBF monitoring framework (CBD Secretariat, 2021; 2022; Jetz et al., 2022), the SHI has been integrated into the Map of Life (https://mol.org), enabling the tracking of habitat changes over the past ~20 years for several species (e.g., Jetz et al., 2012). Beyond retrospective analyses, the SHI can be projected forward under different shared socioeconomic pathways (SSPs) (Powers & Jetz, 2019; Simkin et al., 2022), allowing for assessments of the potential impacts of future climate and land-use changes on biodiversity.

By providing high temporal and spatial resolution, the SHI offers key advantages over traditional biodiversity indicators like the IUCN Red List Index (RLI, see Butchart et al., 2004), which operates on relatively coarse temporal and spatial scales and may result in a lag before status changes are detected (Tittensor et al., 2014). Furthermore, SHI's capacity to integrate data from multiple species across taxonomic groups and geographic regions addresses limitations of indicators such as the Living Planet Index (LPI), which lacks representation for several groups such as invertebrates, plants, and fungi (Ledger et al., 2023). Additionally, its applicability at the national level offers a locally relevant index that optimises resource allocation and enhances national biodiversity reporting against global commitments.

Despite its potential, the SHI has primarily been applied to well-documented taxa such as mammals and birds (Powers & Jetz, 2019; Simkin et al., 2022). Broader utilisation of the SHI has been largely constrained by significant data gaps, particularly for understudied groups such as plants, fungi, and invertebrates, which lack comprehensive range maps, habitat

preferences, and elevation data. For example, approaches for mapping plant distributions typically include the use of coarse-scale polygons (e.g., World Geographic Scheme for Recording Plant Distributions, Brummitt 2001) or collations of georeferenced occurrence data, which can, in turn, be converted into polygons using geospatial techniques (Willis et al., 2003; Moat, 2020). Georeferenced occurrences can also be integrated with environmental layers to create statistically robust species distribution models (SDMs), providing spatially explicit habitat suitability estimates (Phillips et al., 2006; Guisan et al., 2017; Borgelt et al., 2022). The accuracy of the different methods depends on the data quality and assumptions underpinning each approach, potentially affecting SHI calculations. Evaluating the impact of different mapping techniques on SHI accuracy is therefore critical for extending its application to data-limited taxa and regions.

This study estimates the SHI for plants in Ethiopia, a country characterised by high species richness and significant conservation challenges (Myers et al., 2000; Mittermeier et al., 2005; Dinerstein et al., 2017), that includes habitat fragmentation primarily driven by anthropogenic land-use change (Figure 1; Nyssen et al., 2014; Tolessa et al., 2017). Ethiopia's ecological heterogeneity, spanning from arid lowlands to Afroalpine zones (Mittermeier et al., 2005; Friis et al., 2010; Dinerstein et al., 2017), means that species may experience habitat changes across diverse environmental gradients, offering important context for interpreting SHI across different ecological settings. With over 5,500 plant species and a substantial number of endemic (Friis et al., 2005; Kelbessa & Demissew, 2014; Demissew et al., 2021) and/or threatened species (Abro et al., 2024), Ethiopia is an ideal case study for evaluating the applicability of SHI as a national-level index for plants. Developing a national-level SHI for Ethiopia enables assessments of land-cover modification on species' suitable habitat and supports conservation prioritisation and evidence-based policy decisions.

In this study, we first examine how methodological choices impact the assessment of changes in species' suitable habitat through the SHI. Specifically, we employ an ensemble of range-mapping methods using species occurrences, including simple geometry-based polygons alongside SDMs, to evaluate whether these approaches yield consistent trends in SHI. Second, we assess whether Ethiopian plant species have experienced net gains or losses in suitable habitat over time, exploring how species' ecological attributes—endemicity and life form—influence SHI trends. Third, we identify the habitats and administrative zones (woredas) with the highest concentrations of species with declining SHI trends and interpret these patterns in relation to the major vegetation systems of Ethiopia (Friis et al., 2010). This provides an ecologically meaningful and spatially explicit basis for prioritising conservation actions relevant to Ethiopian policymakers. Finally, we discuss the potential of the SHI to guide conservation efforts, examining its utility as a key tool for advancing biodiversity conservation.

2 – METHODS

2.1 – Conservation Assessment, Elevation and Habitat Preferences

To establish a robust dataset for estimating the SHI for Ethiopian plants, we initially compiled data for those species with extinction risk assessments published on the IUCN Red List of Threatened Species (IUCN, 2024). These assessments provide detailed textual information on elevation and habitat preferences, which are necessary for estimating SHI. Using the advanced search of the IUCN Red List (IUCN, 2024; version 2024.1, accessed in July 2024), we retrieved data for 1,236 plant species recorded in Ethiopia. To expand this dataset, we incorporated species from ongoing Red List assessment efforts, including initiatives from the Global Centre on Biodiversity for Climate (GCBC) queued for release in upcoming Red List updates (E. Lulekal, S. Alemu & T.R. Pearce, unpublished). These efforts contributed 203 species to the dataset. After harmonising taxonomy using the package rWCVP (Brown et al., 2023) and excluding species lacking habitat data, the final dataset comprised 1,247 species spanning 141 families. This included 340 endemic species, representing approximately two thirds of Ethiopia's endemics and one fifth of the country's total flora. Of these, 554 are classified as woody (e.g., tree and shrubs) and 693 as non-woody (e.g., herbs, epiphytes, succulents). In terms of conservation status, 935 species are assessed as non-threatened (LC, NT), while 312 are assessed as threatened or data deficient (DD, VU, EN, CR).

To account for incomplete and inconsistent data, we assigned default values reflecting Ethiopia's extremes (-115 m for the Danakil Depression and 4,530 m for the Semien Mountains; Asefa et al., 2020) to 382 species (~30% of the total) with missing or ambiguous elevation data (e.g., identical lower and upper limits). We addressed the lack of spatially explicit, multi-year habitat classification datasets aligned with the IUCN Habitats Classification Scheme (IUCN, 2012b) by utilising an expert-based conversion table (available as supplementary material in Santini et al., 2019) to reclassify habitats into categories compatible with the European Space Agency Climate Change Initiative (ESA-CCI) land-cover layers (Harper et al., 2023). To reduce noise in SHI calculations, we excluded aquatic and marginal habitats due to high inter-annual variability and retained only primary terrestrial habitats for each species.

2.2 – Occurrence Records

Verified occurrence data from the IUCN Red List (IUCN, 2024) and unpublished Ethiopian endemic species database (E. Lulekal, S. Alemu & T.R. Pearce, unpublished) were integrated

with data from multiple sources, including the Global Biodiversity Information Facility (GBIF; https://www.gbif.org/), the Botanical Information and Ecology Network (BIEN; https://bien.nceas.ucsb.edu/bien/), and RAINBIO (Dauby et al., 2016). All records were consolidated using the bdc package (Ribeiro et al., 2022) and filtered to include only those records collected from the year 1950 onwards within Africa. To ensure geospatial data quality, we implemented a set of data cleaning procedures in the package CoordinateCleaner (Zizka et al., 2019), removing records with potentially erroneous coordinates. This included removing records that: (i) fell within country or province centroids; (ii) were located in capital cities or near botanical institutes; (iii) had invalid or missing coordinates; or (iv) occurred along coastlines. To further improve geospatial data quality, we performed a spatial thinning process using the occ_filt_geo function from the flexsdm package (Velazco et al., 2022), thinning the records to a minimum distance of 1 km between occurrences.

2.3 – Elevation and Land-cover

We obtained elevation data at a resolution of 30 arc-seconds (approximately 1 km^2 at the equator) from the Shuttle Radar Topography Mission (SRTM) DEM Digital Elevation Database of the Consortium for Spatial Information (CGIAR-CSI) using the geodata package (Hijmans et al., 2023). Due to the lack of a spatially explicit habitat classification aligned with the IUCN Habitats Classification Scheme (IUCN, 2012b) and suitable for calculating SHI over large time scales—i.e., Jung et al.'s (2020) product only covers five years (2015—2019)—we utilised land-cover data from the ESA-CCI. Available at a resolution of 10 arc-seconds (approximately 300 m; Harper et al., 2023), this dataset spans a period of 29 years (1992—2020), offering the advantage of providing a long time series. To ensure spatial compatibility and preserve accurate area calculations, all layers were projected to a Cylindrical Equal Area (CEA) coordinate system centred on Ethiopia (latitude: 9°, longitude: 39°) and resampled to a 1 km resolution using the nearest neighbour method in the terra package (Hijmans, 2023) in the R statistical environment (R Core Team, 2025).

2.4 – SHI Estimation

To assess temporal changes in suitable habitat, we first estimated Area of Habitat (AOH) for each species for every year from 1992 to 2020. We generated annual AOH maps by removing raster cells coded with unsuitable habitats and elevations from species' range maps (Brooks et al., 2019). This resulted in a series of 29 AOH maps per species, capturing interannual variation in availability of suitable habitat. We then calculated the SHI as the percentage

change in AOH area over time within Ethiopia, relative to the baseline year 1992. For non-endemic species, this SHI is analogous to the species stewardship metric, which represents the proportion of global AOH for a species within a given country (GEO BON, 2015; Jetz et al., 2012; 2019; Powers & Jetz, 2019). While the original SHI framework can incorporate habitat connectivity (e.g., Jetz et al., 2012; GEO BON, 2015; CBD Secretariat, 2021), our analysis focuses solely on the net change in AOH over time. This SHI workflow was used across both the comparison of range-mapping methods (Section 2.5), and the national-scale SHI estimation for the plants of Ethiopia (Section 2.6) and is summarised in Figure 2.

2.5 – Testing Range-Mapping Methods for SHI

Estimating SHI requires annual maps of a species' AOH, which are built upon defined spatial range maps representing the potential extent of the species' distribution (Rondinini et al., 2006; Brooks et al., 2019). While range maps for well-known groups such as birds and mammals are often available through expert-drawn polygons (e.g., Powers & Jetz, 2019; Lumbierres et al., 2022; Simkin et al., 2022), they are rarely available for plant species. Consequently, range maps for plants must often be derived from occurrence record data using either statistical or geometric approaches.

In this study, we used Species Distribution Models (SDMs) as the benchmark method for generating species' range maps. By integrating bioclimatic and environmental variables, SDMs can reduce commission (inclusion of unsuitable areas) and omission errors (exclusion of suitable areas) more effectively than simpler geometry-based range-mapping methods (Phillips et al., 2006; Guisan et al., 2017; Borgelt et al., 2022). We focused on a subset of 727 species with ten or more unique records after data cleaning (Section 2.2). This threshold aligns with established recommendations for reliable SDMs (van Proosdij et al., 2016) and allowed us to develop statistically robust models using MaxEnt, implemented via the SDMtune package (Vignali et al., 2020). We converted continuous suitability outputs into binary (presence/absence) maps using a True Skill Statistic (TSS) thresholding approach. Subsequently, each SDM binary map was used to generate the annual AOH maps from which SHI values were calculated, following the procedures described in Section 2.4.

Because SDMs are usually resource-intensive, we tested the performance of more accessible, geometry-based range mapping methods that can be applied more broadly, especially for understudied taxa like plants. These methods are relatively easy to implement and can be largely automated using available spatial analysis tools (e.g., R packages such as sf, rCAT, and terra), offering a scalable alternative for SHI assessments based on more complex mapping methods. We compared SHI trends derived from five alternative range-mapping

methods against those derived from benchmark SDMs (Supplementary Figure S1). The five geometry-based methods, representing varying levels of omission and commission errors, included: (i) convex hull (C-hull), defined as the minimum polygon enclosing all occurrence points; (ii) alpha hull (A-hull), a non-convex polygon that considers spatial density of points; (iii) 10 km buffer (Buffer), creating a 10 km radius area surrounding each point; (iv) Rapoport's Mean Propinquity polygons (Rapo), which subdivides subpopulations based on interpoint distances derived from a minimum spanning tree (Rapoport, 1982; Willis et al., 2003); and (v) a country-wide range (Country) that spans the whole extension of Ethiopia for all species. All geometry-based species range maps were generated using the R packages sf (Pebesma, 2018; Pebesma & Bivand, 2023) and rCAT (Moat, 2020) and were rasterized to a 1 km resolution using the terra package (Hijmans, 2023). We then applied the same SHI workflow as with SDMs (described in Section 2.4 and illustrated in Figure 2) for each species across all range-mapping methods.

To quantify the extent to which geometry-based range-mapping methods approximate SHI trends derived from the benchmark SDMs, we calculated Pearson and Spearman correlation coefficients based on the 29 annual AOH values for each species and method. These metrics provide complementary insights into the agreement between methods; while Pearson assesses the strength of the linear relationship and is sensitive to absolute differences in SHI magnitude, Spearman assesses whether the relative ordering of values is preserved over time. Additionally, we calculated Root Mean Square Error (RMSE) and Mean Square Error (MSE) to quantify the average deviation between SHI values derived from geometry-based methods and SDMs. To account for the multi-temporal nature of SHI and reduce the influence of heterogeneous species trends, we calculated correlation and error metrics per species and averaged them across mapping methods. Species with less than 10 km^2 of suitable habitat in 1992 (265 species, or 36.5% of the total) were excluded to reduce the influence of unrealistic percentage changes resulting from very small initial AOH values. Correlation coefficients were calculated using the cor function in base R (R Core Team, 2025), while RMSE and MSE were calculated using the Metrics package (Hamner & Frasco, 2018).

2.6 – National SHI Estimation

To assess national level SHI trends for the flora of Ethiopia, we analysed a dataset of 1,247 species, combining SDMs and geometry-based methods. For the 727 species with 10 or more occurrence records, we used the SDMs described above. For the remaining 520 species, range maps were developed using Rapo, the best-performing polygon method based on results from the subset analysis (see Section 3.1). For species with only one or two records

(61 species), we created 10 km buffer polygons around occurrence records. This approach facilitated the inclusion of species lacking sufficient data for SDM generation, increasing the national SHI coverage. For all species, SHI was calculated following the procedure described in Section 2.4.

To explore how ecological characteristics influence trends in habitat suitability, we tested whether SHI trends varied by biogeographical status (endemic vs. non-endemic) and functional group (woody vs. non-woody) using a two-step analysis. We first evaluated temporal trends in SHI by fitting simple linear regressions independently for each species, utilising the percentage of change as the response variable and year as the predictor. The resulting slope coefficients reflected the direction and magnitude of habitat change over time. In the second step, we used these species-level SHI slopes as the response variable in a linear model, with biogeographical status and functional group included as independent variables. All analyses were conducted using the stats package in the R statistical environment (R Core Team, 2025).

2.7 – Identifying Conservation Priorities through SHI Trends

To identify priority habitats and regions for plant conservation in Ethiopia, we analysed the ecological and spatial distribution of species with declining SHI trends. Based on species-specific SHI trends (Section 2.6), we classified species as either declining (negative slope) or non-declining (including both stable and increasing trends). To explore whether these two groups are associated with distinct sets of habitats, we constructed a binary species × land-cover matrix using ESA-CCI land-cover profiles. We employed a Non-Metric Multidimensional Scaling (NMDS) with Jaccard dissimilarity to ordinate species into a reduced habitat space, followed by a Permutational Analysis of Variance (PERMANOVA) to test whether declining and non-declining species exhibit significantly different associations with ESA-CCI land-cover classes. To identify which land-cover classes most strongly shaped differences between these groups, we used the envfit function to fit habitat vectors to the NMDS ordination and conducted a Similarity Percentage (SIMPER) analysis to quantify the relative contributions of individual ESA-CCI land-cover classes to the observed dissimilarities. All these analyses were conducted using functions from the vegan package (Oksanen et al., 2025).

In parallel, we conducted spatial analysis to identify Ethiopia's administrative zones with high conservation importance based on SHI trends. For each zone, we quantified the number of species with declining SHI trends by overlaying species' annual AOH maps with the woredas (third level administrative units) obtained *via* the geoBoundaries package (Runfola et al., 2020). A species was considered as present if any portion of its AOH intersected the zone in any year from 1992 to 2020. To classify zones according to conservation priority, we ranked

zones into five equal-size categories (quintiles) using the ntile() function from the dplyr package (Wickham et al., 2023), ranging from Very Low to Very High priority. This analysis was conducted separately for all species, endemic species, and non-endemic species. Spatial analyses were conducted using the sf (Pebesma, 2018; Pebesma & Bivand, 2023), terra (Hijmans, 2023), and exactextractr (Baston, 2023) packages for vector and raster operations, and visualizations were generated with ggplot2 (Wickham, 2016).

Because ESA-CCI land-cover classes represent structural categories derived from remote sensing rather than vegetation types recognised in major classification schemes, we interpreted both the land-cover associations identified in the NMDS analysis and the spatial patterns of priority woredas in relation to the major vegetation systems described in the Atlas of the Potential Vegetation of Ethiopia (Friis et al., 2010). This approach allowed us to discuss the results within the ecological context of Ethiopia's major vegetations while maintaining consistency with the ESA-CCI land-cover classification used in the analyses

3 – RESULTS

3.1 – Land-Cover Changes in Ethiopia (1992–2020)

From 1992 to 2020, approximately 6.0% of Ethiopia's land surface (66,651 km²) experienced land-cover change according to the ESA-CCI dataset (Supplementary Figures S2—S4; Supplementary Table S1). The most notable increases were observed in tree-dominated classes, particularly Broadleaf Deciduous Forest, which expanded 14,587 km². Additional increases were recorded in Open Broadleaf Deciduous Forest (+9,264 km²), Mosaic Tree/Shrub >50% (+7,236 km²) and Broadleaf Evergreen Forest (+4,984 km²). Furthermore, Grasslands also showed substantial increase (7,192 km²) during the study period.

In contrast, the largest declines occurred in shrub-dominated and mixed vegetation, particularly Shrubland, which experienced the greatest net loss among all ESA classes (-23,451 km²). Substantial reductions were also observed in Mosaic Natural Vegetation (-10,003 km²), Bare Areas (-5,377 km²), and Sparse Vegetation (-4,953 km²). Notably, despite their smaller absolute net losses, classes such as Sparse Herbaceous and Needleleaf Evergreen Forest experienced considerable proportional reductions (e.g., >90%), suggesting complete or near-complete conversions at the national scale. Overall, these results indicate that land-cover changes in Ethiopia during the study period were primarily characterised by transitions toward more tree-dominated classes.

3.2 – The impact of Range-Mapping Methods on SHI Trends

Our correlation analyses revealed that SHI derived from most geometry-based mapping methods closely matched SDM-based trends (Figure 3; Supplementary Figure S5). Both Pearson (0.714–0.826) and Spearman (0.691–0.798) correlations were high across range mapping methods, indicating a strong agreement in both the direction and relative magnitude of SHI trends. These correlations were statistically significant ($p < 0.05$) for most species: between 90.3% and 93.7% for Pearson, and between 89.3% and 92.2% for Spearman correlations. Among methods, Rapo showed the best overall performance, with the highest average correlation to SDM-based SHI (Pearson = 0.826; Spearman = 0.798) and lowest error (MSE = 341; RMSE = 7.40). The C-hull method also performed well (Pearson = 0.804; Spearman = 0.781; RMSE = 7.30). In contrast, the Buffer (Pearson = 0.714; Spearman = 0.691), A-hull (Pearson = 0.760; Spearman = 0.733) and the Country (Pearson = 0.775; Spearman = 0.769) methods performed less effectively, indicating lower capacity to replicate SHI trends derived from SDM.

Methods also differed in their ability to produce valid SHI estimates (i.e., those with non-zero area in 1992). Approximately 36.5% (265 species) lacked AOH for at least one range mapping method. However, the number of species lacking suitable AOH—and thus lacking valid SHI estimates—for each range mapping method also varied considerably (Supplementary Figure S6). The Buffer method had the highest number of species without valid SHI (127 species). In contrast, the Country method produced invalid SHI for only three species. C-hull, Rapo, and SDM presented intermediate levels of invalid SHI outputs (18, 23, and 31 species, respectively).

3.3 – National SHI for Ethiopia's Flora

Our analysis of the national trends of SHI for Ethiopia's flora showed that median SHI increased by 0.51% between 1992 and 2020, indicating that most Ethiopian species likely experienced modest gains in habitat suitability (Figure 4). Moreover, our linear model showed that both biogeographical status and functional group influenced SHI trends (Table 1; Supplementary Figures S7—S8). Woody, non-endemic species have experienced significantly higher SHI (Estimate = 0.645, SE = 0.065, $p < 0.001$), indicating that this group experienced the most consistent gains in suitable habitat. In contrast, non-woody species had significantly lower SHI slopes relative to woody species (Estimate = –0.388, SE = 0.089, $p < 0.001$), and endemic species also showed significantly lower slopes compared to non-endemics (Estimate = –0.400, SE = 0.100, $p < 0.001$), suggesting reduced gains or net losses in suitable habitat. Overall, these findings indicate that while some plant groups—particularly

woody, non-endemic species—have experienced positive SHI trends, endemic and non-woody species are more likely to be vulnerable to habitat loss.

3.4 – Identifying Conservation Priorities through SHI Trends

Our analyses showed that species experiencing declines in their SHI (439 species, of which 402 were statistically significant at $p < 0.05$) differed significantly in their associations with ESA-CCI land-cover classes from species exhibiting stable or increasing SHI (574 species, including 535 with statistically significant trends; Figure 5). PERMANOVA showed that these differences explained 17.7% of the variation ($R^2 = 0.177$, $F = 197.5$, $p < 0.001$). NMDS ordination (2D, stress = 0.108) revealed clear separation with only modest overlap between groups (Figure 5A). Land-cover classes like Broadleaf Evergreen Forest (TC-BE, 7.9%), Broadleaf Deciduous Forest (TC-BD, 7.9%), Shrubland (SH, 7.9%), and Deciduous Shrubland (SH-D, 7.8%) emerged as key contributors to overall dissimilarity between groups. Notably, shrub-dominated land-cover classes like Deciduous Shrubland and Shrubland were strongly associated with declining species, while tree-dominated land-cover classes like Broadleaf Deciduous Forest and Broadleaf Evergreen Forest were more closely associated with non-declining species.

Spatially, Ethiopia's administrative zones (woredas) of Tselemt (181 species), Beyeda (171), Janamora (170), Meda Welabu (170), and Mena (168) contained the largest numbers of species experiencing declining SHI trends across different species groups (overall, non-endemics, and endemics; Figure 6). For total and non-endemic species, zones with high numbers of declining taxa are more widely distributed, spanning both the central and southern highlands (Fig. 6A-D). In contrast, declining endemic species are more geographically concentrated in the northern highlands of Amhara (Fig. 6E-F), with Janamora (45 endemic species), Beyeda (43), Tselemt (42), Debark (40), and Mena (38) emerging as key hotspots.

4 – DISCUSSION

4.1 – The Impact of Range-Mapping Methods on SHI Trends

We show that geometry-based range mapping methods, especially those producing large spatial extents, yield SHI estimates that closely match those derived from SDMs (Figure 3). This is consistent with earlier evidence suggesting that variation among range map methods has limited impact at broader macroecological patterns (Aronsson et al., 2024). The nature of AOH (and consequently SHI) estimation likely contributes to the observed agreement among

methods, as the removal of unsuitable areas mitigates commission errors commonly associated with coarse range maps (Brooks et al., 2019; Lumbierres et al., 2021; Lumbierres et al., 2022). As a result, methods characterised by high commission errors can still perform well in SHI estimation, whereas those prone to high omission errors (e.g., Buffers) tend to exclude suitable habitat, leading to less informative SHI trends.

Both correlation and error metrics showed that methods like Rapoport's Mean Propinquity polygons (Rapo), and convex hull (C-hull) show the strongest agreement with SDM outputs (Figure 3). Their superior performance relative to broader methods such as Country suggests that some spatial restriction is necessary to reflect historical and ecological limits constraining dispersal. The Rapoport method likely performs well because it adapts to the spatial configuration of occurrence records, generating either broad, continuous ranges (comparable to C-hull and Country) for widely distributed species or smaller, fragmented ranges for restricted species for which records are likely concentrated (Rapoport, 1982; Willis et al., 2003; Rivers et al., 2010). This flexibility enables the method to balance between avoiding omission of suitable habitat while retaining spatial realism for species with a discontinuous distribution, which is particularly relevant in topographically and ecologically complex regions like Ethiopia, where many plant species often have restricted or discontinuous habitat preferences (Friis et al., 2005; Kelbessa & Demissew, 2014).

These results underscore the potential applicability of geometry-based methods, particularly Rapo and C-hull, as viable and scalable alternatives for estimating SHI across taxonomic groups or geographic regions for which data are limited. Because these methods require only occurrence data and basic spatial tools (e.g., R packages like sf and rCAT, Pebesma & Bivand, 2023; Moat, 2020), they are particularly useful for hyper-diverse countries in the Global South—e.g., biodiversity hotspots *sensu* Myers et al. (2000)—where governments often face financial and technical capacity constraints in meeting biodiversity monitoring requirements. While lack of comprehensive occurrence data remains a major limitation, these simplified mapping methods offer a way to accelerate biodiversity monitoring by enabling countries to generate species-level habitat indicators rapidly and cost-effectively. This can ultimately improve the pace and scope of biodiversity monitoring, supporting global conservation assessment and planning, as well as reporting capacity against the Global Biodiversity Framework (CBD Secretariat, 2022).

4.2 – National SHI for Ethiopia's Flora

At the national scale, median SHI increased slightly (+ 0.51%), suggesting that overall Ethiopian plants have experienced modest gains in habitat area from 1992 to 2020. Woody,

non-endemic species show most consistent increase (Estimate = 0.645, SE = 0.065, $p < 0.001$; Supplementary Figure S8), suggesting these taxa have likely benefited from land-cover changes. These trends likely reflect the dual advantage of the broad environmental tolerances that characterise species with wide geographic ranges (Jetz et al., 2008), and the enhanced dispersal capacity associated with woody life-forms, especially trees (Beckman & Sullivan, 2023), which together facilitate persistence and expansion within changing landscapes. In contrast, the weaker or negative SHI trends observed for endemic species likely reflect their higher sensitivity to habitat change, which has already contributed to documented population declines among many Ethiopian species (Gebrehiwot et al., 2019; Abro et al., 2024). Overall, these findings emphasise that trait-environment interactions—particularly those involving range size and dispersal ability—appear to mediate species' response to land-cover change in Ethiopia, underscoring the need for targeted conservation interventions that account for differences in species' biogeography and function, particularly for endemic and non-woody species at greater risk of habitat loss

Nonetheless, the apparently positive scenario for woody, non-endemic species must be interpreted with caution. SHI reflects changes in the extent of structurally suitable habitat but does not capture ecological quality or species-specific viability. The ability of species to colonise newly available habitats depends on several factors, including dispersal capacity, and competition (Zhang et al., 2018), leading to mismatches between potential and realised distributions. In some cases, gains in suitable habitat may reflect anthropogenic reforestation (see Kassa et al., 2022) or afforestation with non-native species (e.g., *Eucalyptus*; Belachew & Minale, 2025), replicating the structural but not functional characteristics of native ecosystems. Similarly, land-cover transitions interpreted as forest expansion may, in fact, represent woody encroachment, a process that is widely documented in Ethiopia (Liao et al., 2018) and that leads to degradation of vegetation quality and reduced capacity to support certain plant species (Rundel et al., 2014). This interpretation is supported by observed shifts from primarily herbaceous (e.g., different types of croplands and savanna; Supplementary Figure S2) to tree-dominated land-cover classes (e.g., Open Broadleaf Deciduous Forest expanded by over 400% in Ethiopia during the study period; Supplementary Figures S3—S4), a pathway that aligns with documented encroachment in Ethiopia (Liao et al., 2018). Thus, SHI trends may overestimate habitat recovery and should ideally be paired with ecological field validation to assess habitat quality.

4.3 – Identifying Conservation Priorities through SHI Trends

Our analyses indicate that species experiencing declining SHI trends in Ethiopia are disproportionally associated with shrubland, grassland and mosaic herbaceous ESA-CCI land-cover classes (Figure 5) and are concentrated in woredas (administrative zones) located in northern and southern Ethiopian highlands (Figure 6). Taken together, these findings suggest that species that are increasingly threatened by habitat change are largely concentrated in highland regions where Afro-alpine and Dry Evergreen Afromontane Forest and Grassland Complex vegetation systems occur (Friis et al. 2010). Habitat reduction poses a major threat in these ecosystems, and many constituent species have been documented as experiencing population declines (Gebrehiwot et al., 2019; Abro et al., 2024) due to habitat modification driven by human activities (Nyssen et al., 2014; Tolessa et al., 2017). In particular, the Afro-alpine grasslands—often associated with restricted microenvironmental conditions (Gole et al., 2008)—are increasingly degraded by expanding human settlements and related activities, which have exacerbated habitat degradation and exposed many species to significant threats (Gebrehiwot et al., 2019). As these habitats continue to decline, the survival of many species, especially those with restricted distributions, becomes increasingly threatened, further increasing their extinction risk (Gole et al., 2008; Gebrehiwot et al., 2019; Wang et al. 2020; Abro et al., 2024).

Importantly, the Afro-alpine and Dry Evergreen Afromontane Forest and Grassland Complex vegetation systems fall largely outside or only partially overlap with Ethiopia's national protected area network (IUCN ESARO, 2020). This mismatch indicates that Ethiopian plant communities facing the highest pressure from habitat change are also those with the lowest level of formal protection, exacerbating their vulnerability to land-use change and further habitat degradation. The under-protection of these habitats reflects a broader Biome Awareness Disparity (Silveira et al., 2022), where non-tree-dominated vegetation systems such as grasslands, shrublands and savannas receive less attention in conservation policy and funding than forests. Indeed, a recent study by Jago et al. (2025) found that ecosystems like the Ethiopian montane grasslands and woodlands (mostly congruent with Dry Evergreen Afromontane Forest and Grassland Complex in Friis et al. 2010), and the Acacia-Commiphora bushlands and thickets have disproportionately low coverage within the national protected area network. A main concern is that, once degraded, these non-tree-dominated systems rarely recover their original complexity and resilience (Nerlekar & Veldman, 2020; Pilon et al., 2023), making immediate conservation the most effective strategy for mitigating biodiversity loss. In this context, our SHI-based analysis reinforces the urgent need to recognise and protect species in these ecosystems at levels comparable to those of forests (Pilon et al., 2025), not only globally but also within national conservation agendas in Ethiopia.

These findings highlight the value of SHI as a tool for identifying conservation priorities beyond traditional biodiversity metrics. By revealing the habitats and zones where plant diversity is declining most severely, SHI provides tools for Ethiopian policymakers and conservation practitioners to target ongoing conservation and restoration efforts to better account for overlooked ecosystems. As Ethiopia advances towards GBF targets, incorporating SHI into its national monitoring framework offers a practical means to better align conservation efforts to ecological priorities. For example, current major conservation and restoration programmes such as Ethiopia's Green Legacy (https://sdgs.un.org/partnerships/green-legacy-initiative), the expansion of the protected area network (Langley et al., 2025; Jago et al., 2025), and collaborative identification of Tropical Important Plant Areas (TIPAS; Darbyshire et al., 2017), could benefit from SHI-based assessments to track conservation progress and guide restoration investments.

4.4 – The SHI as an Indicator for the Global Biodiversity Framework

The SHI is a component indicator for the Global Biodiversity Framework (CBD Secretariat, 2021; 2022), but its wider application remains constrained by data and processing requirements. Our findings show that relatively simple range-mapping methods can approximate SHI estimations derived from more complex approaches such as SDMs, providing an accessible means for countries to monitor species distributions and address gaps in biodiversity assessments while supporting progress toward international conservation targets. Specifically, the SHI supports Goal A of the GBF (to maintain and restore biodiversity and ecosystem integrity) by tracking suitable habitat for species over time (CBD Secretariat, 2021; CBD Secretariat, 2022). Additionally, by allowing the identification of taxa, habitats and geographic regions experiencing most decline, the SHI contributes directly to tracking progress towards Target 2 (restoration of degraded ecosystems) and Target 4 (halting species extinction). As such, the SHI facilitates the national-scale assessment of species' suitable habitats and their trends, which is a key requirement for tracking progress towards biodiversity conservation and ecosystem integrity, thereby providing a robust foundation for evidence-based conservation planning and reporting under the GBF.

However, our analyses also highlight several challenges in further refining SHI estimates. For example, while Ethiopia harbours more than 5,500 vascular plant species (Friis et al., 2005; Kelbessa & Demissew, 2014; Demissew et al., 2021), only about 22% (1,247) could be included in our national-scale SHI analysis, largely due to data limitations in the IUCN Red List and occurrence datasets. This coverage gap reflects the low proportion of plant species in global assessments, with approximately 20% assessed on the IUCN Red List compared to

near-complete coverage for vertebrates (IUCN, 2024). Moreover, we were unable to generate SHI for some species despite apparently adequate data (i.e., valid range map and complete IUCN textual habitat and elevation information), including cases where AOH was absent for all years analysed (Supplementary Figure S7). While this may partially result from overly restrictive assumptions of our study (e.g., exclusion of marginal habitats), it likely reflects issues with the input data, including poor-quality occurrence records or inaccurate habitat and elevation information for some species.

Additionally, although expert-based conversion tables have been shown to perform comparably to data-driven approaches (Lumbierres et al., 2021), effectively linking purely structural land-cover classes to ecologically meaningful habitat types remains a key challenge (Tomaselli et al., 2013; Joppa et al., 2016). While recent efforts (e.g., Jung et al., 2020) have produced spatially explicit habitat classifications aligned with the IUCN habitat classification scheme (IUCN, 2012b), their limited temporal coverage (spanning only 5 years) restricts their utility for long-term SHI assessments. Expanding these datasets to cover broader temporal scales would certainly enhance their applicability in tracking habitat changes and refining SHI estimations.

Addressing these limitations is critical to realising SHI as a globally representative and taxonomically inclusive indicator. Key priorities to achieve this are: (i) focusing efforts on mobilising (e.g., through digitisation and georeferencing) and collecting more data; (ii) expanding the Red List assessments for plants and other underrepresented taxa; and (iii) improving the temporal and geographic resolution of land-cover datasets aligned to IUCN habitat schemes. In summary, strengthening these data foundations will be essential to support comprehensive biodiversity monitoring and effective implementation of the Global Biodiversity Framework targets.

5 – CONCLUSIONS

This study investigated how different range-mapping approaches influence estimates of the SHI, a biodiversity metric relevant for conservation decisions that may offer a complementary perspective to existing indicators like the Red List Index (RLI; Butchart et al., 2004) and the Living Planet Index (LPI; Ledger et al., 2023). Focusing on plants, a group that is little represented in global biodiversity metrics, we demonstrate that SHI can be feasibly estimated for data-limited taxa and geographic regions using relatively simple approaches. In particular, our findings show that accessible and straightforward mapping approaches can be applied in a hyper-diverse, data-limited context such as Ethiopia, with potential for application in other hyper-diverse countries facing similar data and resources constraints, enabling broader

adoption of SHI as a biodiversity monitoring tool. However, continued efforts to improve data collection will be essential for refining SHI estimates and ensuring their reliability for conservation decision-making, ultimately contributing to global efforts to reduce biodiversity loss.

At the national scale, we identified uneven declines in suitable habitat across Ethiopia's flora, with endemic and non-woody species associated with non-tree-dominated ecosystems of the highlands experiencing the most severe losses. These declines are especially concerning given that non-tree-dominated ecosystems remain underrepresented in conservation planning (Silveira et al., 2022) and poorly covered by the protected area network in the country, particularly the Afro-alpine, Dry Evergreen Afromontane Forest and Grassland Complex, and the *Acacia–Commiphora* bushlands and thickets (Friis et al., 2010; IUCN ESARO, 2020; Jago et al., 2025). By highlighting both high-risk species groups and priority ecosystems, this study provides an applied framework for monitoring biodiversity trends and informing conservation priorities. As Ethiopia advances implementation of the Global Biodiversity Framework, SHI could serve as a dynamic and objective indicator to support evidence-based conservation planning.

6 – DATA AVAILABILITY

Except for data for 203 species, which queued for release in upcoming Red List updates, all data analysed during this study is freely available online without restrictions. The habitat and elevation preferences of species can be accessed on the IUCN Red List (https://www.iucnredlist.org/). Occurrence records are available on GBIF (https://www.gbif.org/), RAINBIO (https://gdauby.github.io/rainbio/) and BIEN (https://bien.nceas.ucsb.edu/bien/). Land-cover layers can be found on the European Spatial Agency (http://maps.elie.ucl.ac.be/CCI/viewer/download.php). The codes used to perform the analyses in this study are available on GitHub (https://github.com/moabeffernandes/shi-ethiopia).

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8 – AUTHOR CONTRIBUTION

Moabe F. Fernandes conceived the study, conducted the analyses, and wrote the manuscript. Joseph White contributed to the analyses. James Borrell, Steve Bachman, and Carolina Tovar conceived the study, supervised the research, and contributed to writing and editing. Ermias Lulekal and Sebsebe Demissew provided expert input on Ethiopian vegetation and contributed to manuscript review. Alexandra Roberts, Becca Davis, Emily Terry, Gabriella Hoban, Henry Miller, Seth Ratcliffe, Vida Svahnström, Bezawit Genanaw, Efrata Mekebib, Hanny Lidetu, Lidet Mehari, and Tesfanesh Feseha contributed to data curation and species assessments. Iain Darbyshire and Sileshi Nemomissa contributed to data curation and project administration. Amy Barker and Jack F. Plummer contributed to assessment coordination and project administration. Harry Smith, Jenna Willis, Lynda Murray, Paloma Moore, Andrew Budden, and Liz Brogan contributed to specimen data collation. Tim Pearce and Shambel Alemu contributed to database curation. Kelda F.V.A. Elliott contributed to project coordination. All authors contributed to manuscript review and approved the final version.

9 – REFERENCES

Abro, T. W., Desta, A. B., Debie, E., & Alemu, D. M. (2024). Endemic plant species and threats to their sustainability in Ethiopia: A systematic review. *Trees, Forests and People*, 17, 100634. https://doi.org/10.1016/j.tfp.2024.100634

Aronsson, H., Zizka, A., Antonelli, A., & Faurby, S. (2024). Expert-based range maps cannot be replicated using data-driven methods but macroecological conclusions arising from them can. *Journal of Biogeography*, 51, 1549–1559. https://doi.org/10.1111/jbi.14847

Asefa, M., Cao, M., He, Y., Mekonnen, E., Song, X., & Yang, J. (2020). Ethiopian vegetation types, climate, and topography. *Plant Diversity*, 42, 302–311. https://doi.org/10.1016/j.pld.2020.04.004

Baston, D. (2023). exactextractr: Fast extraction from raster datasets using polygons. R package version 0.10.0. https://CRAN.R-project.org/package=exactextractr

Beckman, N. G., & Sullivan, L. L. (2023). The causes and consequences of seed dispersal. *Annual Review of Ecology, Evolution, and Systematics*, 54, 403–427. https://doi.org/10.1146/annurev-ecolsys-102320-104739

Belachew, K. G., & Minale, W. K. (2025). Socioeconomic and environmental impacts of Eucalyptus plantations in Ethiopia: An evaluation of benefits, challenges, and sustainable practices. *The Scientific World Journal*, 1780293. https://doi.org/10.1155/tswj/1780293

Bird, J. P., Buchanan, G. M., Lees, A. C., Clay, R. P., Develey, P. F., Yépez, I., & Butchart, S. H. M. (2012). Integrating spatially explicit habitat projections into extinction risk assessments: A reassessment of Amazonian avifauna incorporating projected deforestation. *Diversity and Distributions*, 18, 273–281.

Borgelt, J., Sicacha-Parada, J., Skarpaas, O., & Verones, F. (2022). Native range estimates for red-listed vascular plants. *Scientific Data*, 9, 117. https://doi.org/10.1038/s41597-022-01233-5

Brooks, T. M., Pimm, S. L., Akçakaya, H. R., Buchanan, G. M., Butchart, S. H. M., Foden, W., Hilton-Taylor, C., Hoffmann, M., Jenkins, C. N., Joppa, L., Li, B. V., Menon, V., Ocampo-Peñuela, N., & Rondinini, C. (2019). Measuring terrestrial area of habitat (AOH) and its utility for the IUCN Red List. *Trends in Ecology & Evolution*, 34, 977–986. https://doi.org/10.1016/j.tree.2019.06.009

Brown, M. J. M., Walker, B. E., Black, N., Govaerts, R. H. A., Ondo, I., Turner, R., & Nic Lughadha, E. (2023). rWCVP: A companion R package for the World Checklist of Vascular Plants. *New Phytologist*, 240, 1355–1365.

Brummitt, R. K. (2001). *World geographic scheme for recording plant distributions* (2nd ed.). Hunt Institute for Botanical Documentation.

Butchart, S. H. M., Stattersfield, A. J., Bennun, L. A., Shutes, S. M., Akçakaya, H. R., Baillie, J. E. M., Stuart, S. N., Hilton-Taylor, C., & Mace, G. M. (2004). Measuring global trends in the status of biodiversity: Red List indices for birds. *PLoS Biology*, 2(12), e383.

CBD Secretariat. (2021). *Measuring ecosystem integrity (Goal A) in the post-2020 global biodiversity framework: The GEO BON species habitat index*.

CBD Secretariat. (2022). *Monitoring framework for the Kunming-Montreal Global Biodiversity Framework*. Convention on Biological Diversity.

Darbyshire, I., Anderson, S., Asatryan, A., Byfield, A., Cheek, M., Clubbe, C., Ghrabi, Z., Harris, T., Heatubun, C. D., Kalema, J., Magassouba, S., McCarthy, B., Milliken, W., de Montmollin, B., Nic Lughadha, E., Onana, J. M., Saïdou, D., Sârbu, A., Shrestha, K., & Radford, E. A. (2017). Important plant areas: Revised selection criteria for a global approach to plant conservation. *Biodiversity and Conservation*, 26, 1767–1800. https://doi.org/10.1007/s10531-017-1336-6

Dauby, G., Zaiss, R., Blach-Overgaard, A., Catarino, L., Damen, T., Deblauwe, V., Dessein, S., Dransfield, J., Droissart, V., Duarte, M. C., Engledow, H., Fadeur, G., Figueira, R., Gereau, R. E., Hardy, O. J., Harris, D. J., de Heij, J., Janssens, S., Klomberg, Y., Ley, A. C., Mackinder,

B. A., Meerts, P., van de Poel, J. L., Sonké, B., Sosef, M. S. M., Stévart, T., Stoffelen, P., Svenning, J. C., Sepulchre, P., van der Burgt, X., Wieringa, J. J., & Couvreur, T. L. P. (2016). RAINBIO: A mega-database of tropical African vascular plant distributions. *PhytoKeys*, 74, 9723.

Demissew, S., Friis, I., & Weber, O. (2021). Diversity and endemism of the flora of Ethiopia and Eritrea: State of knowledge and future perspectives. Rendiconti Lincei. *Scienze Fisiche e Naturali*, 32, 675–697.

Díaz, S., Settele, J., Brondízio, E. S., Ngo, H. T., Agard, J., Arneth, A., Balvanera, P., Brauman, K. A., Butchart, S. H. M., Chan, K. M. A., Garibaldi, L. A., Ichii, K., Liu, J., Subramanian, S. M., Midgley, G. F., Miloslavich, P., Molnár, Z., Obura, D., Pfaff, A., Polasky, S., Purvis, A., Razzaque, J., Reyers, B., Chowdhury, R. R., Shin, Y. J., Visseren-Hamakers, I., Willis, K. J., & Zayas, C. N. (2019). Pervasive human-driven decline of life on Earth points to the need for transformative change. *Science*, 366, eaax3100. https://doi.org/10.1126/science.aax3100

Dinerstein, E., Olson, D., Joshi, A., Vynne, C., Burgess, N. D., Wikramanayake, E., Hahn, N., Palminteri, S., Hedao, P., Noss, R., Hansen, M., Locke, H., Ellis, E. C., Jones, B., Barber, C. V., Hayes, R., Kormos, C., Martin, V., Crist, E., Sechrest, W., Price, L., Baillie, J. E. M., Weeden, D., Suckling, K., Davis, C., Sizer, N., Moore, R., Thau, D., Birch, T., Potapov, P., Turubanova, S., Tyukavina, A., Souza, N., Pintea, L., Brito, J. C., Llewellyn, O. A., Miller, A. G., Patzelt, A., Ghazanfar, S. A., Timberlake, J., Klöser, H., Shennan-Farpón, Y., Kindt, R., Lillesø, P. B., van Breugel, P., Graudal, L., Voge, M., Al-Shammari, K. F., & Saleem, M. (2017). An ecoregion-based approach to protecting half the terrestrial realm. *BioScience*, 67, 534–545.

Friis, I., Demissew, S., & van Breugel, P. (2010). *Atlas of the Potential Vegetation of Ethiopia*.

Friis, I., Thulin, M., Adsersen, H., & Burger, A.-M. (2005). Patterns of plant diversity and endemism in the Horn of Africa. *Biologiske Skrifter*, 55, 289–314.

Gebrehiwot, K., Demissew, S., Woldu, Z., Fekadu, M., Desalegn, T., & Teferi, E. (2019). Elevational changes in vascular plants richness, diversity, and distribution pattern in Abune Yosef mountain range, Northern Ethiopia. *Plant Diversity*, 41(4), 220–228.

GEO BON. (2015). *Global biodiversity change indicators (Version 1.2)*. Group on Earth Observations Biodiversity Observation Network.

Gole, T. W., Borsch, T., Denich, M., & Teketay, D. (2008). Floristic composition and environmental factors characterizing coffee forests in southwest Ethiopia. *Forest Ecology and Management*, 255(7), 2138–2150. https://doi.org/10.1016/j.foreco.2007.12.028

718 Guisan, A., Thuiller, W., & Zimmermann, N. E. (2017). *Habitat suitability and distribution*
719 *models: With applications in R*. Cambridge University Press.

720 Hamner, B., & Frasco, M. (2018). *Metrics: Evaluation metrics for machine learning*. R package
721 version 0.1.4. https://CRAN.R-project.org/package=Metrics

722 Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A.,
723 Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L.,
724 Justice, C. O., & Townshend, J. R. G. (2013). High-resolution global maps of 21st-century
725 forest cover change. *Science*, 342(6160), 850–853.

726 Hansen, M. C., Stehman, S. V., & Potapov, P. V. (2010). Quantification of global gross forest
727 cover loss. *Proceedings of the National Academy of Sciences*, 107, 8650–8655.

728 Harper, K. L., Lamarche, C., Hartley, A., Peylin, P., Ottlé, C., Bastrikov, V., San Martín, R.,
729 Bohnenstengel, S. I., Kirches, G., Boettcher, M., Shevchuk, R., Brockmann, C., & Defourny,
730 P. (2023). A 29-year time series of annual 300 m resolution plant-functional-type maps for
731 climate models. *Earth System Science Data*, 15, 1465–1499. https://doi.org/10.5194/essd-15-
732 1465-2023

733 Hijmans, R. (2023). *terra: Spatial data analysis*. R package version 1.7-65. https://CRAN.R-
734 project.org/package=terra

735 Hijmans, R. J., Barbosa, M., Ghosh, A., & Mandel, A. (2023). *geodata: Download geographic*
736 *data*. R package version 0.5-9. https://CRAN.R-project.org/package=geodata

737 IUCN. (2012a). *IUCN Red List categories and criteria: Version 3.1*. IUCN.

738 IUCN. (2012b). *Habitats classification scheme (version 3.1)*.
739 https://www.iucnredlist.org/resources/habitat-classification-scheme

740 IUCN. (2016). *A global standard for the identification of key biodiversity areas*.

741 IUCN. (2024). *The IUCN Red List of threatened species*. https://www.iucnredlist.org Accessed
742 on 24 July 2024

743 IUCN ESARO. (2020) *State of Protected and Conserved Areas Report Series No. 1*. IUCN
744 ESARO.

745 Jago, S., Gizaw, G., Genanaw, B., Langley, J., Lulekal, E., White, J. D. M., Rowlands, A. N.,
746 Geda, T., Wakjira, K., Regassa, F., Demissew, S., Woldeyes, F., Abebe, W., Jones, J. P. G.,
747 Smith, R. J., & Borrell, J. (2025). Trade-offs between nature and people reveal challenges in
748 translating global conservation targets into national realities. *EcoEvoRxiv*.
749 https://doi.org/10.32942/X2306T

Jetz, W., Şekercioğlu, Ç. H., & Watson, J. E. M. (2008). Ecological correlates and conservation implications of overestimating species geographic ranges. *Conservation Biology*, 22(1), 110–119. https://doi.org/10.1111/j.1523-1739.2007.00847.x

Jetz, W., McGeoch, M. A., Guralnick, R., Ferrier, S., Beck, J., Costello, M. J., Fernandez, M., Geller, G. N., Keil, P., Merow, C., Meyer, C., Muller-Karger, F. E., Pereira, H. M., Regan, E. C., Schmeller, D. S., & Turak, E. (2019). Essential biodiversity variables for mapping and monitoring species populations. *Nature Ecology & Evolution*, 3, 539–551. https://doi.org/10.1038/s41559-019-0826-1

Jetz, W., McGowan, J., Rinnan, D. S., Possingham, H. P., Visconti, P., O'Donnell, B., & Londoño-Murcia, M. C. (2022). Include biodiversity representation indicators in area-based conservation targets. *Nature Ecology & Evolution*, 6, 123–126. https://doi.org/10.1038/s41559-021-01620-y

Jetz, W., McPherson, J. M., & Guralnick, R. P. (2012). Integrating biodiversity distribution knowledge: Toward a global map of life. *Trends in Ecology & Evolution*, 27, 151–159. https://doi.org/10.1016/j.tree.2011.09.007

Joppa, L. N., O'Connor, B., Visconti, P., Smith, C., Geldmann, J., Hoffmann, M., Watson, J. E. M., Butchart, S. H. M., Virah-Sawmy, M., Halpern, B. S., Ahmed, S. E., Balmford, A., Sutherland, W. J., Harfoot, M., Hilton-Taylor, C., Foden, W., Di Minin, E., Pagad, S., Genovesi, P., Hutton, J., & Burgess, N. D. (2016). Filling in biodiversity threat gaps. *Science*, 352, 199.

Jung, M., Dahal, P. R., Butchart, S. H. M., Donald, P. F., De Lamo, X., Lesiv, M., Kapos, V., Rondinini, C., & Visconti, P. (2020). A global map of terrestrial habitat types. *Scientific Data*, 7, 256. https://doi.org/10.1038/s41597-020-00599-8

Kassa, H., Abiyu, A., Hagazi, N., Mokria, M., Kassawmar, T., & Gitz, V. (2022). Forest landscape restoration in Ethiopia: Progress and challenges. *Frontiers in Forests and Global Change*, 5, 796106. https://doi.org/10.3389/ffgc.2022.796106

KBA Standards and Appeals Committee. (2019). *Guidelines for using a global standard for the identification of key biodiversity areas*. IUCN

Kelbessa, E., & Demissew, S. (2014). Diversity of vascular plant taxa of the flora of Ethiopia and Eritrea. *Ethiopian Journal of Biological Sciences*, 13, 37–45.

Langley, J., Starnes, T., Fernandes, M., Bachman, S., Plumptre, A. J., Crowe, O., Kor, L., Jago, S., Perez, F., Smith, R. J., White, J. D. M., Tovar, C., Darbyshire, I., & Borrell, J. (2025). Key biodiversity areas and important plant areas can help build ecologically representative

protected and conserved area networks to meet 30-by-30. *EcoEvoRxiv*. https://doi.org/10.32942/X27S7C

Ledger, S. E. H., Loh, J., Almond, R., Böhm, M., Clements, C. F., Currie, J., Deinet, S., Galewski, T., Grooten, M., Jenkins, M., Marconi, V., Painter, B., Scott-Gatty, K., Young, L., Hoffmann, M., Freeman, R., & McRae, L. (2023). Past, present, and future of the Living Planet Index. *npj Biodiversity*, 2, 12. https://doi.org/10.1038/s44185-023-00017-3

Liao, C., Clark, P. E., & DeGloria, S. D. (2018). Bush encroachment dynamics and rangeland management implications in southern Ethiopia. *Ecology and Evolution*, 8, 11694–11703. https://doi.org/10.1002/ece3.4621

Lumbierres, M., Dahal, P. R., Di Marco, M., Butchart, S. H. M., Donald, P. F., & Rondinini, C. (2021). Translating habitat class to land cover to map area of habitat of terrestrial vertebrates. *Conservation Biology*, 36, e13851. https://doi.org/10.1111/cobi.13851

Lumbierres, M., Dahal, P. R., Soria, C. D., Di Marco, M., Butchart, S. H. M., Donald, P. F., & Rondinini, C. (2022). Area of habitat maps for the world's terrestrial birds and mammals. *Scientific Data*, 9, 749. https://doi.org/10.1038/s41597-022-01838-w

Mittermeier, R. A., Gil, P. R., Hoffmann, M., Pilgrim, J., Brooks, T., Mittermeier, C. G., Lamoreux, J., & Fonseca, G. A. B. (2005). *Hotspots revisited: Earth's biologically richest and most endangered terrestrial ecoregions*. Conservation International.

Moat, J. (2020). *rCAT: Conservation assessment tools*. R package.

Myers, N., Mittermeier, R. A., Mittermeier, C. G., Fonseca, G. A. B., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, 403, 853–858.

Nerlekar, A. N., & Veldman, J. W. (2020). High plant diversity and slow assembly of old-growth grasslands. *Proceedings of the National Academy of Sciences*, 117, 18550–18556. https://doi.org/10.1073/pnas.1922266117

Nyssen, J., Frankl, A., Haile, M., Hurni, H., Descheemaeker, K., Crummey, D., Ritler, A., Portner, B., Nievergelt, B., Moeyersons, J., Munro, N., Deckers, J., Billi, P., & Poesen, J. (2014). Environmental conditions and human drivers for changes to north Ethiopian mountain landscapes over 145 years. *Science of the Total Environment*, 485, 164–179.

Oksanen, J., Simpson, G., Blanchet, F., Kindt, R., Legendre, P., Minchin, P., O'Hara, R., Solymos, P., Stevens, M., Szoecs, E., Wagner, H., Barbour, M., Bedward, M., Bolker, B., Borcard, D., Borman, T., Carvalho, G., Chirico, M., De Cáceres, M., Durand, S., Evangelista, H., FitzJohn, R., Friendly, M., Furneaux, B., Hannigan, G., Hill, M., Lahti, L., Martino, C.,

McGlinn, D., Ouellette, M., Ribeiro Cunha, E., Smith, T., Stier, A., Ter Braak, C., & Weedon, J. (2025). *vegan: Community ecology package*. R package.

Pebesma, E. (2018). *Simple features for R: Standardized support for spatial vector data*. The R Journal, 10(1), 439–446.

Pebesma, E., & Bivand, R. (2023). *Spatial data science: With applications in R*. Chapman and Hall/CRC.

Pettorelli, N., Safi, K., & Turner, W. (2014). Introduction: Satellite remote sensing, biodiversity research, and conservation of the future. *Philosophical Transactions of the Royal Society B*, 369, 20130190.

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

Pilon, N., Campos, B. H., Durigan, G., Cava, M. G., Rowland, L., Schmidt, I., Sampaio, A., & Oliveira, R. S. (2023). Challenges and directions for open ecosystems biodiversity restoration. *Journal of Applied Ecology*, 60, 849–858. https://doi.org/10.1111/1365-2664.14368

Pilon, N., Peixoto, F., Oliveira, R. S., Oliveira, A. C. A., et al. (2025). Open letter: There are more than just trees and forests to be conserved and restored. *Plants, People, Planet*, 10.1002/ppp3.10635

Powers, R. P., & Jetz, W. (2019). Global habitat loss and extinction risk of terrestrial vertebrates under future land-use-change scenarios. Nature Climate Change, 9, 323–329.

Rapoport, E. H. (1982). *Areography: Geographical strategies of species*. Pergamon Press.

R Core Team. (2025). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.

Ribeiro, B. R., Velazco, S. J., Guidoni-Martins, K., Tessarolo, G., Jardim, L., Bachman, S. P., & Loyola, R. (2022). bdc: A toolkit for standardizing, integrating, and cleaning biodiversity data. *Methods in Ecology and Evolution*, 13, 1421–1428. https://doi.org/10.1111/2041-210X.13868

Rivers, M. C., Bachman, S. P., Meagher, T. R., Nic Lughadha, E., & Brummitt, N. A. (2010). Subpopulations, locations, and fragmentation: Applying IUCN Red List criteria to herbarium specimen data. *Biodiversity and Conservation*, 19, 2071–2085. https://doi.org/10.1007/s10531-010-9826-9

Rondinini, C., Di Marco, M., Chiozza, F., Santulli, G., Baisero, D., Visconti, P., Hoffmann, M., Schipper, J., Stuart, S. N., Tognelli, M. F., Amori, G., Falcucci, A., Maiorano, L., & Boitani, L.

(2011). Global habitat suitability models of terrestrial mammals. *Philosophical Transactions of the Royal Society B*, 366, 2633–2641.

Rondinini, C., Wilson, K. A., Boitani, L., Grantham, H., & Possingham, H. P. (2006). Tradeoffs of different types of species occurrence data for use in systematic conservation planning. *Ecology Letters*, 9, 1136–1145.

Rundel, P. W., Dickie, I. A., & Richardson, D. M. (2014). Tree invasions into treeless areas: Mechanisms and ecosystem processes. *Biological Invasions*, 16, 663–675.

Runfola, D., Anderson, A., Baier, H., Crittenden, M., Dowker, E., Fuhrig, S., Goodman, S., Grimsley, G., Layko, R., Melville, G., Mulder, M., Oberman, R., Panganiban, J., Peck, A., Seitz, L., Shea, S., Slevin, H., Youngerman, R., & Hobbs, L. (2020). geoBoundaries: A global database of political administrative boundaries. *PLoS ONE*, 15(4), e0231866.

Santini, L., Butchart, S. H. M., Rondinini, C., Benítez-López, A., Hilbers, J. P., Schipper, A. M., Cengic, M., Tobias, J. A., & Huijbregts, M. A. J. (2019). Applying habitat and population-density models to land-cover time series to inform IUCN Red List assessments. *Conservation Biology*, 33, 1084–1093.

Silveira, F. A. O., Ordóñez-Parra, C. A., Moura, L. C., Schmidt, I. B., Andersen, A. N., Bond, W., Buisson, E., Durigan, G., Fidelis, A., Oliveira, R. S., Parr, C., Rowland, L., Veldman, J. W., & Pennington, R. T. (2022). Biome awareness disparity is BAD for tropical ecosystem conservation and restoration. *Journal of Applied Ecology*, 59, 1967–1975.

Simkin, R. D., Seto, K. C., McDonald, R. I., & Jetz, W. (2022). Biodiversity impacts and conservation implications of urban land expansion projected to 2050. *Proceedings of the National Academy of Sciences*, 119, e2117297119.

Tittensor, D. P., Walpole, M., Hill, S. L. L., Boyce, D. G., et al. (2014). A mid-term analysis of progress toward international biodiversity targets. *Science*, 346, 241–244.

Tolessa, T., Senbete, F., & Kidane, M. (2017). The impact of land use/land cover change on ecosystem services in the central highlands of Ethiopia. *Ecosystem Services*, 23, 47–54.

Tomaselli, V., Dimopoulos, P., Marangi, C., Kallimanis, A. S., Adamo, M., Tarantino, C., Panitsa, M., Terzi, M., Veronico, G., Lovergine, F., Nagendra, H., Lucas, R., Mairota, P., Mücher, C. A., & Blonda, P. (2013). Translating land cover classifications to habitat taxonomies for landscape monitoring. *Landscape Ecology*, 28, 905–930.

van Proosdij, A. S. J., Sosef, M. S. M., Wieringa, J. J., & Raes, N. (2016). Minimum required number of specimen records to develop accurate species distribution models. *Ecography*, 39, 542–552.

Velazco, S. J., Rose, M. B., de Andrade, A. F., Minoli, I., & Franklin, J. (2022). flexsdm: An R package for supporting a comprehensive and flexible species distribution modelling workflow. *Methods in Ecology and Evolution*, 13, 1661–1669.

Vignali, S., Barras, A. G., Arlettaz, R., & Braunisch, V. (2020). SDMtune: An R package to tune and evaluate species distribution models. *Ecology and Evolution*, 10, 11488–11506.

Visconti, P., Bakkenes, M., Baisero, D., Brooks, T., Butchart, S. H. M., Joppa, L., Alkemade, R., Di Marco, M., Santini, L., Hoffmann, M., Maiorano, L., Pressey, R. L., Arponen, A., Boitani, L., Reside, A. E., van Vuuren, D. P., & Rondinini, C. (2016). Projecting global biodiversity indicators under future development scenarios. *Conservation Letters*, 9, 5–13.

Wang, S. W., Boru, B. H., Njogu, A. W., Ochola, A. C., Hu, G. W., Zhou, Y. D., & Wang, Q. F. (2020). Floristic composition and endemism pattern of vascular plants in Ethiopia and Eritrea. *Journal of Systematics and Evolution*, 58, 33–42.

Wickham, H., François, R., Henry, L., Müller, K., & Vaughan, D. (2023). *dplyr: A grammar of data manipulation*. R package.

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer.

Willis, F., Moat, J., & Paton, A. (2003). Defining a role for herbarium data in Red List assessments: A case study of Plectranthus from eastern and southern tropical Africa. *Biodiversity and Conservation*, 12, 1537–1552.

Zhang, H., Qi, W., & Liu, K. (2018). Functional traits associated with plant colonizing and competitive ability influence species abundance during secondary succession. *Ecology and Evolution*, 8, 6529–6536.

Zizka, A., Silvestro, D., Andermann, T., Azevedo, J., Ritter, C. D., Edler, D., Farooq, H., Herdean, A., Ariza, M., Scharn, R., Svantesson, S., Wengström, N., Zizka, V., & Antonelli, A. (2019). CoordinateCleaner: Standardized cleaning of occurrence records from biological collection databases. *Methods in Ecology and Evolution*, 10, 744–751.

TABLES AND FIGURES

Table 1. Parameter estimates from the linear model examining the effects of biogeographical status and functional group on SHI trends.

Linear Model Predicting SHI Slope

Effect of Life Form and Endemism

Predictor	Estimate	Std. Error	95% CI (Lower)	95% CI (Upper)	p-value
Woody, Non-endemic (Intercept)	0.645	0.065	0.518	0.773	< 0.001
Non-woody (vs. Woody)	−0.388	0.089	−0.562	−0.213	< 0.001
Endemic (vs. Non-endemic)	−0.400	0.100	−0.596	−0.204	< 0.001

Model: `lm(slope ~ life_form + endemicity)`

SHI trends are represented by slope coefficients derived from species-specific regressions over time.

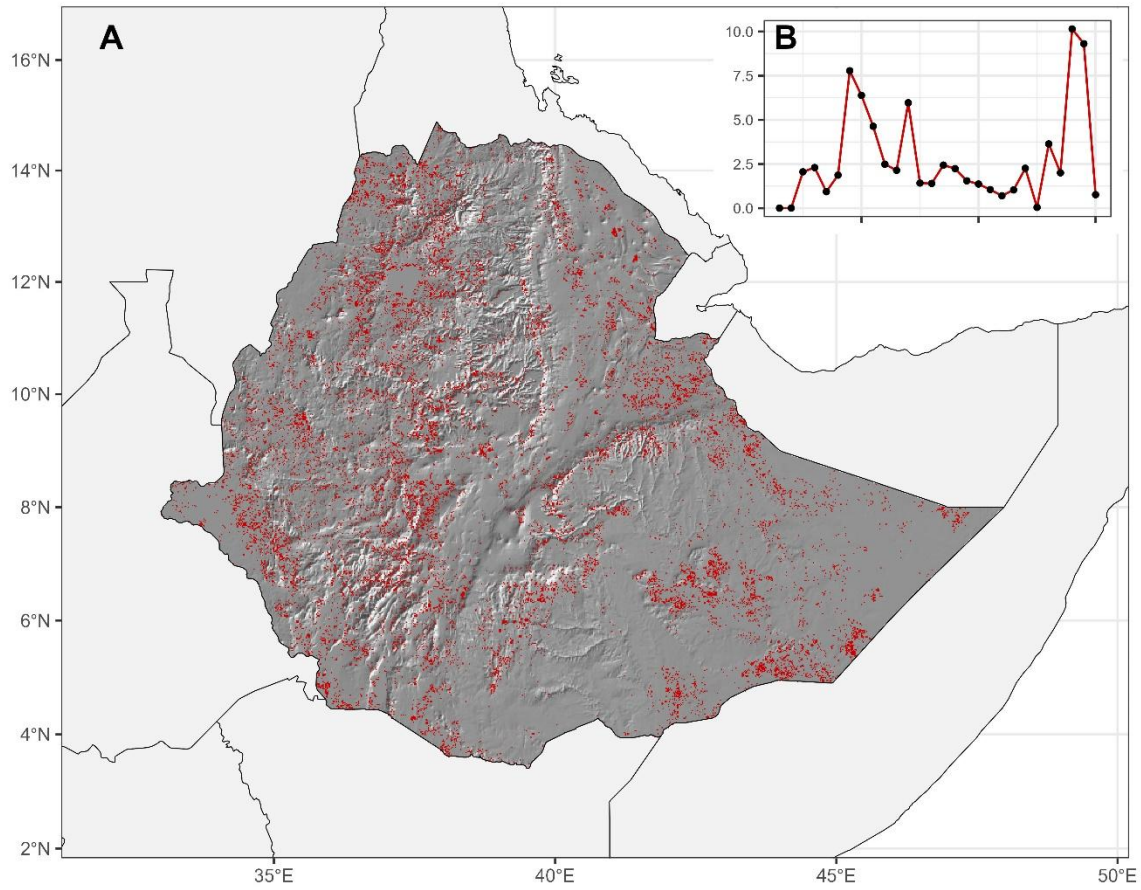

Figure 1. Spatial distribution and temporal trends of land-cover modification in Ethiopia from 1992 to 2020. (A) Map showing the spatial extent of land-cover modification, with red cells indicating areas of change overlaid over topographic hillshade. (B) Annual total area of land-cover modification (thousands of km²) over time. Overall, approximately 6% of Ethiopia's total area has experienced land-cover modification between 1992 and 2020, with peaks between 1998–2000 and 2017–2019. Both graphics are based on the assessment of 25 land-cover classes as depicted in products developed by the European Space Agency (ESA; Harper et al., 2023).

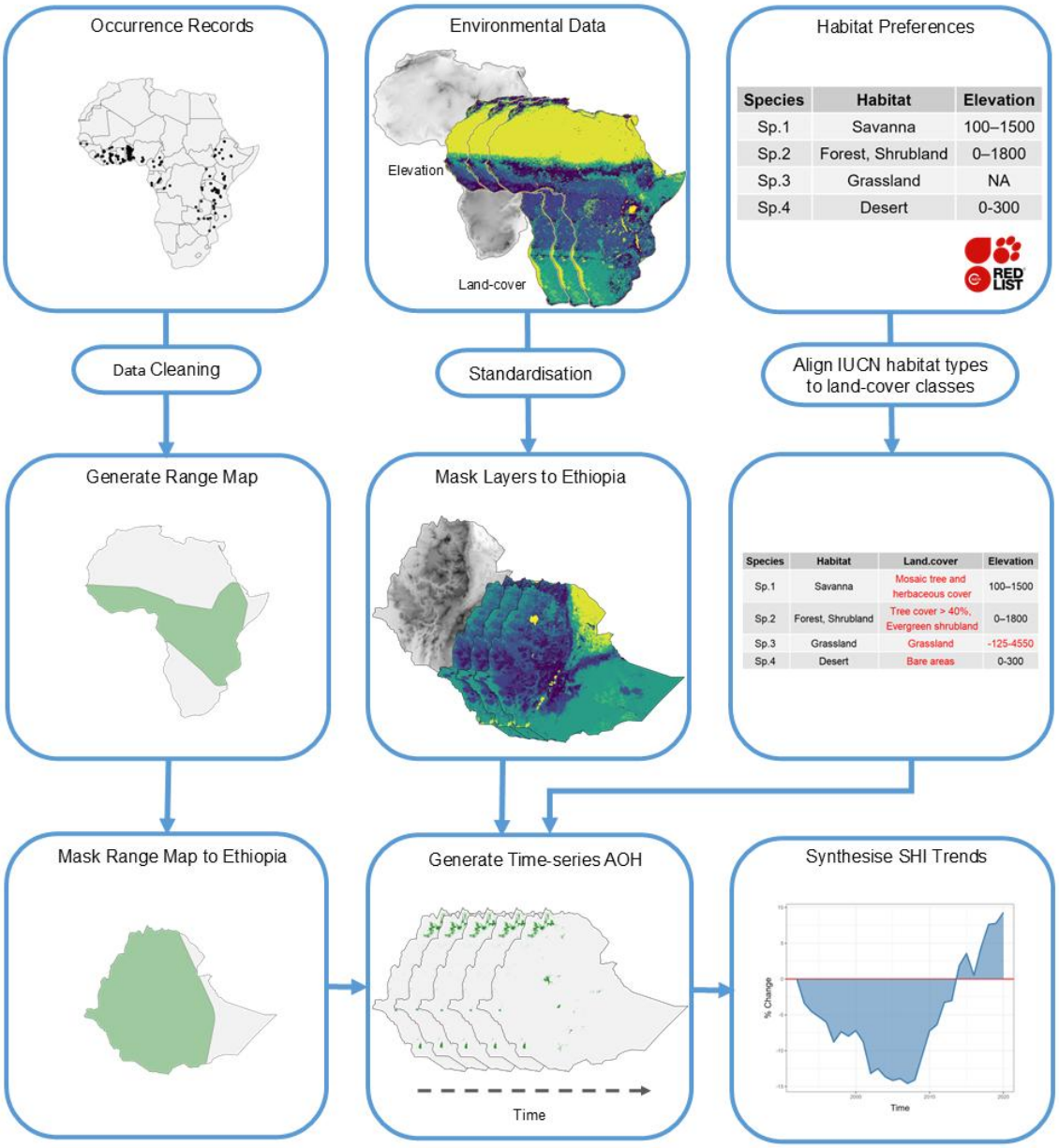

Figure 2. Analytical workflow for estimating SHI from species occurrences, habitat, and land-cover data. Occurrence records are processed to generate range maps for individual species, which are masked to the area of interest. Elevation and land-cover layers are rescaled and masked accordingly to ensure compatibility of further geospatial operations. Additionally, an expert-based conversion table (*e.g.*, available in Santini *et al.*, 2019) is employed to align IUCN habitat preferences information with the European Space Agency (ESA) land-cover classes (*Harper et al.*, 2023). In the analyses, the intersection of species ranges with suitable habitat and elevation layers produces annual Area of Habitat (AOH) maps from 1992 to 2020. This time-series AOH is used to calculate the SHI as the percent change in suitable habitat over time relative to 1992. This final SHI for multiple species can be aggregated into a regional or country-level index.

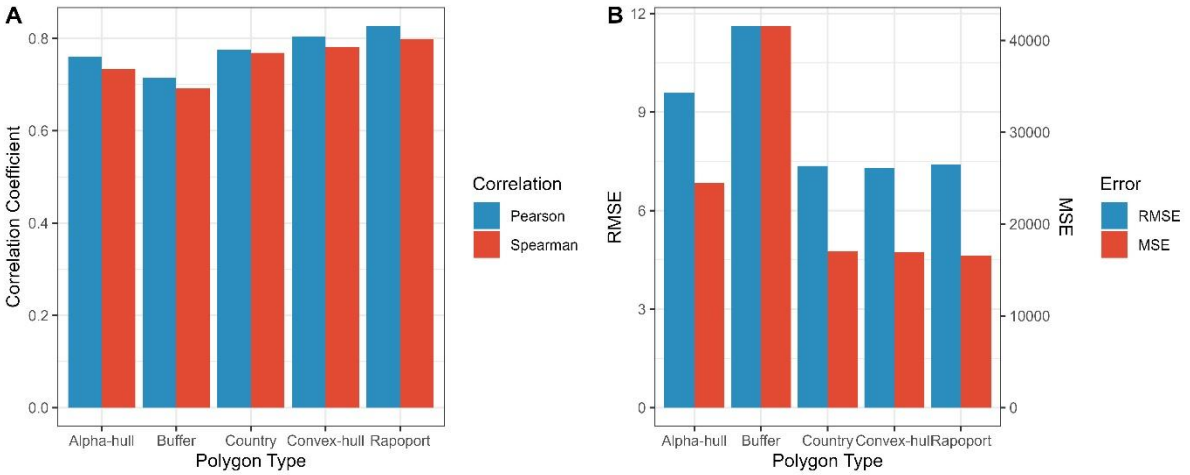

Figure 3. Agreement between SHI estimates derived from SDMs and alternative geometry-based range-mapping methods. (A) Pearson and Spearman correlation coefficients. (B) Root Mean Squared Error (RMSE) and Mean Squared Error (MSE). All geometry-based methods show significant correlations with SDM-based SHI; MSE values are rescaled for visualisation while maintaining the correct relative differences.

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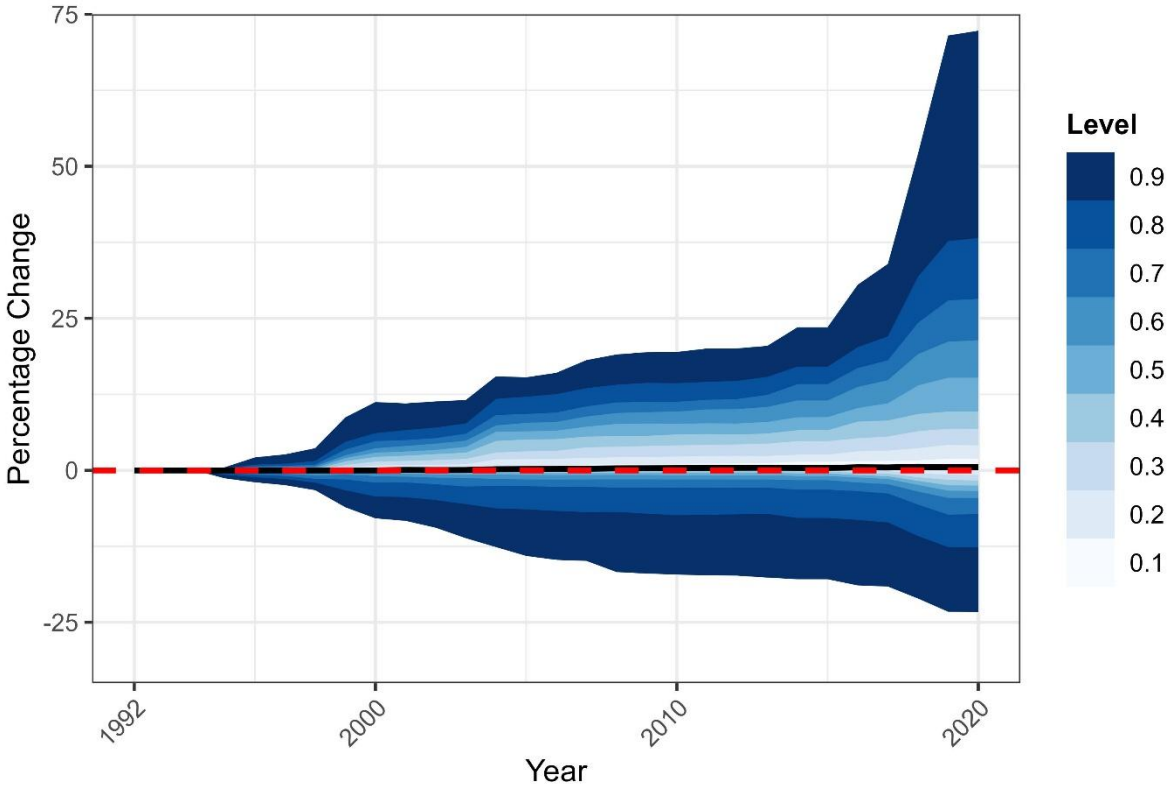

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943 Figure 4. Summary of SHI changes for Ethiopian plant species from 1992 to 2020. Line ribbon charts show changes
944 in percentage of area (measured as the number of 1 x 1km cells), with coloured bands representing the proportion
945 of species within a particular 10%-interval class. The black line indicates the median SHI change across species.

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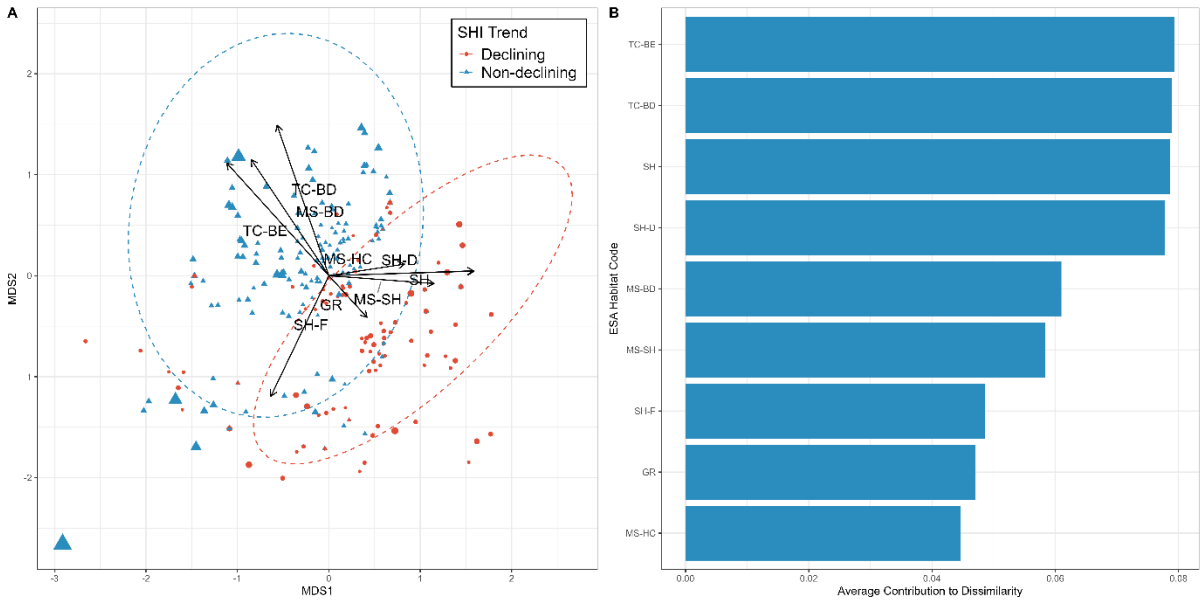


Figure 5. Differences in ESA-CCI land-cover class associations between declining and non-declining species. (A) NMDS ordination of species' land-cover associations (Jaccard dissimilarities), with symbols and colours indicating SHI trend class and size proportional to the absolute value of SHI slope (*i.e.*, the magnitude of change). Dashed ellipses indicate 95% confidence regions for each group. Overlaid vectors represent ESA land-cover classes contributing strongly to group separation, as identified by SIMPER analysis. (B) Relative contribution of the top ESA land-cover classes to dissimilarity between groups (SIMPER analysis). Land-cover classes are ordered by contribution and labelled using ESA codes (GR: Grassland; SH: Shrubland; SH-D: Deciduous shrubland; SH-F: Shrub/herbaceous, flooded; MS-BD: Mosaic tree, shrub; MS-HC: Mosaic herbaceous >50%; MS-SH: Mosaic shrub >50%; TC-BE: Tree cover, broadleaf evergreen; TC-DB: Tree cover, broadleaf deciduous).

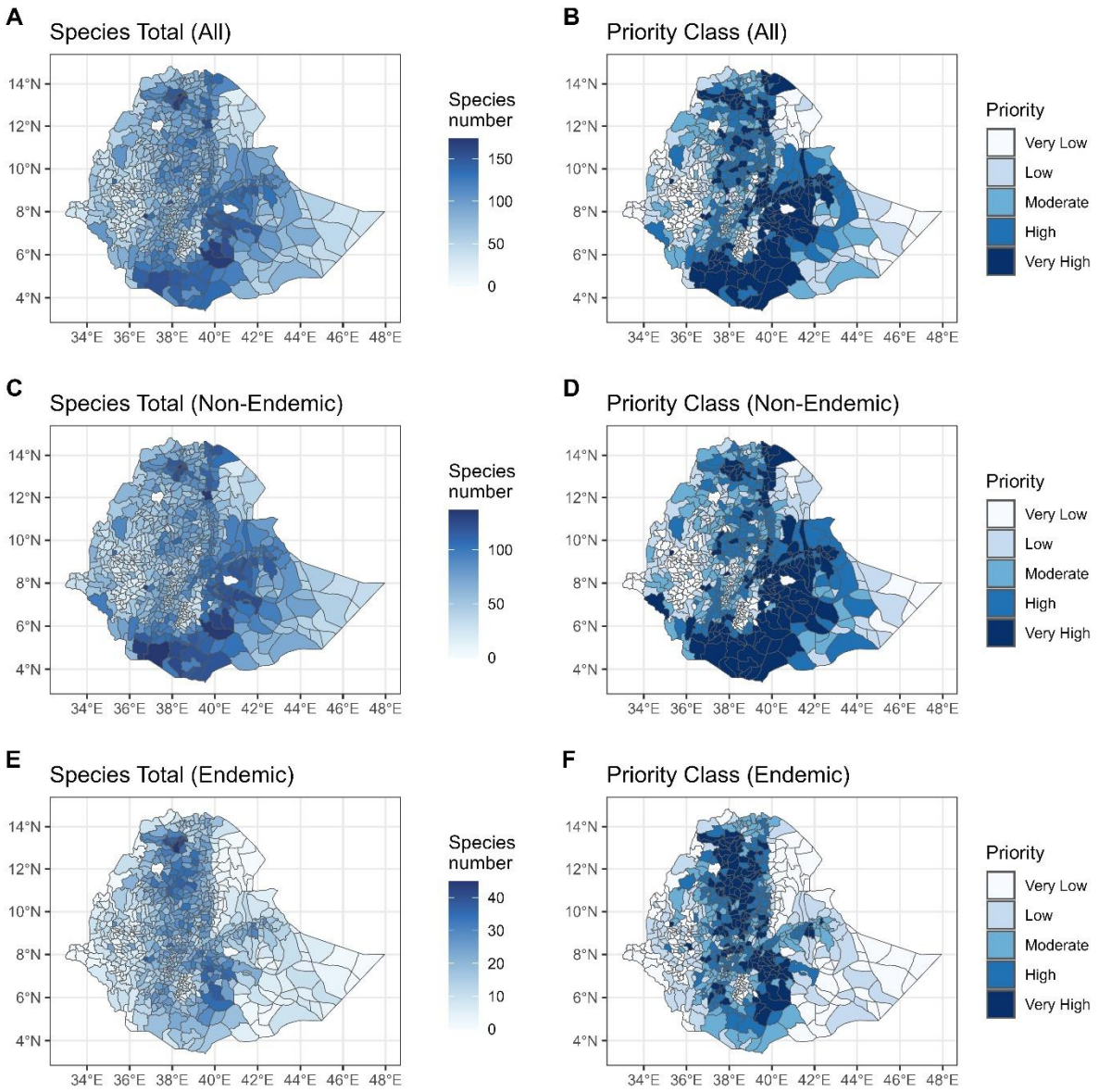


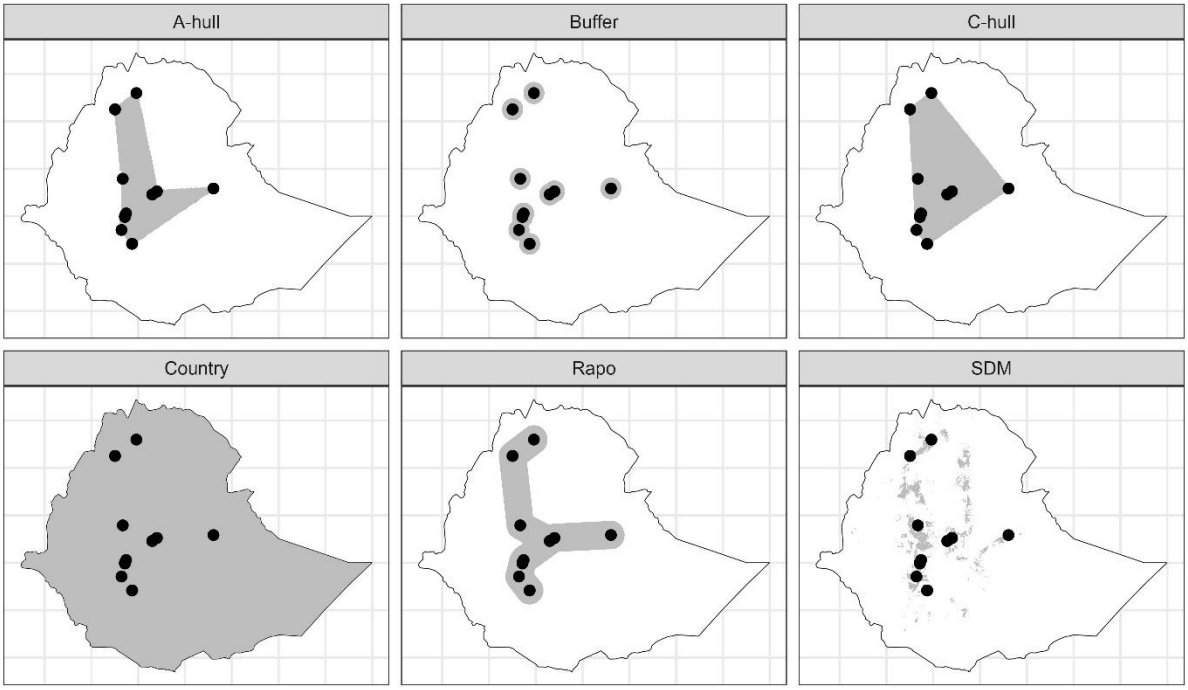
Figure 6. Spatial distribution of species with declining SHI and corresponding conservation priority zones (woredas) in Ethiopia. (A–C) Number of species with declining habitat per zone. (D–F) Priority classes based on quintile ranks of declining species in each zone, ranging from Very Low to Very High. Panels show results for all species (A, D), non-endemic species only (B, E), and endemic species only (C, F).

SUPPLEMENTARY MATERIAL

SUPPLEMENTARY TABLES AND FIGURES

Table S1. Summary of land-cover change by ESA-CCI class in Ethiopia (1992–2020)

Land-Cover Change (ESA Classes)					
	Change (1992-2020)			Relative Metrics	
Land-Cover Class	Gain (km²)	Loss (km²)	Net Change (km²)	Class-Level Change (%)	Share of Total Change (%)
Tree cover, flooded	372	118	254	29.88	0.27
Tree, broadleaf deciduous	17,561	2,974	14,587	465.44	15.58
Tree, broadleaf deciduous open	11,425	2,161	9,264	6.39	9.89
Tree, broadleaf evergreen	5,996	1,012	4,984	12.21	5.32
Tree, mixed leaf type	0	86	−86	−100.00	0.09
Tree, needleleaf evergreen	14	180	−166	−92.22	0.18
Deciduous shrubland	41	256	−215	−7.63	0.23
Grassland	9,931	2,019	7,912	12.98	8.45
Shrub/herbaceous, flooded	29	81	−52	−3.02	0.06
Shrubland	3,848	27,299	−23,451	−4.97	25.04
Sparse herbaceous	0	16	−16	−26.67	0.02
Sparse shrub	6	113	−107	−25.54	0.11
Sparse vegetation	1,789	6,742	−4,953	−61.84	5.29
Mosaic cropland >50%	2,465	4,009	−1,544	−3.08	1.65
Mosaic herbaceous >50%	1,310	1,421	−111	−0.70	0.12
Mosaic natural veg >50%	3,102	13,105	−10,003	−12.19	10.68
Mosaic tree/shrub >50%	8,157	921	7,236	40.84	7.73
Cropland, irrigated	606	252	354	6.56	0.38
Cropland, rainfed	3,661	4,274	−613	−0.51	0.65
Cropland, rainfed, herbaceous cover	2,060	683	1,377	6.93	1.47
Bare areas	1,069	6,446	−5,377	−7.78	5.74
Consolidated bare	120	249	−129	−2.29	0.14
Unconsolidated bare	0	0	0	0.00	0.00
Urban areas	845	0	845	258.41	0.90
Water bodies	610	600	10	0.13	0.01



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971 Figure S1. Examples of geometry-based range mapping methods used to estimate SHI for plant species in
972 Ethiopia. Each panel shows a different method applied to the same set of occurrence records (black dots). The
973 shaded polygons represent the inferred range map using alpha hull, buffer, convex hull, country-wide extent,
974 Rapoport's mean propinquity method and SDM approaches.

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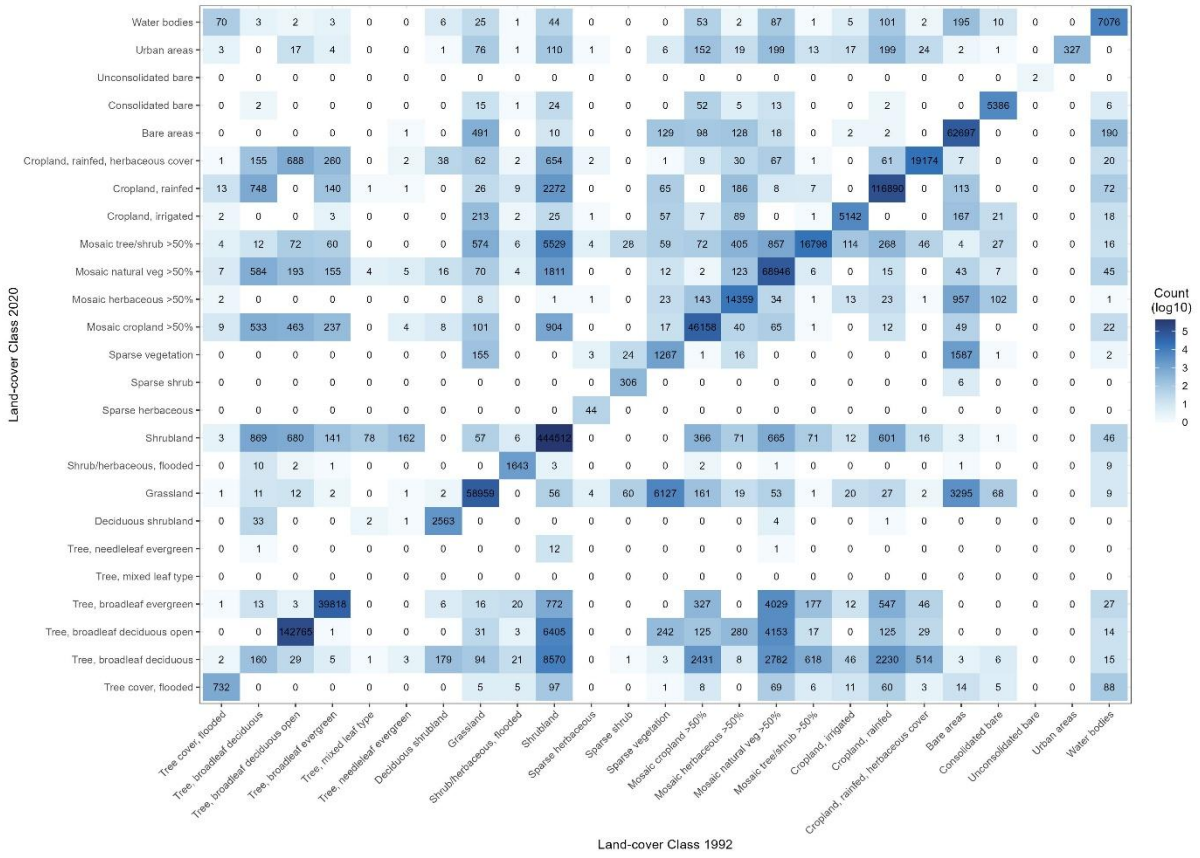

Figure S2. Transitions between land-cover classes from 1992 to 2020. Cell colours represent log10-transformed area of transitions between land-cover classes, with darker colours indicating larger areas. Names on the axes refer to the ESA-CCI land-cover classes occurring in Ethiopia.

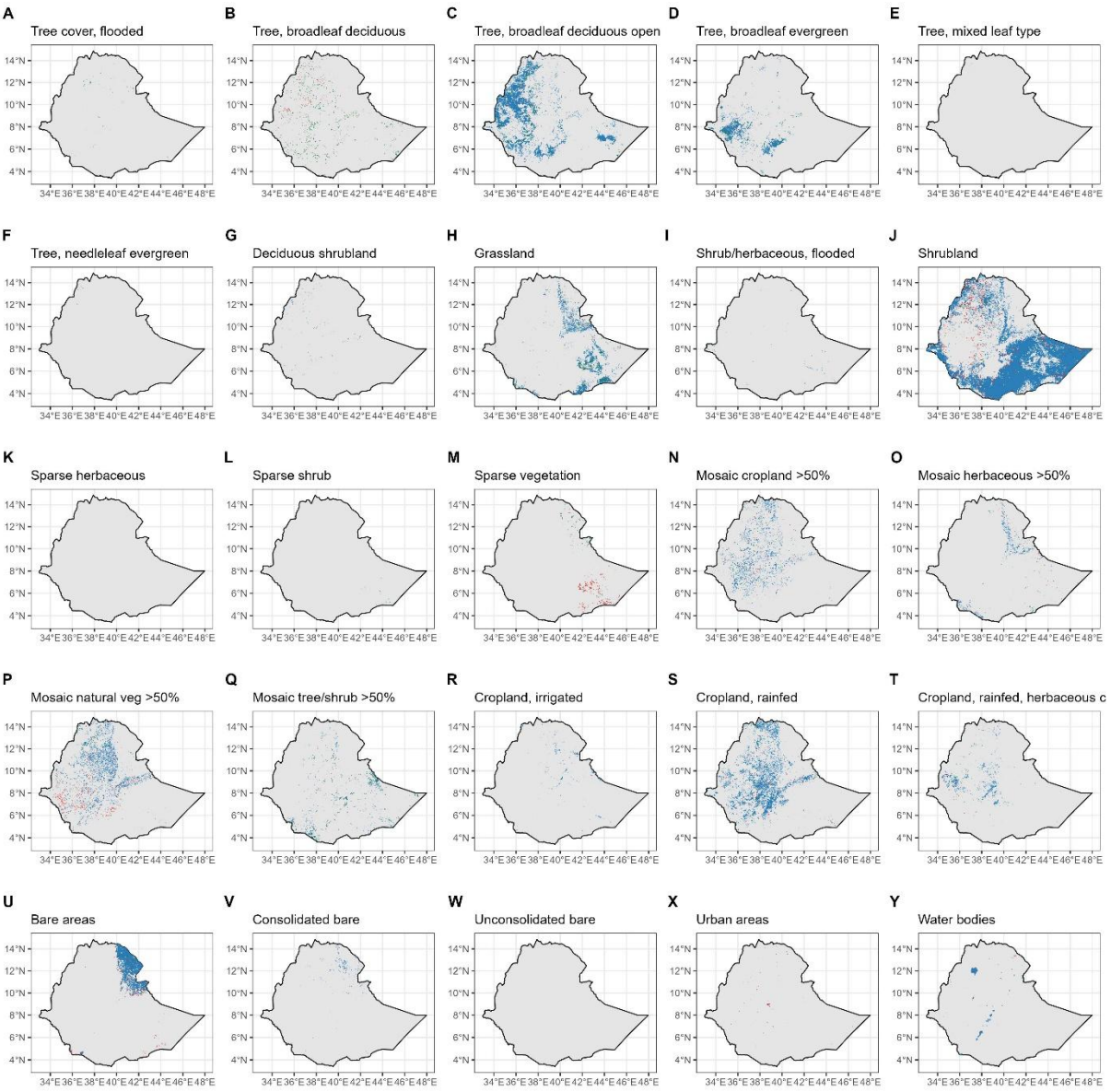

Figure S3. Spatial patterns of land-cover class change from 1992 to 2020. In all panels, grey represents stable absence, blue stable areas presence, red loss, and green gain in each land-cover class.

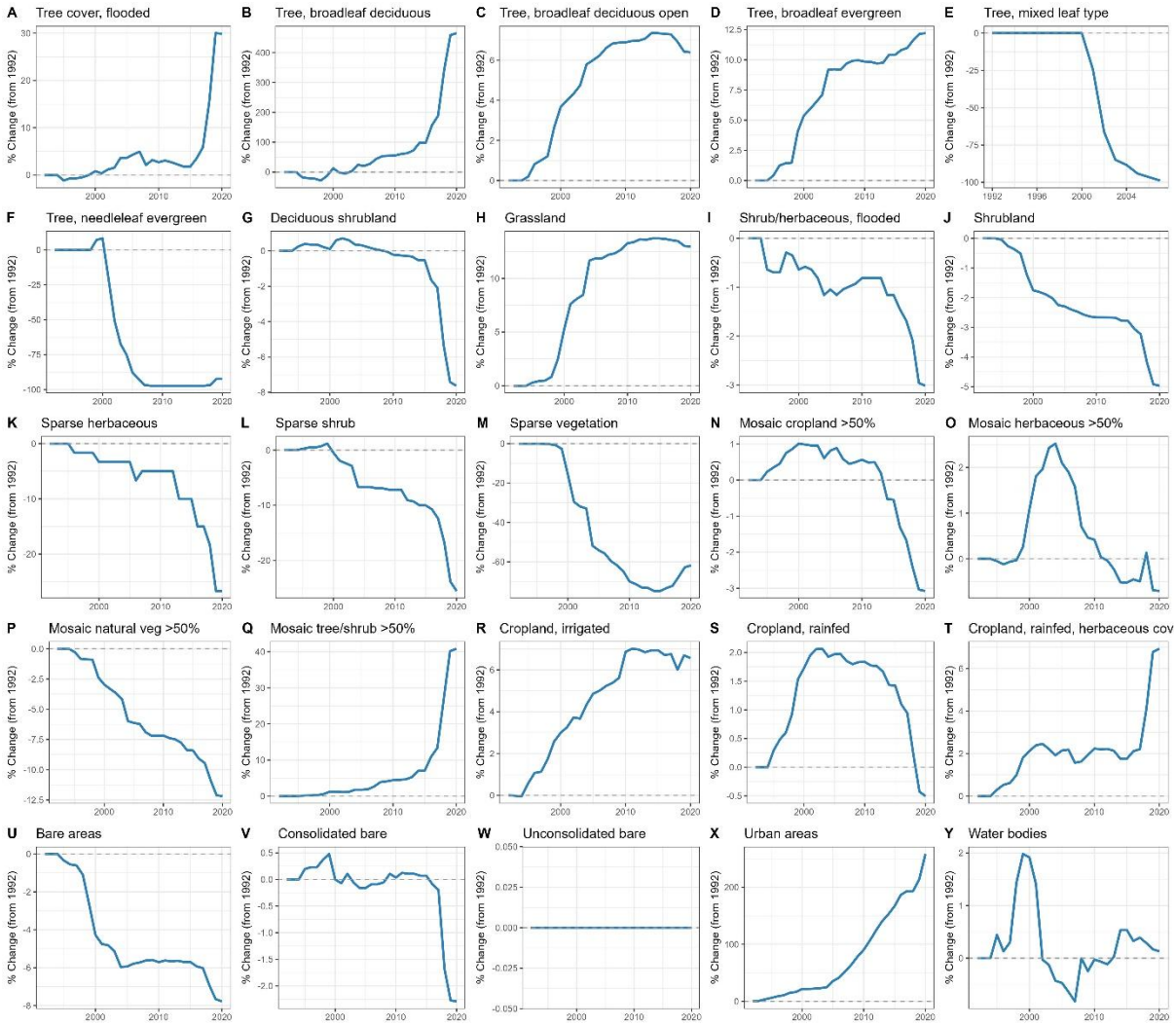

Figure S4. Temporal trends in land-cover class change from 1992 to 2020. Values in the y axis represent the percentage change in land-cover relative to the 1992 baseline year.

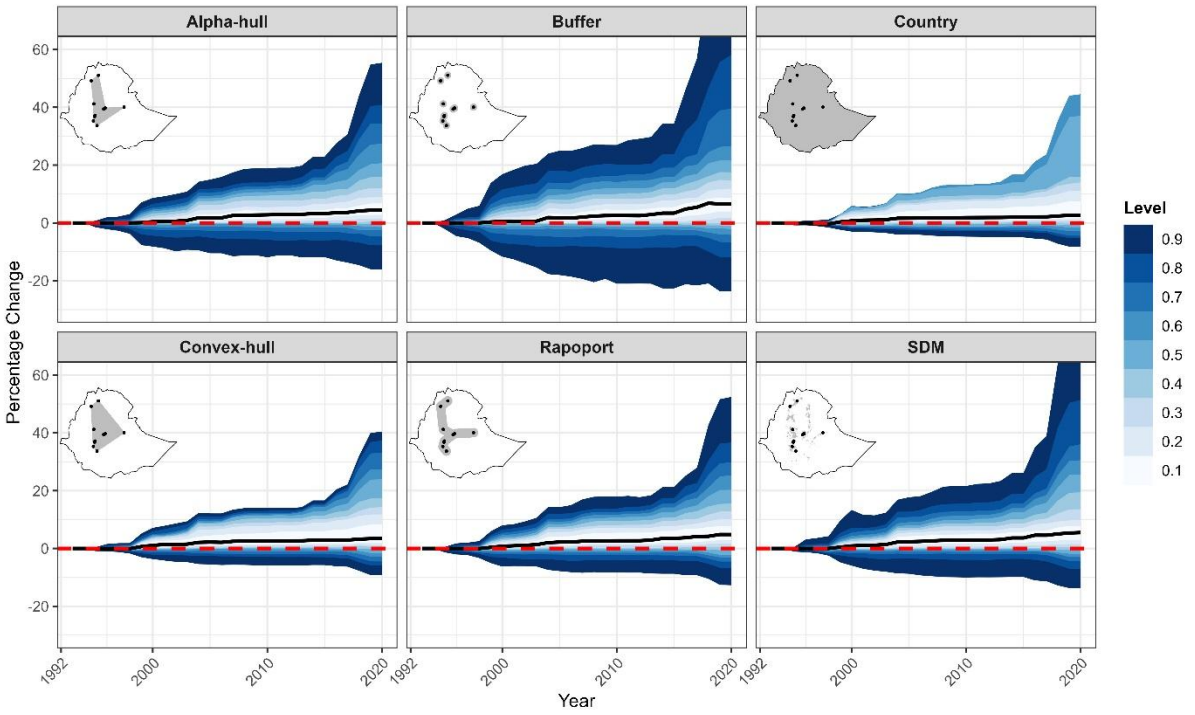

Figure S5. Summary of SHI for Ethiopian species under six range-mapping methods. Coloured ribbons represent the proportion of species within a particular 10%-interval class. The black line indicates the median SHI change across species.

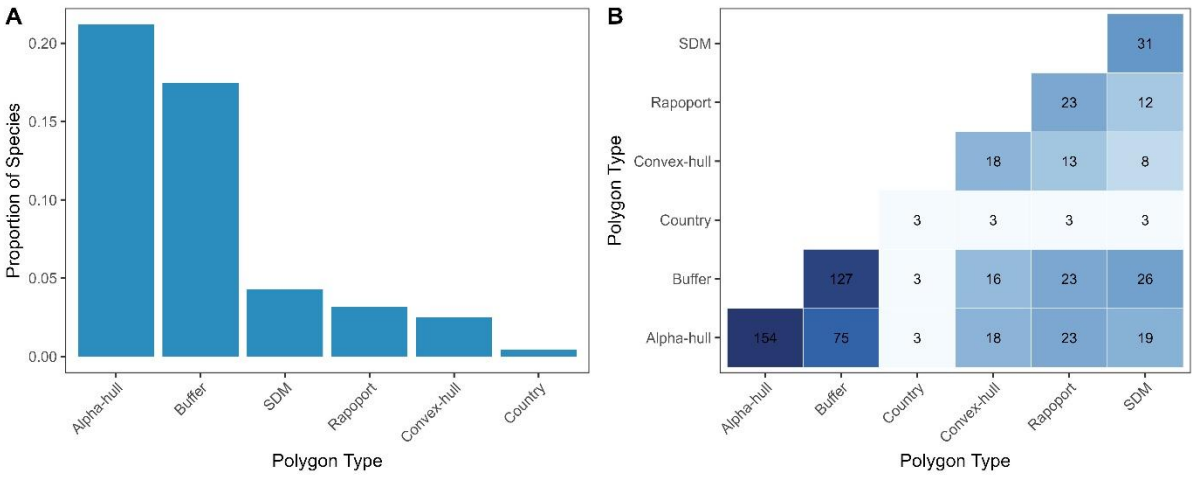

Figure S6. Frequency and overlap of species lacking valid AOH across range-mapping methods. (A) Proportion of species (total species = 727) without AOH in 1992 by method. (B) Shared occurrence of invalid AOH across range-mapping methods.

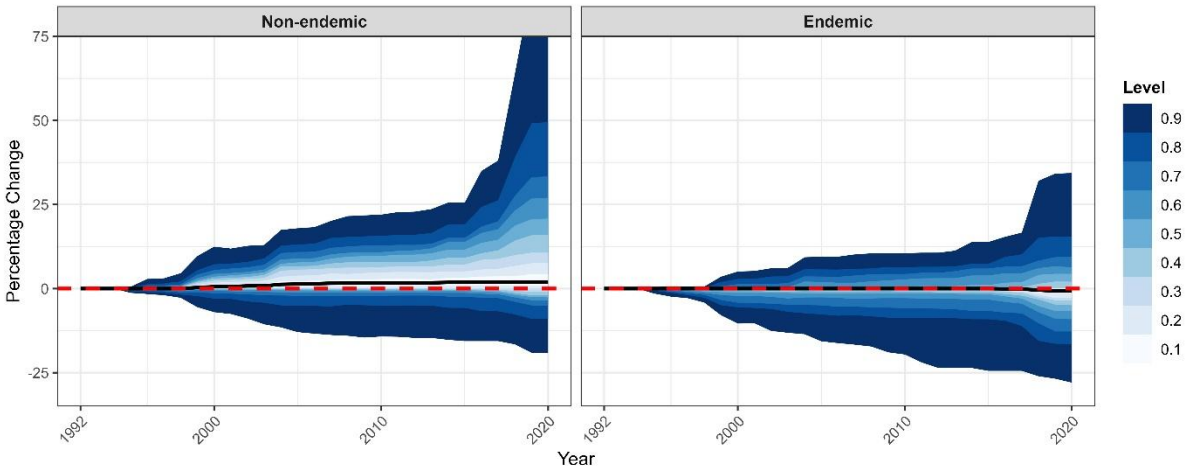

Figure S7. Summary of SHI changes for endemic and non-endemic Ethiopian species. Coloured bands represent the proportion of species within a particular 10%-interval class. The black line indicates the median SHI change across species.

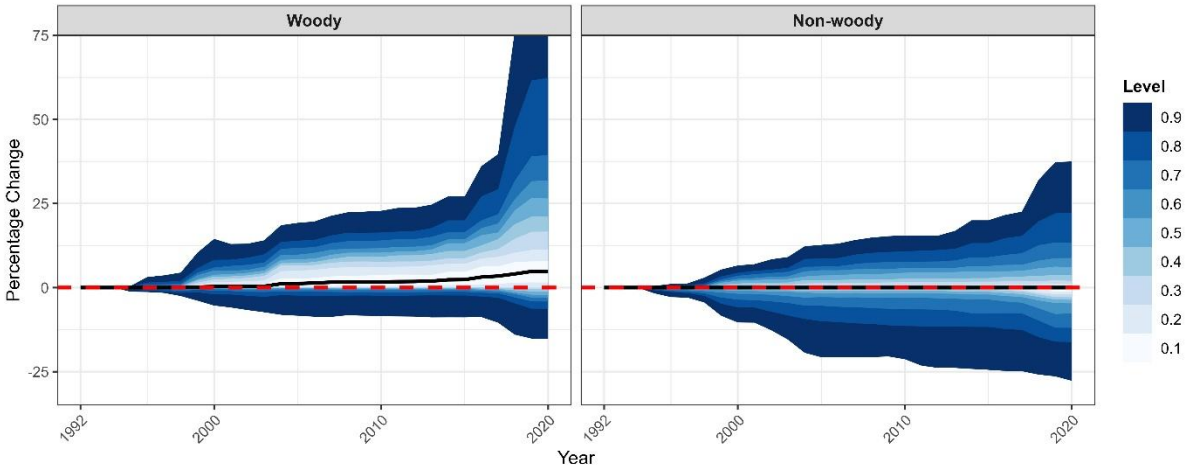

Figure S8. Summary of SHI change for woody and non-woody Ethiopian species. Coloured bands represent the proportion of species within a particular 10%-interval class. The black line indicates the median SHI change across species.