Assessing the species habitats in Colombia’s tropical dry forest over a 20-year period

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Abstract

Countries worldwide are collaborating under the Convention on Biological Diversity to address biodiversity loss. As part of this effort, the monitoring framework of the Kunming-Montreal Global Biodiversity Framework (K-M GBF) includes a set of indicators to track progress toward its goals and targets. One of these is the Species Habitat Index (SHI), a component indicator supporting Goal A, which measures changes in habitat extent and connectivity for multiple species. In this study, we applied the SHI to assess the status and trends of species' habitats in Colombia’s Tropical Dry Forests (TDF) from 2000 to 2020. These forests have undergone extensive degradation and fragmentation, being reduced to less than 2% of their original extent in some regions, with much of their original extent reduced to small, isolated patches. Overall, we found that Colombia’s TDF has lost nearly one-third of its cover since 1990, despite modest gains between 2010 and 2018. Most forest loss resulted from conversion to pasture, although some recovery of degraded forest was observed. We calculated SHI values for 755 bird (237), mammal (68), and plant (450) species using land cover data. To assess habitat connectivity, we used GISFrag and Omniscape and compared outputs. Across the potential TDF area, habitat and connectivity declined by approximately 20% between 2000 and 2020, leaving only ~860,000 ha of habitat. Species associated with natural habitats showed lower SHI values than those adapted to artificial environments, and mammals, many of which are threatened, had the lowest scores overall. We also evaluated the representativeness of protected areas and found that less than 13% of the remaining habitat lies within protected areas. The increasing extent of successional forests, now over 1,000,000 ha, presents an opportunity for ecological restoration. These results underscore the urgency of implementing nature based solutions. Regionally tailored strategies will be critical to maintaining connectivity in this highly fragmented ecosystem.

Resumen

Países de todo el mundo colaboran en el marco del Convenio sobre la Diversidad Biológica para hacer frente a la pérdida de biodiversidad. Como parte de este esfuerzo, el marco de monitoreo del Marco Global de Biodiversidad Kunming-Montreal (KM-GBF) incluye una serie de indicadores para hacer seguimiento a los avances hacia sus objetivos y metas. Uno de ellos es el Índice de Hábitat de Especies (SHI), un indicador de componente que da soporte a los indicadores del Objetivo A, que mide los cambios en la extensión del hábitat y la conectividad de múltiples especies. En este estudio, aplicamos el SHI para evaluar el estado y las tendencias de los hábitats de las especies en los Bosques Secos Tropicales (TDF) de Colombia entre 2000 y 2020. Estos bosques han sufrido una extensa degradación y fragmentación, reduciéndose a menos del 2% de su extensión original en algunas regiones, con gran parte de su extensión original reducida a pequeños parches aislados. En general, encontramos que los BST de Colombia ha perdido casi un tercio de su cobertura desde 1990, a pesar de pequeñas ganancias entre 2010 y 2018. La mayor parte de la pérdida de bosque fue resultado de la conversión a pastizales, aunque se observó cierta recuperación del bosque degradado. Calculamos los valores de SHI para 755 especies de aves (237), mamíferos (68) y plantas (450) utilizando datos de cobertura terrestre. Para evaluar la conectividad del hábitat, utilizamos GISFrag y Omniscape y comparamos los resultados. En toda el área potencial del BST, el hábitat y la conectividad disminuyeron aproximadamente un 20% entre 2000 y 2020, dejando sólo unas 860.000 ha de hábitat. Las especies asociadas a hábitats naturales mostraron valores de SHI más bajos que las adaptadas a entornos artificiales, y los mamíferos, muchos de los cuales están amenazados, obtuvieron los valores de índice más bajos en general. También evaluamos la representatividad de las zonas protegidas y descubrimos que menos del 13% del hábitat restante se encuentra dentro de zonas protegidas. La creciente extensión de los bosques sucesionales, que ahora superan el millón de hectáreas, ofrece una oportunidad para la restauración ecológica. Estos resultados subrayan la urgencia de aplicar soluciones

basadas en la naturaleza. Las estrategias adaptadas a cada región serán fundamentales para mantener la conectividad en este ecosistema tan fragmentado.

Highlights

- By 2020, approximately 860,000 ha of habitat remained for the 755 evaluated species.
- Habitat area and connectivity decreased by ~10–20% between 2000 and 2020.
- Mammals showed the lowest species habitat index values among evaluated taxa.
- Over 1,000,000 ha of successional forest are available for restoration.

1. Introduction

Biodiversity loss has reached unprecedented rates in the last century, primarily driven by tropical deforestation and forest degradation (Muthee et al., 2022). The consequences of these trends are highly complex, as their interaction with global change may trigger cascading events that push ecosystems beyond tipping points, potentially leading to ecosystem collapse (Flores et al., 2024; IPBES, 2024). To curb this biodiversity crisis, countries worldwide are collaborating to find multilateral solutions under the Convention on Biological Diversity (CBD).

The Kunming-Montreal Global Biodiversity Framework (KM-GBF), adopted by the CBD, stands as a landmark environmental agreement that sets an ambitious biodiversity agenda for 2030 and 2050. For instance, goal A of the agreement aims to ensure that 'the integrity, connectivity, and resilience of all ecosystems are maintained, enhanced, or restored, substantially increasing the area of natural ecosystems by 2050’ (CBD/COP/15/L.25, 2022). This goal alone contains a group of concepts –such as integrity and resilience– that are complex to define and therefore to measure. Given this, multiple indicators are needed to evaluate progress.

To track progress towards the goals and targets, the KM-GBF includes five types of indicators. i) Headline and ii) binary indicators, which are mandatory and must be reported by countries, yet they alone cannot provide a comprehensive assessment (Affinito et al., 2024). That is why iii) component, iv) complementary and v) national indicators provide additional context and supplement the mandatory indicators. In particular, the Species Habitat Index (SHI) has been proposed as a component indicator to contribute to the information provided by headline indicators from goal A (CBD/COP/15/L.26, 2022). This index measures changes in the size and quality of areas that harbor species populations and how these changes affect their connectivity (CBD/WG2020/3/INF/6, 2021).

The SHI has traditionally been measured at the national scale using global datasets (Jetz et al. 2022). However, species distributions are not restricted to political boundaries. Measuring the SHI at subnational scales offers greater relevance, as species habitats depend on environmental conditions and are thus more closely aligned with ecosystem distribution (Feng et al., 2024). Additionally, species habitat availability is affected by landscape transformation, the intensity of which varies significantly across ecosystems and according to local socioeconomic dynamics. If the purpose of SHI is to inform conservation actions, it is important to note that these actions are most often implemented at ecosystem or regional scales depending on a country's sociopolitical organization (Dallimer & Strange, 2015; Feng et al., 2024; Hébert et al., 2024). Therefore, assessing habitat and connectivity loss using the SHI at the ecosystem scale may provide critical insights for guiding effective conservation strategies.

Evaluating the SHI is therefore particularly urgent in ecosystems that are on the verge of collapse, and a requirement to achieve Goal A of the KM-GBF. This is the case of Tropical dry forests (TDF), highly fragmented and categorized as an ecosystem at critical risk globally, due a long history of human settlements and agricultural activities (Etter et al., 2020; Ferrer-Paris et al., 2019; Pizano & García, 2014; Rodríguez-Buriticá & Rodríguez-Eraso, in press). Land-cover change, grazing, wood extraction, and increasing frequency and intensity of droughts and hurricanes due to climate change are among the threats TDF is facing (Powers et al., 2018). These pressures are threatening a unique biodiversity adapted to a pronounced seasonality, with steep dry and rain seasons, which represent important environmental stress (Dirzo et al., 2011).

Moreover, TDF are one of the less protected ecosystems worldwide (Portillo-Quintero et al., 2015), showing low representativeness, making more difficult to reach KM-GBF goals. Given TDF high rates of endemism and species turnover within a limited area, resulting in high beta diversity (Dirzo et al., 2011), measuring the SHI is particularly relevant. Then SHI combines landscape metrics with species level information and thereby provides a more integrative approach. Specifically, it enables a habitat-focused analysis that goes beyond forest cover, allowing for a deeper assessment of the TDF's condition and its impact on the ecosystem’s unique biodiversity. This index incorporates species' habitat preferences, which may include anthropogenically modified areas or be restricted to regions with minimal or no human intervention.

Here, we aimed to assess the state and changes in the species' habitat within Colombia's TDF over the last 20 years (2000–2020) using the SHI. In Colombia, TDF has suffered one of the most drastic processes of habitat loss and fragmentation historically (Correa Ayram et al., 2020; Etter et al., 2008, 2017). By 2014, it was estimated that this ecosystem covered almost 720.000 ha, indicating that over 90% of Colombian TDF have been deforested and replaced by human-modified land covers (González-M et al., 2018). More recently, by 2020, forest loss in the Caribbean and inter-andean valleys TDF reached 98% and 92%, respectively (Etter et al., 2020). In the same year, protected areas represented only 3.8% of the regions with TDF in the country (Corzo et al., 2023). Despite a nearly 70% increase in the representation of protected areas within the TDF between 2010 and 2020 (rising from 2.2% to 3.8%) (Corzo et al., 2023), coverage remains well below the national average of 16% and the 30% from KM-GBF Target 3, which aims to protect 30% of land and sea by 2030.

Specifically, we evaluated (1) how land use changed in the TDF between 2000 and 2020. Next, we used the SHI to evaluate (2) what is the state of the habitat of the species distributed within the TDF and how it changed in the last decades depending on the taxonomic group, conservation status or habitat preference. Based on outputs from species’ habitat and not just forest cover, we evaluated (3) how was the representativeness of the protected areas within the TDF by considering the remaining species’ habitats.

2. Methods

2.1. Study area

Tropical Dry Forests occur in areas with an elevation under 1,200 meters above sea level, a mean annual temperature of 25 °C, and annual precipitation between 250 and 2,000 millimeters (mm) (González-M et al., 2018; Instituto de Investigación de Recursos Biológicos Alexander Von Humboldt, 1998; Pizano & García, 2014). These forests have a marked seasonality driven by a dry period of at least three months (<300 mm total rainfall,~100 mm · month^{-1}) where evapotranspiration values are higher than precipitation (González-M et al., 2018; Instituto de Investigación de Recursos Biológicos Alexander Von Humboldt, 1998; Pizano & García, 2014). In Colombia, this ecosystem can be found in four of the six biogeographical regions (the Caribbean, Orinoco, Andes, and Insular), with a larger presence on the Caribbean coast. Although the San Andrés, Providencia, and Santa Catalina archipelago, located on the east coast of Nicaragua and the Insular region, include part of this biome, they were not included in this study because of a lack of official land cover information during the evaluated period.

The potential distribution of TDF covered almost 9 million hectares of the country, following the Colombian ecosystems map (Etter et al., 2017, 2020), which was based on abiotic factors such as elevation, edaphic and climatic variables. This initial recognition of TDF in Colombia excluded the Orinoco region, which has been considered an ecosystem in itself. Recently, Corzo et al., (2023) updated the map for the TDF in the Andes and included some forested areas of the Orinoco, as they experience a marked seasonality, adding ~2 million hectares to the map for the potential distribution of TDF, for a total of ~11,000,000 ha. The map in Figure 1 was used to reference the TDF in this study. The Andean region was subdivided into four subregions: North Andean and Cauca, Magdalena and Patia river valleys (Figure 1).

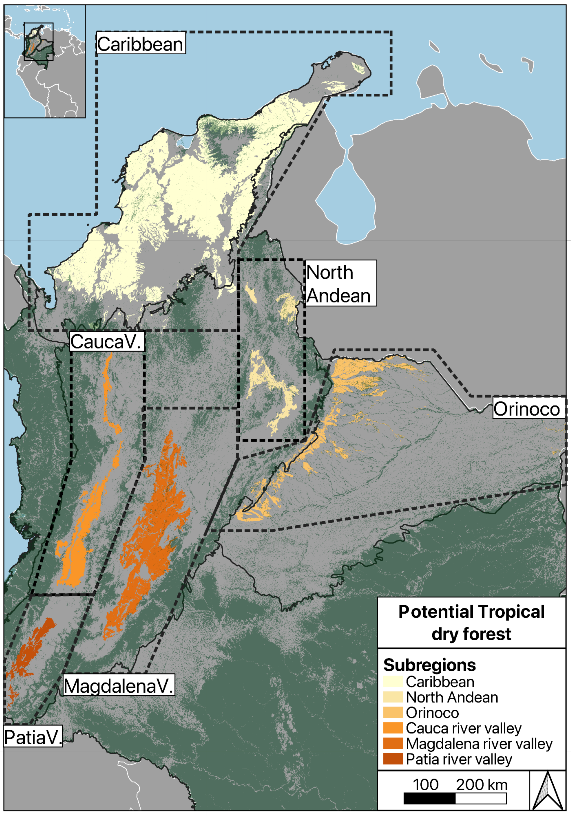


Figure 1. Map of Colombia with the potential area for the TDF based on Corzo et al., (2023) in yellow to orange. Dark green areas show the total forest cover left by 2020 according to the forest non-forest layers produced by the Institute of Hydrology, Meteorology and Environmental Studies in Colombia. We used world administrative boundaries from the United Nations Agency.

2.2. Trends of change in land use

To assess changes in TDF over the past 30 years, we used two sets of the official national cartographic data produced by the Institute of Hydrology, Meteorology and Environmental Studies in Colombia (IDEAM). Since this index is intended to be used in official reports of the state of the TDF in Colombia, we used the national official information. The first dataset (forest) consisted of rasters of 30m resolution distinguishing pixels with changes in forest cover from those with no changes and from those with no forest cover. These layers are available for 1990, 2000, 2005, 2010, 2012, and yearly from 2013 to 2020. The second set (corine) was based on land cover polygon layers classified using the Corine Land Cover

(CLC) methodology with a scale of 1:100.000 (IDEAM, 2010). At the time of the study analysis, these maps were available in three periods of time: 2000–2002 (used as proxy for 2000), 2010–2012 (used as proxy for 2010), and 2018, which represented the most recent data available at the time of analysis.

Using successive layers from both datasets, we first evaluated changes in forest cover within the potential area of the TDF (here 11 million ha, Corzo et al., 2023). For the forest dataset, IDEAM defines forest pixels as areas where forest cover prevails, with a minimum canopy density of 30%, a minimum height of 5 m and contained in patches of at least 1 hectare (Galindo et al., 2014). For this study, the time periods of analysis were time steps of 10 years: 1990-2000, 2000-2010 and 2010-2020. For the corine dataset the forest category included three CLC subcategories which together are more closely aligned with the forest definition in the forest dataset: dense forest (3.1.1), open forest (3.1.2), and riparian forest (3.1.4). Time steps evaluated with the corine dataset were 2000-2010 and 2010-2018.

Next, to track the shifts from forest categories to other types of land cover, such as pastureland or plantations, the CLC categories in corine dataset were reclassified as follows: (i) forest, (ii) successional forest (it includes cover types different than forest and canopy density is less than 30%), (iii) pastureland, (iv) arable land and plantations, (v) shrubland and grassland (natural cover dominated by bushes and herbs), and (vi) other less represented categories (Appendix 1). We used these new categories to evaluate how they transitioned between 2000-2010 and 2010-2018 to other categories. All these analyses were done at a 25m resolution to keep consistency with further analyses within this study.

2.3. Species habitat

To understand how trends of change in land use have affected the species' habitat in TDF, we used the Species Habitat Index (SHI) (find a description of the species selection process at the end of this section and in Appendix 2). To measure this index, first, a Species Habitat Score (SHS) is calculated for each species as the mean between an area score (AS) and a connectivity score (CS) (Figure 2) (CBD/SBSTTA/24/INF/38, 2022). These scores represent the habitat available for the species (AS) and its connectivity (CS) relative to a baseline or year of reference. The SHI, a species-based index, is the mean of the SHS across species. Both the SHI and SHS indices range from 0 to 100% where 0 indicates a complete loss of the remaining species' habitat and its connectivity compared to a baseline, and 100 indicates no change in habitat or connectivity over time. For instance, an SHS equal to 95% may correspond to a species for which there was a 4% and 6% decrease in area and connectivity, respectively. Hence, the area score is 96% and the connectivity score 94% (CBD/SBSTTA/24/INF/38, 2022).

To consider the different representation of the species' habitat inside the TDF, we measured the Stewardship SHI, a weighted mean of the SHI (CBD/SBSTTA/24/INF/38, 2022). We assigned weights based on the proportion of each species' habitat within potential areas of TDF distribution relative to the species' total habitat area in Colombia. The Stewardship SHI assigns greater weight to species with a higher proportion of their habitat within the TDF and less weight to those with a broader distribution across other ecosystems (e.g., *Saguinus oedipus*, an endemic monkey of the TDF, had higher weight than *Panthera onca*, the jaguar, that is distributed throughout all of Colombia). These weights were also used to create a weighted mean habitat layer for all the species evaluated based on the AS maps (Figure 2).

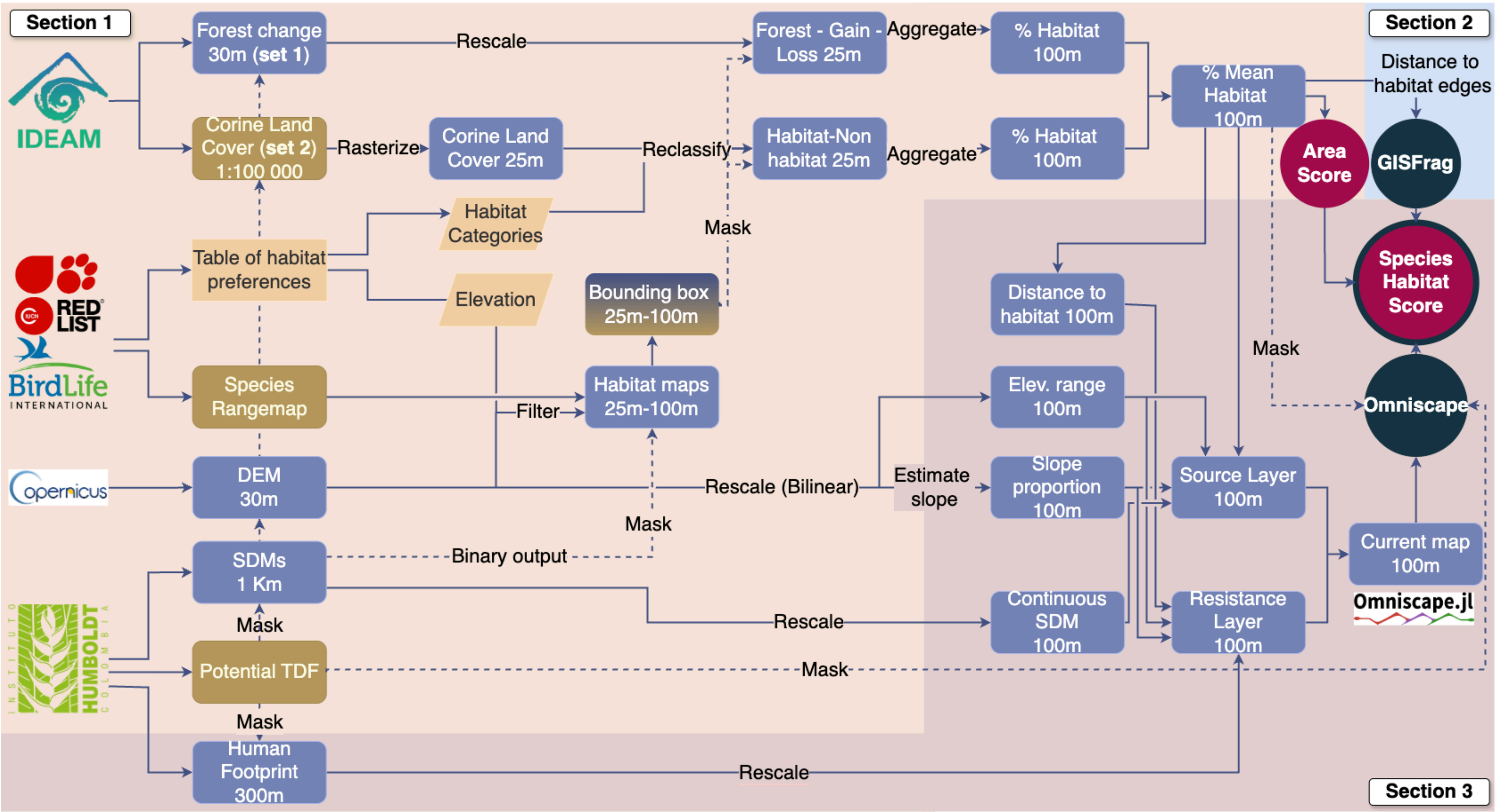


Figure 2. Steps to measure the SHI. Purple boxes are raster data and mustard boxes are polygons. Section 1 calculates area of habitat. Section 2 gets the area and GISFrag connectivity scores and section 3 gets the Omniscape layers for the alternative connectivity score.

2.3.1. Area Score (AS)

To define the geographic distribution of the species, the SHI metadata sheet (CBD/SBSTTA/24/INF/38, 2022) recommends using either an expert range map or a species distribution model (SDM). For all species, we used binary SDMs at 1 km resolution obtained from BioModelos, a tool developed by researchers at the Instituto de Investigación de Recursos Biológicos Alexander von Humboldt in Colombia. This tool generates binary and continuous SDMs based on species occurrences and climate data in the country (Ayerbe Quiñones, 2022; Henao Diaz et al., 2020; Noguera-Urbano et al., 2023; Velásquez-Tibatá et al., 2019). When range maps obtained from the IUCN webpage (https://www.iucnredlist.org/resources/spatial-data-download) as well as BirdLife (https://datazone.birdlife.org/species/requestdis) were available, we cropped the SDMs (not yet validated by experts). Next, we restricted these species maps to the preferred elevation ranges for each species (CBD/SBSTTA/24/INF/38, 2022) using data available from the IUCN, downloadable through the R package "redlist" (Gearty & Chamberlain, 2022). For 193 plant species without elevation range data from the IUCN, we used occurrence data from González-M et al., (2018) to determine their elevation ranges. We used the 30 m Digital Elevation Model (DEM) from Copernicus to create the elevation range maps and mask the species maps to this extent (Figure 2).

To create maps reflecting species habitat preferences and evaluate changes over time, we used layers from the forest dataset, which provides forest cover values, and CLC types from layers in the corine dataset as follows. We aggregated using proportions the 25m forest layers from the forest dataset to 100m resolution rasters. From these, we calculated the proportions of forest presence, forest loss, and forest gain for the years 2000, 2010, and 2020. For the corine dataset, we used land cover layers from 2000, 2010, and 2018 as proxies for habitat, with the 2018 layer representing 2020, as it was the most recent data available at the time of analysis. For each species, we identified CLC categories associated with its preferred habitat types, as reported by the International Union for Conservation of

Nature (IUCN) (see Appendix 1 for a table with equivalences), and created maps of the presence and absence of preferred habitat. This assumes species have not had changes in their preferred habitat types in time. We then aggregated pixels into a four-by-four grid to create habitat proportion layers of 100m resolution. The resulting habitat layer for each species corresponded to the mean value between forest cover proportions from the forest dataset and habitat proportions from the corine dataset.

Each dataset contributed 50% to the final habitat estimate for the species. For instance, if within a pixel, a species had 30% forest cover (forest dataset) but could also inhabit successional forest, a category identified only in corine dataset, with a habitat proportion value of 50% (with corine dataset), the resulting mean habitat value for that pixel was 40%. At the end of this process we obtained, for each species, maps of 2000, 2010 and 2020, showing the mean percentage of available habitat inside the potential area of the TDF. As habitat is, by definition, suitable for the species (Brooks et al., 2019), we will avoid using the term "suitable habitat" and instead refer to the habitat available for the species, filtered by elevation ranges, as the Area of Habitat (AOH).

The temporal baseline used as a reference to measure changes over time (CBD/SBSTTA/24/INF/38, 2022) corresponds to the first year (time zero) of the AOH defined for each species. However, since a significant portion of the TDF has been transformed, with the most drastic changes occurring in the distant past (before 1600) (Etter et al., 2008) when no land cover maps were available, we defined the baselines in two ways. The first baseline assumed no habitat loss across the full potential area of TDF (11 million ha, Corzo et al., 2023). At this point, the habitat for a given species corresponded to the total SDM area, masked by elevation range (and range map, if available) within the potential TDF area. This baseline, referred to here as the hypothetical base year, reflects the general state of the habitat and its potential habitat loss history. For instance, with less than 10% of TDF remaining, the index for the final year will reflect this proportion, representing the amount of habitat remaining compared to the species' potential initial habitat within the TDF. The second way to measure the baseline assumed that the habitat data from the year 2000 represented the time zero. This baseline is sensitive to small changes in recent years, resulting in higher index values that do not reflect the general state of the habitat, but its recent loss. These baselines corresponded to the 100% reference values, which change with habitat loss in subsequent years.

2.3.2. Connectivity Score

We used the estimated AOHs, to evaluate changes in connectivity. The SHI metadata sheet used by the Convention on Biological Diversity (CBD, 2022) suggests the GISFrag metric to measure connectivity for the SHI. This structural connectivity metric is based on the mean distance of each habitat pixel to the nearest edge of the habitat patch (CBD/SBSTTA/24/INF/38, 2022; Crooks et al., 2011; Ripple et al., 1991). Higher values mean more interior habitat, and lower values imply smaller patches of habitat and thus more fragmented (Crooks et al., 2011; Ripple et al., 1991). First, to measure distances, we had to convert the habitat proportion layer into a binary variable (presence-absence), where pixels with more than 10% of habitat cover, or approximately 1,000m^2 of habitat by pixel, were categorized as presence of habitat. Next, we calculated the Euclidean distance from habitat pixels to the nearest non-habitat pixels and the mean distance across the landscape. The GISFrag metric does not account for conditions outside the habitat, as it ignores the surrounding matrix, and conditions inside the suitable habitat, as it considers habitat patches uniform. To address this limitation, we also explored other connectivity metrics that consider inter-patch connectivity and the habitat requirements of each species from a functional perspective (Keeley et al., 2021).

For heavily modified landscapes, like the TDF, Keeley et al., (2021) suggest using metrics based on conductivity surfaces that measure current flow density for both functional and structural connectivity analyses. Current flow in circuit theory can be used to predict movement patterns and thus has been used to model connectivity (B. H. McRae et al., 2008). We used the Omniscape.jl package (Landau et al., 2021; B. McRae et al., 2016) written in the programming language Julia (Bezanson et al., 2017) to evaluate landscape connectivity with a more functional perspective. This package uses the Circuitscape algorithm to calculate landscape connectivity using circuit theory. Omniscape measures the current flow between habitat patches (sources) and incorporates the conditions outside the habitat by including a resistance surface. Omniscape operates, with a user-specified search radius, within a circular moving window for evaluating the movement between sources and target pixels (See Appendix 3 for more detail about the definition of dispersion distances). In this study, we assumed that variables such as species distribution probability, habitat cover percentage, elevation range, and slope (Dickinson et al., 2021; Valderrama-Zafra et al., 2024) influence species movement.

2.3.2.1. Omniscape inputs - Source layer

The source strength raster assigns the relative current for each pixel, indicating where species are more likely to move to other pixels (Appendix 3). To define this layer, we used four variables (Figure 2): 1) a continuous SDM for climate suitability, 2) the mean habitat cover percentage, 3) a binary map of the elevation range, where a value of 1 indicates the area falls within the IUCN-defined range, and 4) a slope layer rescaled using proportions, with the steepest slope as the reference value. We inverted the slope values, assigning 1 to flatter areas and 0 to steeper areas (Figure 2).

For each species, we input these layers into Omniscape within a bounding box area derived from the AOH with an additional buffer. To minimize edge effects, we set this buffer to 50% of the bounding box width (Phillips et al., 2021), calculated as the square root of the bounding box area, assuming a square shape. For flying species like bats and birds, we excluded the slope variable (See Appendix 4). We calculated a weighted mean across these layers, assigning equal weights of 1 to the first two variables and weights of 0.5 to the two layers derived from elevation data. Then, we multiplied the resulting values by 100 to create layers with values ranging from 0 to 100. The highest values appear in areas where habitat is present within the elevation range, with high SDM values and low slopes.

2.3.2.2. *Omniscape inputs - Resistance layer*

The resistance layer represents factors that redirect or reduce species movement. To build this layer, we followed a process similar to the one used for the source layer but with four distinct components: 1) a 300m resolution Colombian human footprint layer (Correa Ayram et al., 2020) rescaled to 100 m. We used the human footprint data for 2000, 2015 (as a proxy for 2010), and 2018 (as a proxy for 2020) while assigning a value of 0 for the hypothetical base year; 2) a layer representing the distance to patches with at least 10% of habitat per pixel (derived from the binary layer used for the GISFrag metric), and rescaled between 0 and 1 by measuring the proportion relative to maximum distance; 3) an inverse elevation range layer, where areas outside the elevation range were assigned a value of 1; and 4) the slope layer (without inverting), where steeper areas had higher resistance values closer to 1 and flatter areas were closer to 0 resistance. Then, we also multiplied the resulting values by 100 to produce a resistance layer with values ranging from 0 to 100. The highest values were assigned to areas farther from the habitat, outside the elevation range, with high human footprint values and steep slopes.

Then, we used three mask categories to extract the Omniscape outputs to get the CS: 1) the AOH for each year (Suitable), 2) the suitable area of only the base year (hypothetical or 2000) (Base year), and 3) the total TDF potential area (Corzo et al., 2023) (All TDF). The mean current value for each year was divided by the mean current for the baseline year to get a percentage of change. This percentage was used as the connectivity score to calculate the SHI. Similarly, as for the area score, maps of the mean distance to the edges and current flow were produced to show spatially explicit outputs with changes of the scores throughout the years (available at https://osf.io/3ch7d/?view_only=3bbef33bd37b4f2c92f047eababa7781).

2.3.3. Species list

We compiled a list of 610 vertebrate animals and 2,627 plant species occurring in TDF according to various sources (Acuña-Vargas et al., 2017; Diaz-Pulido, A., Zurc, D., Jaramillo-Fayad, J. C., & Benítez, A., 2023; Herazo Vitola et al., 2017; Hernández-Jaramillo et al., 2018; Norden et al., 2021; Pizano & García, 2014; Vargas Salinas et al., 2019). However, these species needed to meet specific criteria, such as the availability of data for SDMs, habitat preferences, and dispersal metrics, to be included in the analysis (Appendix 2). We gathered information on each species' habitat preferences and conservation status using the package rredlist (Gearty & Chamberlain, 2022). From the initial list, we prioritized 1668 species, of which 803 could be linked to a dispersion distance metric. We removed herptiles from the list because, at the time of the analysis, we did not have data to establish a clear dispersal range relationship. This left 765 species with SDMs from BioModelos, 318 of which also had range maps from the IUCN. We standardized species names using the 'taxize' package (Chamberlain & Szöcs, 2013).

We further refined the list by removing eight species whose SDMs or range maps did not overlap with the potential TDF area, leaving a total of 757 species. After measuring the AS, two additional species were excluded due to extreme values (greater than or close to two standard deviations from the mean AS values for all species). To assess the variability of the index according to the species included, we performed 100 bootstrap samples with replacement from the 755 species to calculate the SHS. The variation was quantified using the 0.025 and 0.975 quantiles to plot confidence intervals to the index.

2.4. Evaluation of the representativeness of protected areas

To measure the representativeness of the protected areas within the habitat of the species distributed within the TDF, we used the 2023 layer from the National Single Registry of Protected Areas (RUNAP) in Colombia. We restricted the analysis to protected areas within a 100m radius inside the potential TDF area to avoid overlaps with regions merely touching its borders. Protected areas in Colombia can be classified as either public or private (*Decreto 1076 de 2015*, 2015, *Decreto 2811 de 1974 - Gestor Normativo*, 1974). From these, categories included within the evaluated areas were: 1) national and 2) regional natural parks; 3) national and 4) regional protective forest reserves; 5) regional integrated management districts; 6) soil conservation districts; 7) single natural area, 8) sanctuary of fauna and flora and 9) civil society natural reserve (the only private category). Their classification is based on the scale depending if it is national, regional or more local like the civil society reserves, the level of intervention in the structure, composition and function attributes of biodiversity, and the type of use that is allowed, from sustainable use, restoration, preservation, knowledge, and enjoyment (*Decreto 1076 de 2015*, 2015, *Decreto 2811 de 1974 - Gestor Normativo*, 1974).

2.5. Software and computational resources

We conducted all analyses in R 4.3.1 (R Core Team, 2021) using RStudio 2024.12.1 (Posit team, 2023), except for the Omniscape package, which was used in Julia 1.10 (Bezanson et al., 2017) to generate connectivity maps. The scripts are available on GitHub (github.com/MaIsAp/species-habitat-index-tdf-colombia). Computing resources were provided by the Digital Research Alliance of Canada (alliancecan.ca). We used QGIS 3.34.5 (QGIS Development Team, 2009) to produce the map figures and the rescaling and reprojecting of forest and corine datasets.

3. Results

3.1. Land cover trends and transitions for the TDF

We found that by 1990 (forest dataset) only 1,037,435 ha of TDF remained within the 11 million ha of the potential TDF area (Corzo et al., 2023) (Figure 3). By 2018 (corine dataset), forests have decreased 30% to 732,739 ha and by 2020 (forest dataset) only 652,869 ha of forest remained (38% of loss); i.e., nearly one-third of the remaining forest cover was lost over the last 30 years from 1990 to 2020. Between 2000 and 2018, forest cover declined by

11% (corine dataset) and by 23% between 2000 and 2020 (forest dataset). However, between 2010 and 2018, the corine dataset showed a slight increase of approximately 50,000 ha (Figure 3).

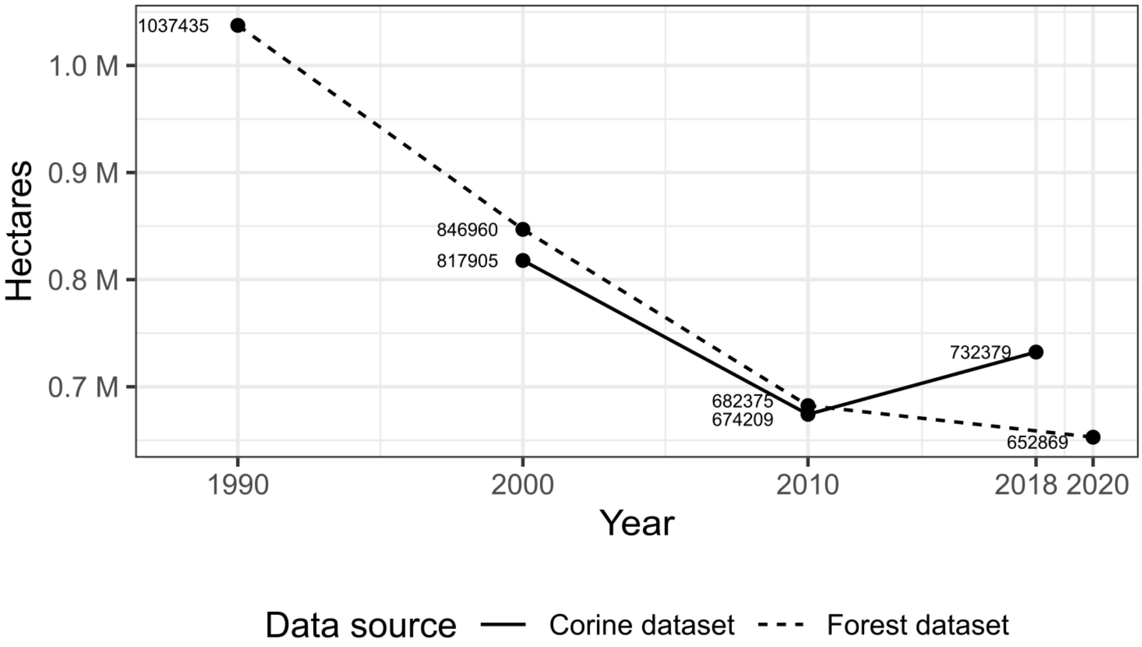
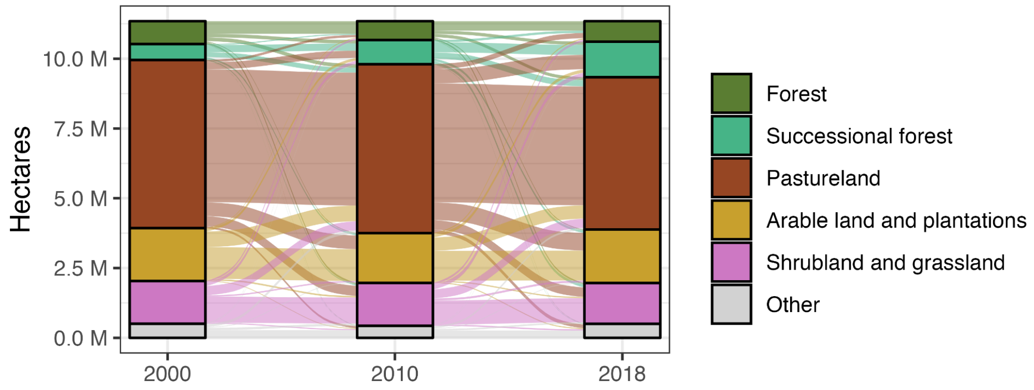
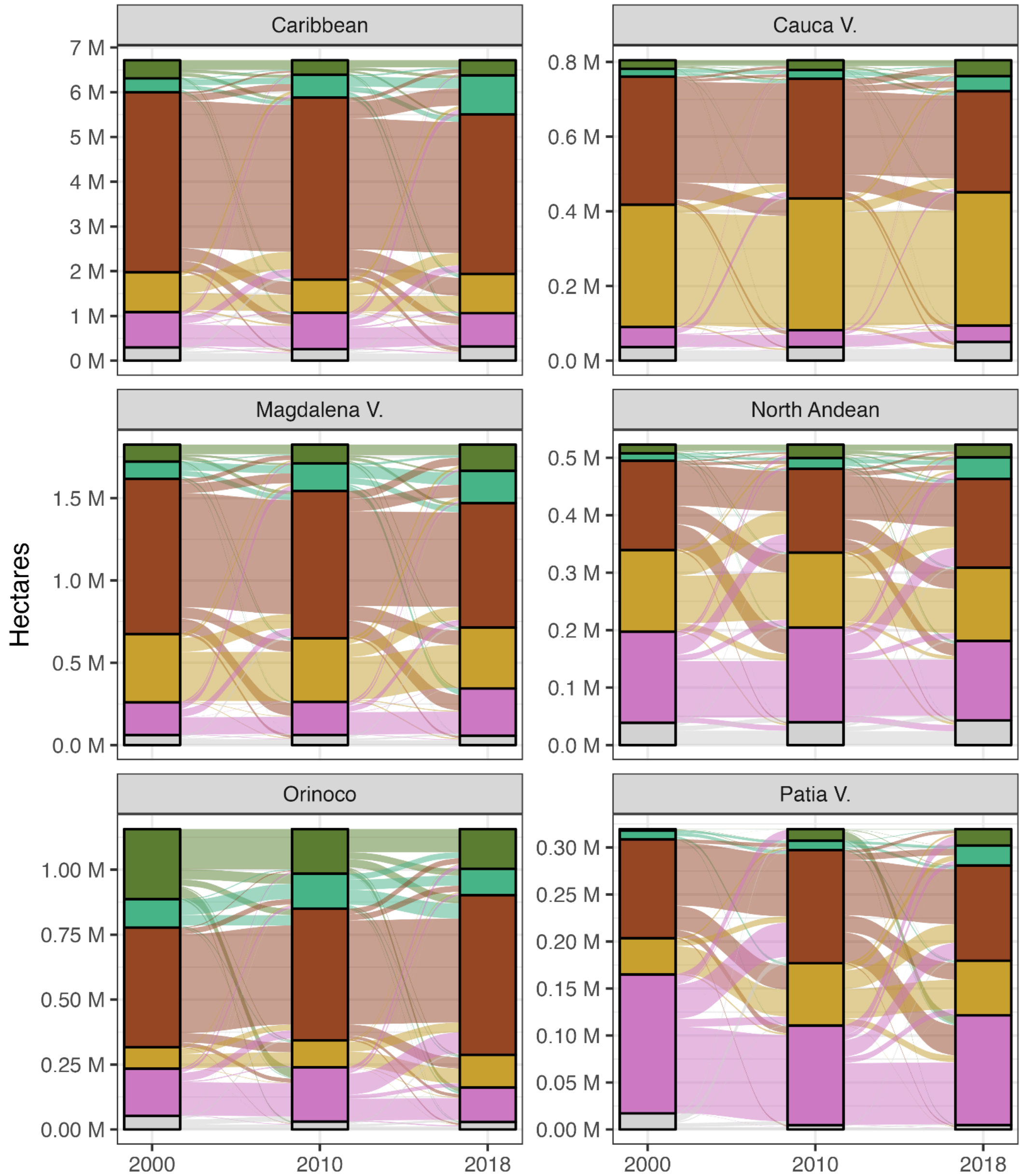


Figure 3. Changes in the hectares of natural forest cover within the potential area for the TDF calculated using two land cover datasets: forest dataset for the years 1990, 2000, 2010, and 2020, and corine dataset for the years 2000, 2010, and 2018.

Forest loss resulted from a wide variety of land cover transitions, but mainly, the conversion to pastures has dominated the land cover change of the TDF in Colombia (Figure 4). Indeed, most of the 11 million hectares covered originally by TDF have been converted to pastures, which today corresponds to about half of the area, followed by arable land and plantations (5,400,000 ha and 1,900,000 ha by 2018, appendix 5). Successional forest occupied 1,270,000 ha by 2018 and was the result of previous forest degradation (around 100,000 ha) and conversion from other land uses, mostly pastures (around 500,000 ha). Between 2010 and 2018, a large portion of pastureland (~30%) passed to other land cover categories, mostly arable land and plantations and successional forest. All subregions experienced an increase in forest and successional forest areas, except for the Orinoco region, where these natural covers, along with shrubland and grassland, showed a clear decline. This was accompanied by an increase in pasturelands, arable land, and plantations. Additionally, for the Caribbean region, the increase was just for the successional forest, but with a decrease in forest. In the Cauca Valley, arable land and plantations surpassed pasturelands in coverage.



(a)



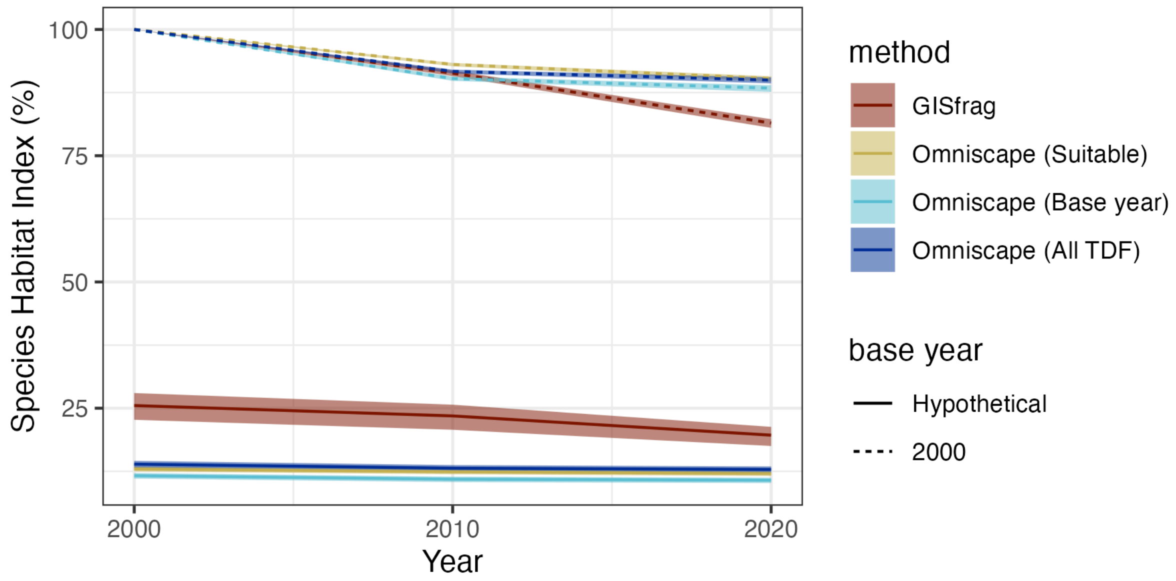
(b)

Figure 4. Transitions of land cover for a) the total area of TDF and b) each subregion resulting from the changes in categories from corine dataset between proxies for 2000, 2010 and 2018. Y-axis indicates million (M) hectares

3.2. Species Habitat Index

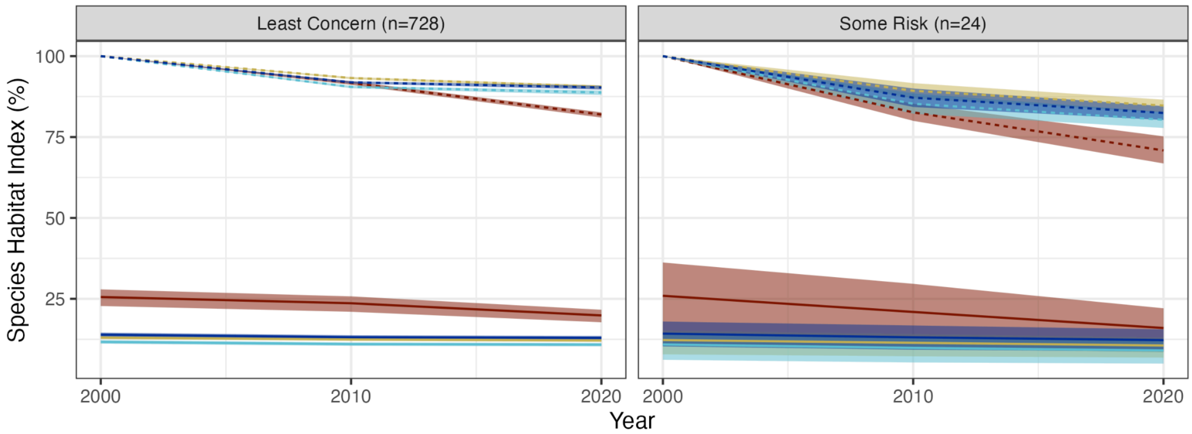
Changes in the SHI for the 755 species varied depending on the method used for the estimation of the CS. Based on GISFrag, ~20% of habitat and connectivity were lost between 2000 and 2020, compared to ~10% using Omniscape (Figure 5a). When considering the potential area of TDF as a hypothetical reference, 80–90% of the habitat and its connectivity had been lost by 2020, according to GISFrag and Omniscape (Figure 5a). See Appendix 6 for the SHS of the 755 species included in this study. We resampled with replacement the SHS 100 times an recalculated the SHI to test the sensitivity of the index according to the inclusion or exclusion of different species. However, except for the species at some risk level, values did not show great variation.

Species with some risk level, according to the IUCN and the national list of threatened species (Ministerio de Ambiente y Desarrollo Sostenible, 2024), showed more pronounced decreases in SHI values than those in Least concern categories, regardless of the method or baseline year used (Figure 5b). Three species with the data-deficient category were removed from the figure. Similarly, species whose habitats were restricted to natural land cover categories (as defined by the IUCN) showed steeper declines compared to species whose habitats included some type of human-modified cover type, referred to as the artificial land cover or human modified category (e.g. successional forest, arable land, pastureland) (Figure 5c). Two species, one associated with introduced vegetation and the other with no specific suitable category, were removed from the graph. Among taxonomic groups, mammals were the most vulnerable according to GISFrag, followed closely by plants when using Omniscape to measure connectivity (Figure 5d).



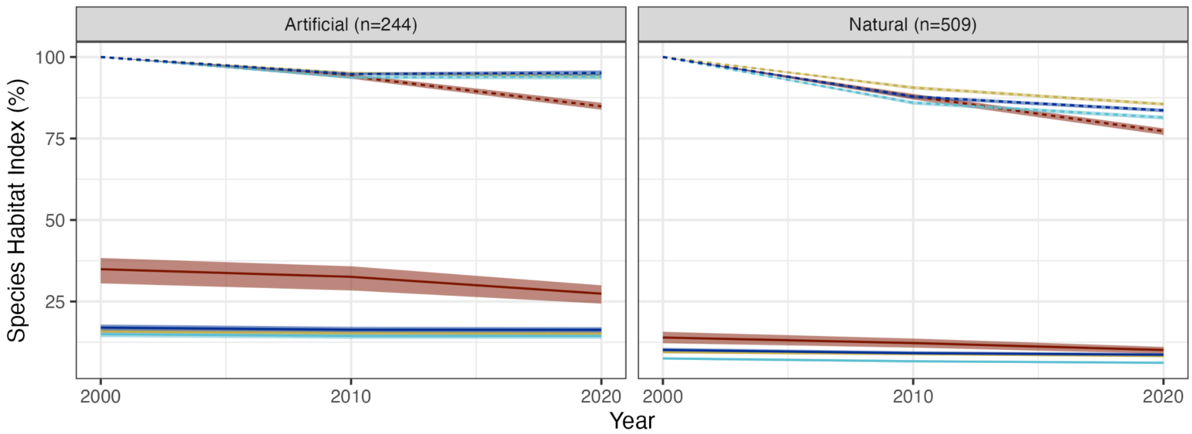
method
GISfrag
Omniscape (Suitable)
Omniscape (Base year)
Omniscape (All TDF)
base year
Hypothetical
2000
Species Habitat Index (%)
100
75
50
25
2000
2010
2020
Year

(a)



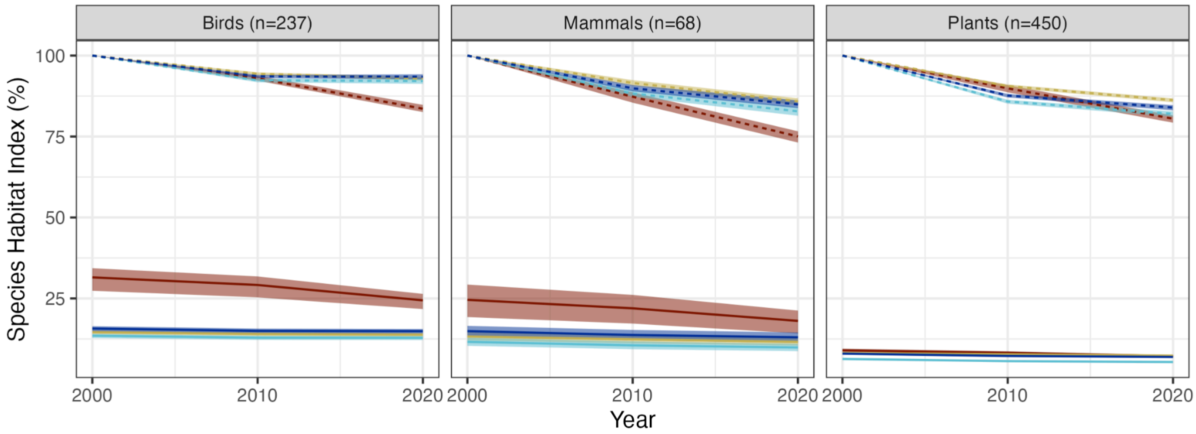
Least Concern (n=728)
Some Risk (n=24)
Species Habitat Index (%)
100
75
50
25
2000
2010
2020
Year

(b)



Artificial (n=244)
Natural (n=509)
Species Habitat Index (%)
100
75
50
25
2000
2010
2020
Year

(c)



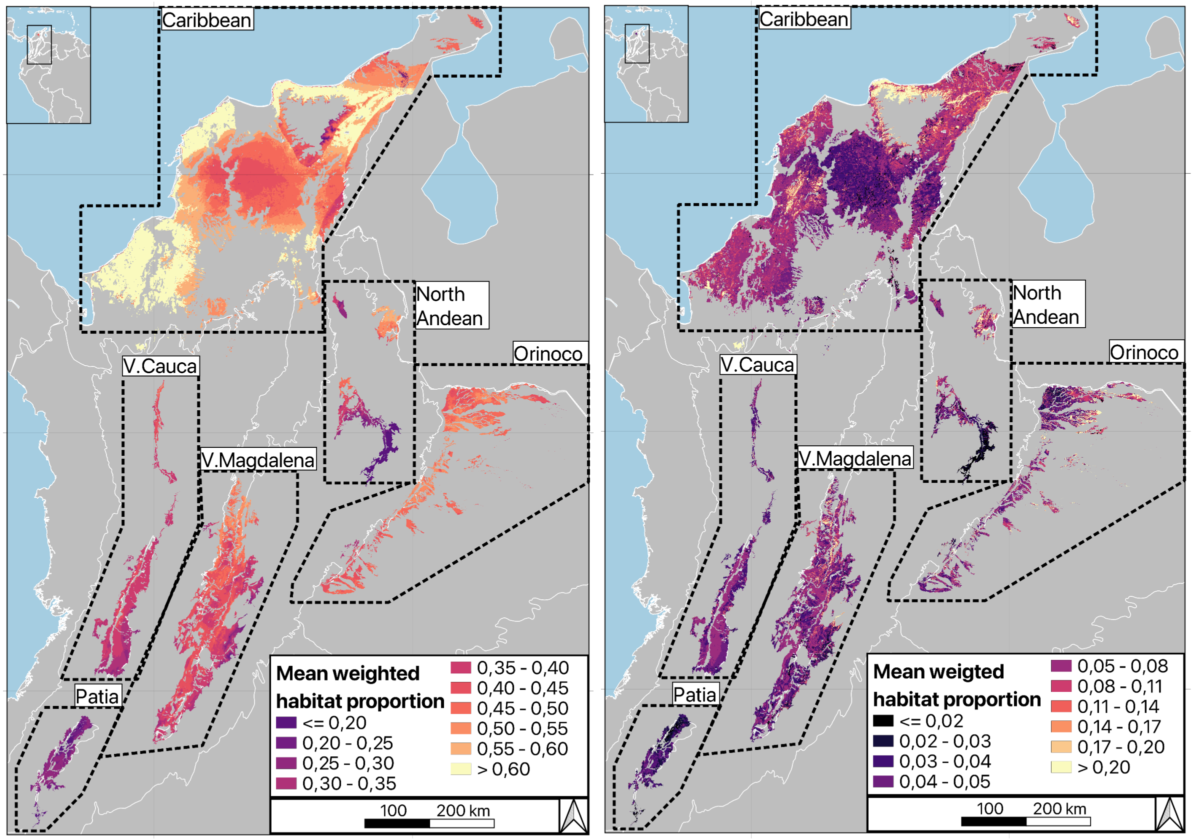
(d)

Figure 5. (a) Species Habitat Index (SHI) with 95% confidence intervals from an N=100 bootstrap done by resampling the species included in the SHI calculation. SHI by (b) IUCN category, (c) habitat type and (d) by taxonomic group. In red are the values using the GISFrag metric and in blue, yellow and green are the Omniscape metrics calculated using the associated masks.

3.3.Changes in the habitat of the species and representativeness of protected areas

Based on the potential area occupied by TDF (11,300,000 ha), around 5,600,000 ha were potential habitats for the 755 species evaluated (Figure 6a). By 2020, only 859,000 ha of these remained, of which ~ 105,000 (12%) are located within some type of protected area (Appendix 7). The Caribbean region harbored the highest mean potential habitat (higher than 50%) (blue and green areas Figure 6a), and this pattern was maintained in 2020, with ~ 547,000 ha of habitat remaining. Of these, ~ 87,000 ha (16%) have some level of protection, with National Natural Park being the category of protected area that covers the higher percentage (61%) (Appendix 7).

The Andean and Orinoco regions harbored almost half of the potential remaining habitats, and by 2020, these were represented by small and highly fragmented patches. For the Andean region, ~ 199,000 ha of habitat in TDF remained in 2020, of which only ~ 15,000 ha (7%) were located within protected areas, with Regional Integrated Management Districts as the category covering the higher percentage of habitat in all subregions. Orinoco region had only ~3% of its area protected, mostly within Natural Reserves of the Civil Society. The mean percentage of protected areas between subregions was 8.5%.



(a) (b)

Figure 6. Mean weighted habitat availability for the 755 species evaluated in (a) hypothetical base year and (b) 2020. Color scales differ between maps. See Appendix 9 for maps with distance to edge and current values for 2020.

4. Discussion

4.1. Land cover trends and transitions for the TDF

Over the past decade, decision making related to TDF in Colombia has been based on an estimated coverage value of 720,000 ha (Ariza et al., 2014; Pizano et al., 2016; Pizano & García, 2014). Here, we show that by 2018-2020, only ~650,000 ha to ~730,000 ha of forest cover remains within the estimated 11,300,000 ha of potential area. While determining an exact value for forest loss is challenging due to methodological differences, both datasets consistently showed a declining trend of TDF cover in the last decades.

TDF loss is the result of multiple processes. Forest transition to pastures started during the times of conquest (1500-1600) and expanded rapidly to the Caribbean and Andean regions and later in the Orinoco during the colonial period (1600-1800) (Etter et al., 2008; Pizano & García, 2014). Thus, what we observe nowadays is the result of these historical processes as pastures dominate the land cover categories in all subregions except for Cauca Valley, where arable land and plantations are more prevalent. This transformation trend has been persistent. Between 1970 and 2015, Correa Ayram et al., (2020) reported an evident increase of human activities within TDF, with extensive cattle ranching established in areas with agricultural and agroforestry potential (Pizano & García, 2014). Overall, this has resulted in underutilization of the soil for these purposes and causing negative social, ecological, and economic impacts, further threatening their conservation (Pizano & García, 2014).

To date, most of the remaining TDF are in an early to intermediate successional stages, embedded within a highly transformed landscape matrix with limited mature forest (González-M et al., 2018; Pizano & García, 2014). Only a small portion, mainly distributed in the Orinoco region, can be considered mature forest (González-M et al., 2018). However, our analysis revealed that the Orinoco region lost over 100,000 ha of forest cover between 2000 and 2018, while pastureland and arable land and plantations increased (Appendix 5). In contrast, the other regions exhibited net gains in forest cover. However, when successional forests are included in the analysis, the Caribbean region aligns with the overall recovery trend. The Orinoco region, on the other hand, continued to show a consistent decline (~33%) even when successional forests were considered. Despite the historical conversion of TDF land to other uses and the overall trend of habitat loss, over 1,000,000 ha of successional forest remain available for restoration (Andrade et al., 2018), with an increasing trend driven by transitions from agricultural activities.

4.2. Consequences of cover loss to the species habitat

Our study shows that, by 2020, human-driven transformations impacted species' habitat and its connectivity by causing a reduction of ~10-20% in SHI since 2000 and near 80-90% of all their potential habitat within the TDF. However, by 2020 the species’ habitat is larger (860,000ha) than the area of forest cover (650,000ha), probably because it includes degraded areas that represent available habitat for generalist species (e.g. successional forest, pasturelands, croplands). For instance, in Montes de Maria (a subregion of the Caribbean), most of the remaining mammals are generalist species, less sensitive to human interventions (Pardo et al., 2024). Vascular plants exhibited a similar pattern, where forest disturbance and early successional stages favored generalist species (González-M et al., 2018).

Unsurprisingly, species that use artificial land cover showed a less pronounced decline in index values compared to those restricted to natural habitats. This trend was also observed in birds, of which 80% (188/237) included artificial covers and had greater dispersal distances, making their habitat and connectivity less affected than that of mammals and plants. Omniscape even detected a slight recovery in the last year, likely due to successional forest gains across several regions (figure 5, appendix 8). Thus, preserving any type of forest cover in heterogeneous landscapes can help enhance connectivity for these groups (Pardo et al., 2024).

Although most of the remaining species in TDF are generalists and 97% (728/752) of the species in our study are classified as Least Concern by the IUCN, the majority (509/753) are exclusively associated with natural habitat types (e.g., forests, shrublands, wetlands), particularly plants (409/450). Mammals, which were also mostly associated with natural habitats (51/68), showed greater variation in SHI values depending on the connectivity metric used. Both plants and especially mammals appear to be more sensitive to habitat loss. Thus, while some TDF species can tolerate human-modified landscapes, most primarily depend on natural habitats and are more vulnerable to forest cover loss. Even the more generalist species have experienced habitat reduction due to deforestation.

Habitat loss restricts species distribution, jeopardizing their functional role in ecosystems as well as their contributions to people. For example, mammals showed the highest habitat loss, they are not only predators of smaller species but also play a critical role in controlling these populations (Pardo et al., 2024). Many other species, especially bats and birds, are seed dispersers or pollinators and continuous habitat loss could affect their interactions with plants species, which in turn may affect plant species use. The species habitat scores would be useful to track changes in the habitat and its connectivity for species of interest and evaluate potential consequences of habitat loss to nature contributions to people.

4.3. Representativeness of protected areas within regions

The mean percentage of habitat within protected areas across regions was 8.5%, based on average habitat values for the 755 species, calculated within pixels where at least 10% of the area was classified as habitat. The Caribbean region had the highest protection (~16%), followed by Cauca Valley (~13%) while the Orinoco region showed the lowest (~3%). When considering only forest cover without measuring habitat, less than 4% of the potential TDF area is protected on average within these regions (Corzo et al., 2023). Although protection increased from 2.2% to 3.8% between 2010 and 2020, TDFs remain the least represented biome in Colombia, with mean connectivity within protected areas below 2% (Corzo et al., 2023). While a greater proportion of TDF is protected when species habitat is evaluated (~9%) compared to forest cover alone (~4%), the declining trends in habitat and connectivity as indicated by the SHI may still compromise the functional connectivity of protected areas within TDF habitats.

Integrated Management Districts, a protected area category that does not imply strict conservation, was predominant throughout the inter-Andean valleys (Patia, Cauca, Magdalena river valleys as well as North Andean subregion). Nonetheless, these areas have shown an increase in forest cover. The Magdalena region held the second largest absolute amount of habitat after the Caribbean region (Orinoco is the second when considering the proportion of habitat relative to total regional area). Meanwhile, the North Andean subregion has been shown to exhibit the highest connectivity among protected areas (Corzo et al., 2023). Regions with the highest forest recovery were those with the lowest habitat values, such as the Cauca and Patia river valleys. The Cauca region, which has the second highest proportion of protected areas, nearly doubled its forest and successional forest cover (from ~44.000 ha to ~83.000 ha), with most protected areas classified as Integrated Management Districts (63% of the protected area). In the Patía region, forest and successional forest cover increased from 4% to 12% by 2018, representing a gain of over 27,000 ha in these land cover types. Additionally, by 2020, more than 20,000 ha were designated as a Regional Integrated Management District in this region.

In contrast, the Caribbean and Orinoco regions experienced a loss of forest cover between 2000 and 2018. The Caribbean region has the largest extent of protected areas, but these are surrounded by a highly transformed matrix, leading to a greater proportion of disconnected protected areas (Corzo et al., 2023). Therefore, conservation efforts should focus on converting productive systems to serve as ecological corridors that enhance connectivity between protected areas and isolated forest remnants. This is particularly important for supporting potential climate refugia, especially given that this region is projected to be highly affected by decreased precipitation under climate change scenarios (IDEAM et al., 2017; Muñoz Rodriguez et al., 2023). On the other hand, although the Orinoco region has the highest habitat coverage relative to its total area (~10%), it also recorded the greatest forest loss. As in the Caribbean region, this area exhibits high vulnerability to climate change, primarily due to the greater distances to higher elevations that could offer more favorable climatic conditions for species migration. The region is characterized by a largely natural matrix surrounding forest patches, where nature-based solutions and sustainable practices in productive systems could be effectively implemented. Furthermore, the active participation of Indigenous territories, shown to contribute significantly to regional connectivity, should be recognized as a key complement to the existing protected area network (Corzo et al., 2025).

While conservation policies in the past focused primarily on strict preservation, there is now a growing shift among conservation biologists and policymakers toward more inclusive strategies. These include incorporating small remnant patches and even transformed lands into new conservation frameworks, such as nature-based solutions. Environmentally friendly practices (e.g agroforestry, agroecology, silvopastoral systems, and regenerative agriculture and cattle raising) can play a key role in buffer zones around protected areas. These approaches are essential for preserving small TDF remnants that may serve as critical stepping stones for species movement, improving connectivity and habitat quality, and promoting multifunctional landscapes (Garibaldi et al., 2023).

4.4 SHI as an indicator for monitoring

Although the SHI is not a headline indicator in the KM-GBF, it goes further than indexes only based on forest area. By integrating habitat and connectivity information from the species, it is useful to track conservation targets regarding habitat protection (Jetz et al., 2022; Pillay et al., 2024; Suarez-Castro et al., 2022). Additionally, connectivity outputs from the index can be used for deeper analyses of the connectivity within the ecosystem, particularly within protected areas (Albert et al., 2017; Castillo et al., 2020; Corzo et al., 2023; Fida et al., 2025; Linero-Triana et al., 2023). Outcomes of multispecies habitat analyses can help prioritize connectivity based on species habitat preferences. However, as this index by itself does not provide information on forest cover dynamics, we encourage users to study land cover transitions to better understand the context of the area evaluated.

Both Omniscape and GISFrag assess connectivity beyond a least-cost path, acknowledging that species movement is not solely guided by cost efficiency (Correa Ayram et al., 2016). However, it is important to keep in mind that different connectivity metrics can lead to different outputs. GISFrag, a structural connectivity metric geared more toward assessing fragmentation than connectivity, is more sensitive to patch abundance and assumes uniform habitat quality within patches (Crooks et al., 2011). This can lead to an overestimation of connectivity when small patches (often with short distances to edges) are lost, as index values may increase. Conversely, the recovery of small forest patches can lead to lower GISFrag values. This may explain the lower SHI values obtained with GISFrag in 2020 compared to Omniscape, coinciding with forest recovery reported with the Corine dataset across most regions. This pattern was more evident in generalist species capable of persisting in areas classified as artificial cover, including categories such as successional forest, which showed a notable increase by the last year evaluated. GISFrag does not account for within-patch habitat conditions and may therefore underestimate connectivity loss within the habitat. This was evident in the hypothetical year scenario, where GISFrag produced higher connectivity values than Omniscape.

Despite its limitations, GISFrag is computationally efficient, widely used, and does not require arbitrary cost distances (Crooks et al., 2011; Jetz & GEO BON Secretariat, 2022; Ripple et al., 1991). In turn, Omniscape incorporates habitat irregularities, an advantage when evaluating highly fragmented ecosystems, where it is more accurate for detecting the effects of short-term forest recovery and changes within the habitat. However, its practicality for index calculation is more limited due to search radius constraints and computing requirements.

Although the SHI can be calculated at various scales depending on data availability, it is critical to consider scale in its application. Overall, it provides a general overview of species' habitat status, but when applied at different scales, it allows for the planning of effective interventions that require analyses at finer scales aligned with regional and political contexts (Hébert et al., 2024). For instance, the Caribbean region, which has the most remaining habitat, may be driving the overall SHI trend. This can potentially mask more critical regional patterns, such as severe forest loss in the Orinoco and its impact on species’ habitat or forest gains in other regions.

4.5 Methodological considerations

For our analysis, we used national official land cover layers, despite methodological inconsistencies in land cover classification between years that can lead to over or underestimation of land cover changes. Given the high fragmentation of TDF, higher-resolution datasets (e.g., Sentinel-2 products) could be used to better assess the role of stepping-stone patches for different taxonomic groups (Hinsley, 2000). A simplified version, currently using Global Forest Watch data and projected to include land cover data from the European Space Agency, is available through the BON in a Box tool from the Group on Earth Observations Biodiversity Observation Network (GEO BON) (Griffith et al., 2025). However, for the index to be used in national official reports, we had to use official land cover layers.

Several assumptions were necessary to define habitat and Omniscape parameters (i.e. dispersion distances, weights for components within resistance and source layers, habitat preferences by the species, cutoff for percentage of habitat patches to be included in the analyses). The use of a hypothetical base year due to the lack of historical land cover data, ignores climate-driven and habitat preferences by the species. To support further refinement, we provide the code for testing alternative SHI approaches (https://github.com/MaIsAp/species-habitat-index-tdf-colombia), including AOH generation and habitat-IUCN category associations (Lumbierres et al., 2022; Suárez-Castro et al., 2024). We include maps with the standard deviation of the habitat and connectivity values (available at https://osf.io/3ch7d/?view_only=3bbef33bd37b4f2c92f047eababa7781), but other additional uncertainty metrics should be studied to include in these outputs (e.g. uncertainty from data sources).

Calculating the SHI for multiple species is computationally demanding. One option to reduce computing requirements is to use expert knowledge to select representative species and group them with others sharing similar distributions. A weight can then be assigned to each group during index calculation, providing an approximate value without processing the full species list, but still capturing key patterns through smaller subsets. Here, we propose a reproducible and adaptable workflow for SHI calculation, acknowledging that different approaches may yield varying results.

5. Conclusions

These findings provide critical insights for TDF management in Colombia. Social, ecological, environmental and economic differences between subregions shape distinct patterns of change. Applying the index at a regional scale yielded valuable insights into local-level changes. Environmental authorities should closely survey forest cover loss in the Orinoco region, where we observed the highest habitat values alongside the highest forest loss by 2018 too. Nature-based solutions and sustainable practices in productive systems could be effectively implemented given its large natural matrix surrounding forest patches. Nonetheless, to effectively guide TDF conservation, the SHI index could be applied at finer, local scales to inform strategies that integrate habitat and connectivity across subregions, particularly within and around protected areas.

The landscape must be managed in an integrative way, considering human needs, cultural traditions, and nature contributions to people. Thus, producers owning the land and the people living in these transformed areas are key for the recovery of the habitat of the species. The successional forest area within the TDF is larger than the amount of forest remaining as it represents more than 1,000,000 ha available to potentially apply restoration initiatives. Given its level of fragmentation, converting productive systems into ecological corridors that enhance connectivity between protected areas and isolated forest remnants would be useful for preserving small TDF remnants that can be key stepping stones for species movement. Most recent gains of forest cover from pasturelands to forest and successional forest, were possibly due to natural regeneration, restoration and sustainable use by land owners. To monitor interventions to restore the TDF, Omniscape can be used as it resulted in a more sensitive connectivity index in the short term to track effects on species' habitat.

CRediT authorship contribution statement

María Isabel Arce-Plata: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing - original draft, Writing - review & editing**, Natalia Norden:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Visualization, Writing - original draft, Writing - review & editing**, Jaime Burbano-Girón:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing - review & editing**, Guillaume Larocque:** Conceptualization, Formal analysis, Methodology, Software, Supervision, Validation, Visualization, Writing - review & editing**, María Camila Díaz:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Writing - review & editing**, Susana Rodriguez-Buriticá:** Supervision, Validation, Writing - review & editing**, Germán Corzo:** Supervision, Writing - review & editing**, Timothée Poisot:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing.

Abbreviations

K-M GBF	Kunming-Montreal Global Biodiversity Framework
TDF	Tropical Dry Forests
SHI	Species Habitat Index
CBD	Convention on biological diversity
IDEAM	Institute of Hydrology, Meteorology and Environmental Studies in Colombia
CLC	Corine land cover
SHS	Species Habitat Score
AS	Area Score
CS	Connectivity score
SDM	Species distribution model
DEM	Digital elevation model
IUCN	International Union for Conservation of Nature
AOH	Area of habitat
RUNAP	National Single Registry of Protected Areas
GEO BON	Group on Earth Observations Biodiversity Observation Network

Data availability

Part of the data is available in an OSF project (https://osf.io/3ch7d/?view_only=3bbef33bd37b4f2c92f047eababa7781) and the code used is stored in a github repository (https://github.com/MaIsAp/species-habitat-index-tdf-colombia).

Acknowledgements

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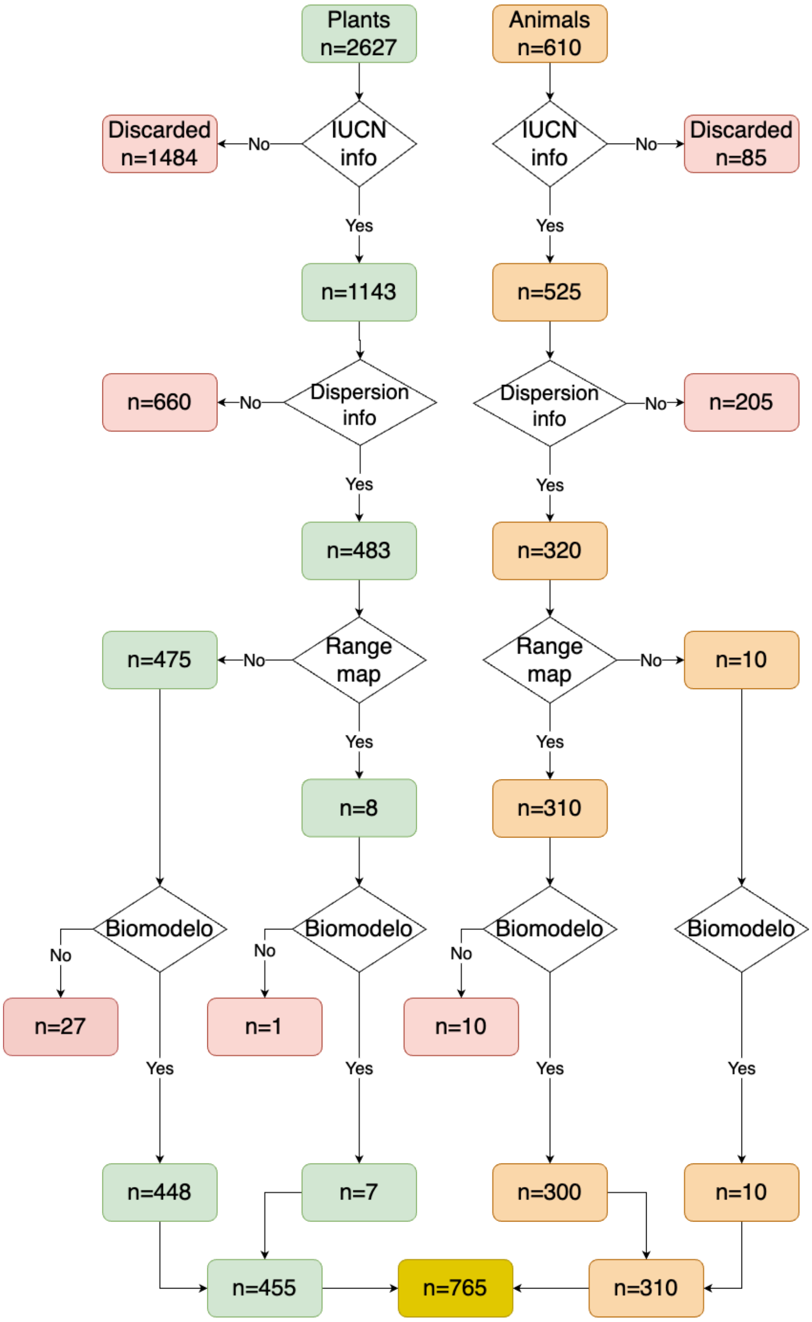
Appendix 1. Corine Land Cover equivalences to IUCN habitat categories and Land Cover Recategorization

IUCN_to_LC_categories_en.xlsx

Appendix 2. Species selected for analysis

Filters were done according to the availability of information needed to run the process. Plant species are represented in green and animal species in orange. Discarded species according to the availability of information are in red. The total number of species with the required information is in yellow.



Eight species were removed from the 765 list since the SDMs and range maps did not overlap with the TDF potential area. Two species were removed for having extreme score values. These species were grouped as follows:

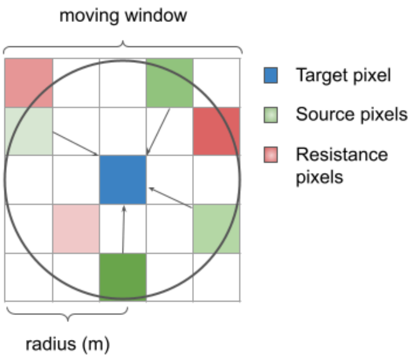
<table>
<tr><th>Taxonomic group</th><th>IUCN category</th><th>Habitat</th><th>n</th></tr>
<tr><td rowspan="4">Birds (n= 237)</td><td rowspan="2">Least concern</td><td>Artificial</td><td>186</td></tr>
<tr><td>Natural</td><td>44</td></tr>
<tr><td rowspan="2">Some risk</td><td>Artificial</td><td>2</td></tr>
<tr><td>Natural</td><td>5</td></tr>
<tr><td rowspan="5">Mammals (n= 68)</td><td>Data deficient</td><td>Natural</td><td>1*</td></tr>
<tr><td rowspan="2">Least concern</td><td>Artificial</td><td>15</td></tr>
<tr><td>Natural</td><td>42</td></tr>
<tr><td rowspan="2">Some risk</td><td>Artificial</td><td>2</td></tr>
<tr><td>Natural</td><td>8</td></tr>
<tr><td rowspan="6">Plants (n=450)</td><td>Data deficient</td><td>Natural</td><td>2*</td></tr>
<tr><td rowspan="4">Least concern</td><td>Artificial</td><td>39</td></tr>
<tr><td>Natural</td><td>402</td></tr>
<tr><td>Other</td><td>1*</td></tr>
<tr><td>No category</td><td>1*</td></tr>
<tr><td>Some risk</td><td>Natural</td><td>7</td></tr>
</table>

* Species removed in figure 5

755 species list with metadata in file: df_tdf_sp_for_omni_batch3_group.csv

Appendix 3. Moving window composition

The moving window method employs a radius as the number of pixels traversing source and resistance layers. For example with pixels of 100 m x 100 m size, a radius of 300m would be equivalent to three pixels. The central pixel is selected as the target if it satisfies naturalness criteria; otherwise, the window shifts to the next target without assessment. Injected current levels depend on the source layer values. Efficiency can be enhanced by grouping pixels into blocks and summing their values. Adapted from McRae et al., (2016).



To define the search radius for each species we used proxies of dispersion distances for mammals, birds and plants. For mammals, we used data from Diaz-Corzo et al., (manuscript in preparation), which estimated three groups of dispersal distances categorized by weight, as the radius of a circle with an area equal to the mean home range. For birds, we used the hand-wing index available in the AVONET database (Tobias et al., 2022) to estimate the dispersion distance following Ocampo-Peñuela et al., (2023). For plants, we used a combination of the dominant dispersal syndrome cited in the literature and the diaspore mass, available from the D3 dispersal and diaspore database (Hintze et al., 2013).

We defined dispersal ranges for plants based on distances of 300m, 1 and 3 km (Table 1). We categorized three diaspore masses as: 1) small (≤ 0.5 mg), 2) medium (> 0.5 mg to 6 mg), or 3) large (> 6 mg). Since these values were not available at the species level, we assigned mean values at the family level. These size classes were paired with four dispersal mechanisms: 1) wind (Anemochory), 2) water (Hydrocory), 3) animals (Zoochory), and 4) other less frequently found methods. We assumed that small, wind-dispersed seeds travel the farthest, followed by animal-dispersed seeds, and large seeded (Dalling et al., 2002; Midgley et al., 2006; Muller-Landau & Hardesty, 2005).

Table 1**.** Dispersion ranges for the combination between seed mass group and dispersion type.

Diaspore mass\ Dispersion type	**Small**	**Medium**	**Large**
Anemochory	3 km	1 km	300 m
Hydrochory	3 km	1 km	300 m
Zoochory	1 km	1 km	300 m
Other	1 km	1 km	300 m

In Omniscape, the search radius is input as the number of pixels. To convert dispersal distances into pixels, we divided the distances in meters by 100, corresponding to the width of the raster cell in meters. We set the minimum dispersal distance for all groups to 300 m, as the algorithm required a minimum search radius of 3. Additionally, a block size can be defined to aggregate pixels for faster processing. To optimize processing times, we calculated the block size based on the species' search radius. For species with a search radius between 3 (300 m) and less than 220 pixels (22 km), the block size was determined by dividing the search radius by 20. For species with a search radius of 220 pixels or more, the search radius was divided by 10. The resulting value was rounded down to the nearest integer, with a minimum block size set at 1. For example, a species with a search radius of 50 (5 km) would have a block size of 1, while a species with a search radius of 240 (24 km) would have a block size of 24. These values were defined arbitrarily to balance processing times while keeping the block size as small as possible. They do not have biological significance, although species with larger dispersal distances, for which small nearby patches play a less critical role in movement, may be less affected by cell aggregation.

Appendix 4. Source and resistance layer components

All layers were rescaled to a 0 to 100 range.

Layer name	Layer detail	Layer values	Coefficient name	Coefficient value
L_{s_1}	Species distribution model (Ayerbe Quiñones, 2022; Henao Diaz et al., 2020; Noguera-Urbano et al., 2023; Velásquez-Tibatá et al., 2019)	[0-1]	s_1	1
L_{s_2}	Mean percentage of habitat cover (taken from the measurement of changes in the habitat from forest and land cover layers)	[0-1]	s_2	1
L_{s_3}	Presence or absence of elevation range	[0,1]	s_3	0.5
L_{s_4}	1 - Slope percentage (L_{r_4}) (using the highest slope value within the habitat of the species as denominator)	[0-1]	s_4	0.5
L_{r_1}	Human footprint (Correa Ayram et al., 2020)	[0-1]	r_1	1
L_{r_2}	Distance to mean habitat of at least 10% of cover	[0-1]	r_2	1
L_{r_3}	1 - Presence or absence of elevation range (L_{s_3})	[0,1]	r_3	0.5
L_{r_4}	Slope percentage	[0-1]	r_4	0.5

The structures of the source layer (s) and resistance (r) layers were:

$$s = 100 * \frac{s_1 \cdot L_{s_1} + s_2 \cdot L_{s_2} + s_3 \cdot L_{s_3} + s_4 \cdot L_{s_4}}{s_1 + s_2 + s_3 + s_4} = 100 * \frac{L_{s_1} + L_{s_2} + 0.5 \cdot L_{s_3} + 0.5 \cdot L_{s_4}}{3},$$

$$r = 100 * \frac{r_1 \cdot L_{r_1} + r_2 \cdot L_{r_2} + r_3 \cdot L_{r_3} + r_4 \cdot L_{r_4}}{r_1 + r_2 + r_3 + r_4} = 100 * \frac{L_{r_1} + L_{r_2} + 0.5 \cdot L_{r_3} + 0.5 \cdot L_{r_4}}{3}$$

For the hypothetical baseline layer L_{r_1} was set to 0, with the assumption that there was no human footprint yet:

$$s = 100 * \frac{L_{s_1} + L_{s_2} + 0.5 \cdot L_{s_3} + 0.5 \cdot L_{s_4}}{3}, r = 100 * \frac{L_{r_2} + 0.5 \cdot L_{r_3} + 0.5 \cdot L_{r_4}}{3}$$

For flying groups of species (bats and birds), s_3 and r_4 were set to 0:

$$s = 100 * \frac{L_{s_1} + L_{s_2} + 0.5 \cdot L_{s_3}}{2.5}, r = 100 * \frac{L_{r_1} + L_{r_2} + 0.5 \cdot L_{r_3}}{2.5}$$

For species where there was no elevation data then L_{s_3} was set to 1 and L_{r_3} to 0:

$$s = \frac{L_{s_1} + L_{s_2} + 1 + 0.5 \cdot L_{s_4}}{3}, r = \frac{L_{r_1} + L_{r_2} + 0.5 \cdot L_{r_4}}{3}$$

Appendix 5. Land cover areas by year and by subregion

Land cover category	2000	2010	2020
Forest	817,905	674,209	732,379
Successional forest	569,343	863,706	1,273,756
Pastureland	6,027,056	6,054,275	5,459,699
Arable land and plantations	1,896,570	1,781,735	1,913,238
Shrubland and grassland	1,529,477	1,541,002	1,464,886
Other	503,856	429,281	500,251

Subregion	Land cover type	2000	2010	2018	Total area by subregion
Caribbean	Forest	405,621	326,536	337,838	6,715,950
	Successional forest	311,422	508,325	876,537	
	Pastureland	4,020,754	4,067,941	3,563,563	
	Arable land and plantations	891,314	742,203	874,901	
	Shrubland and grassland	789,226	815,461	746,787	
	Other	297,613	255,484	316,324	
Cauca V.	Forest	23,200	26,460	42,738	804,751
	Successional forest	20,594	23,228	40,104	
	Pastureland	343,294	320,607	270,646	
	Arable land and plantations	327,448	352,312	357,527	
	Shrubland and grassland	53,525	45,445	43,481	
	Other	36,691	36,699	50,256	
Magdalena V.	Forest	103,171	113,382	159,203	1,824,711

	Successional forest	104,521	168,428	196,099	
	Pastureland	942,537	893,875	755,757	
	Arable land and plantations	414,764	386,107	369,304	
	Shrubland and grassland	198,362	200,999	287,057	
	Other	61,356	61,919	57,291	
North Andean	Forest	15,158	23,307	22,063	522,788
	Successional forest	12,973	18,674	37,767	
	Pastureland	155,230	145,794	154,168	
	Arable land and plantations	142,143	130,641	127,745	
	Shrubland and grassland	158,327	164,459	138,143	
	Other	38,958	39,914	42,903	
Orinoco	Forest	269,334	172,253	152,944	1,156,441
	Successional forest	110,200	134,808	102,157	
	Pastureland	460,210	505,754	614,164	
	Arable land and plantations	82,330	104,349	125,774	
	Shrubland and grassland	182,318	208,599	132,663	
	Other	52,049	30,678	28,740	
Patia V.	Forest	1,422	12,271	17,594	319,567
	Successional forest	9,633	10,245	21,092	
	Pastureland	105,031	120,304	101,401	
	Arable land and plantations	38,572	66,122	57,987	
	Shrubland and grassland	147,720	106,039	116,756	
	Other	17,190	4,586	4,738	

Appendix 6. Species Habitat Scores

Bar plots showing SHS values by 2020 with 2000 as base year for 755 species using GISFrag and Omniscape (Suitable), grouped by taxonomic group (represented by species silhouettes) and habitat type (only natural type or if it includes artificial types). Colors indicate IUCN category: green for least concern, blue for some risk level and yellow for data deficient species.

link to file for GISFrag outputs: img_species_scores.png

link to file for Omniscape outputs: img_species_scores_omnisc.png

We used illustrations from Phylopic to represent taxonomic groups.

1. For mammals *Saguinus bicolor* (instead of *Saguinus eudipus*) available for the genus *Saguinus*, illustration from Andy Wilson https://www.phylopic.org/images/ed672cc6-12c3-49c8-beea-d154687efd80/saguinus-bicolor
2. For birds the ilustration available for the genus *Ortalis* represented by *Ortalis cinereiceps* https://www.phylopic.org/images/a93b67a0-15d5-4835-938b-212928ec6901/ortalis-cinereiceps
3. For plants the ilustration available for the genus Piper *https://www.phylopic.org/images/45553c37-70c3-4261-a9ee-d7f525529c90/piper*

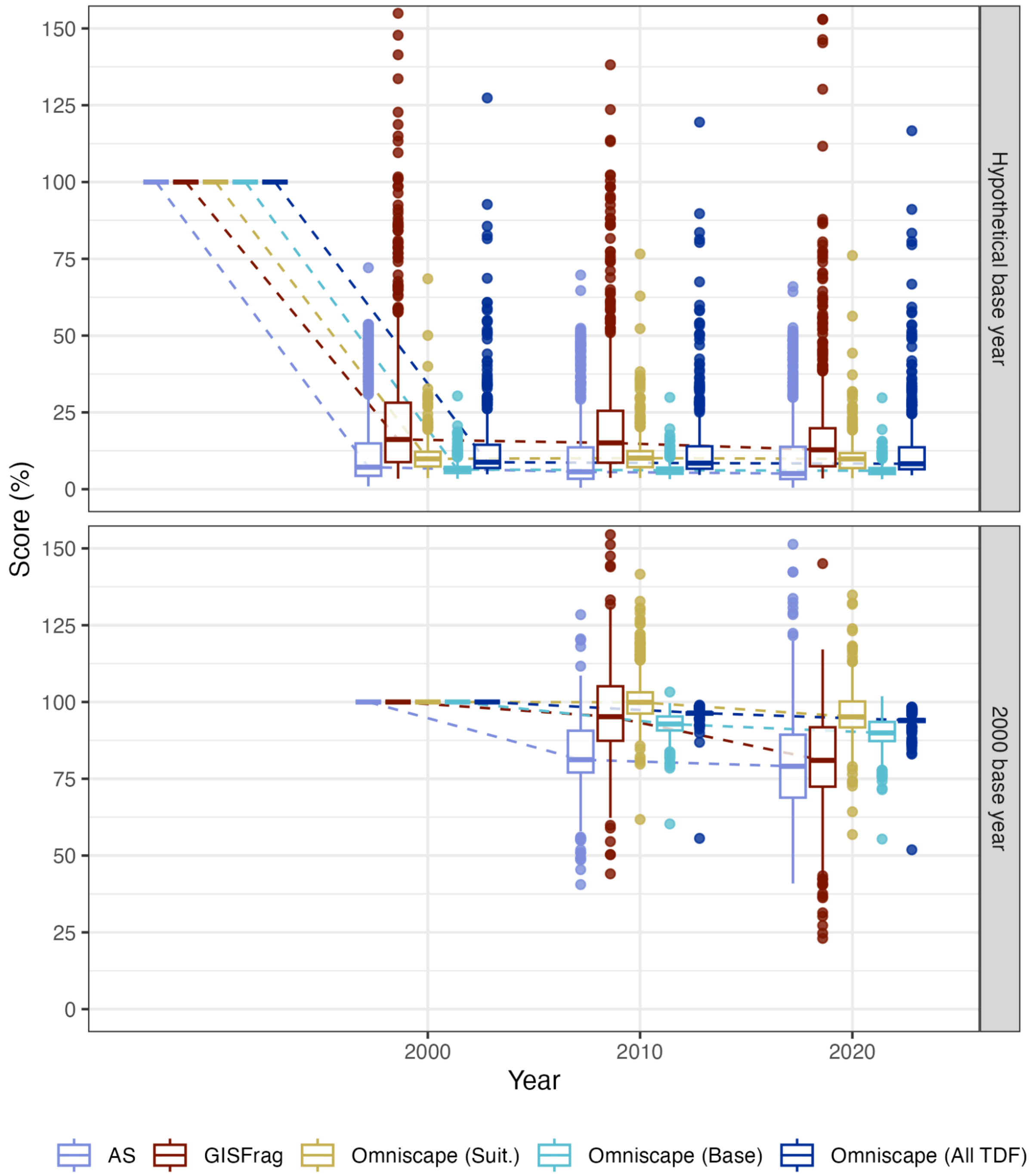
Appendix 7. Habitat areas inside protected areas by biogeographic regions in 2020

Region	Subregion	Area inside region (ha) * (Mean distance to patches | Mean current)	Protected area type (with at least 10 ha of TDF)	n	Habitat inside protected area (ha) (% protected habitat)*
Andean	Cauca river valley	41,471 (86 | 0.14)	Civil Society Natural Reserve	48	158(3.01)
			National Natural Park	1	15(0.29)
			National Protective Forest Reserves	11	927(17.64)
			Regional Integrated Management Districts	12	3,321(63.21)
			Regional Natural Parks	2	19(0.36)
			Soil Conservation Districts	2	814(15.49)
				Total	**5,254(12.67)**
	North Andean	34,786 (49 | 0.2)	Civil Society Natural Reserve	3	29(1.22)
			Regional Integrated Management Districts	5	2,166(91.39)
			Single Natural Area	1	29(1.22)
			Soil Conservation Districts	1	146(6.16)
				Total	**2,370(6.81)**
	Magdalena river valley	112,294 (54 | 0.2)	Civil Society Natural Reserve	47	1,369(19.8)
			National Natural Park	2	853(12.34)
			National Protective Forest Reserves	1	1(0.01)
			Regional Integrated Management Districts	4	4,664(67.46)
			Regional Protective Forest Reserves	4	27(0.39)
				Total	**6,914(6.16)**
	Patia river valley	10,882	Regional Integrated Management Districts	1	743(99.33)
			Regional Natural Parks	1	5(0.67)

		(32 | 0.11)		Total	**748(6.87)**
Caribbean		546,982 (84 | 0.34)	Civil Society Natural Reserve	85	1,710(1.97)
			Fauna and flora sanctuary	2	350(0.4)
			National Natural Park	4	53,515(61.61)
			National Protective Forest Reserves	2	1,818(2.09)
			Regional Integrated Management Districts	18	22,747(26.19)
			Regional Natural Parks	4	802(0.92)
			Regional Protective Forest Reserves	5	3,265(3.76)
			Soil Conservation Districts	3	2,655(3.06)
			Total		**86,862(15.88)**
Orinoco		112,709 (84 | 0.42)	Civil Society Natural Reserve	29	1,930(61.02)
			National Natural Park	1	455(14.39)
			Regional Integrated Management Districts	1	758(23.96)
			Regional Natural Parks	1	20(0.63)
				Total	**3,163(2.81)**
Total		**859,124**		**301**	**105,311(12.26)**

*Area values are approximations and could show small variations according to the software used.

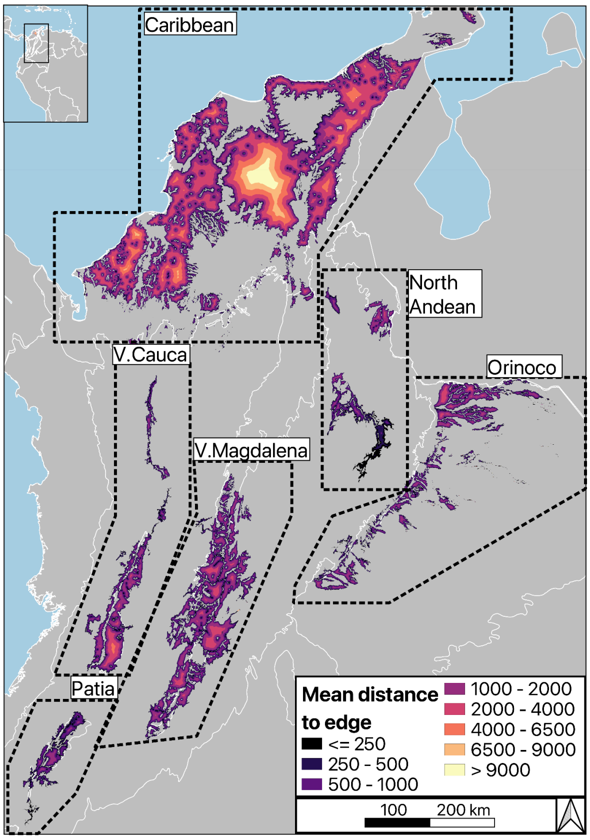
Appendix 8. Area (AS) and Connectivity (CS) Scores by type of connectivity metric, according to the Hypothetical base year and 2000 as base year.

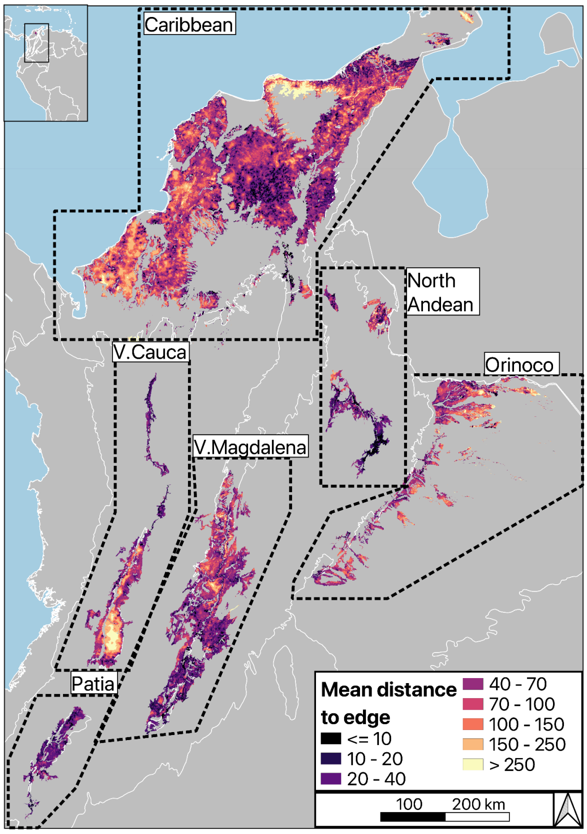


Appendix 9. Connectivity outputs

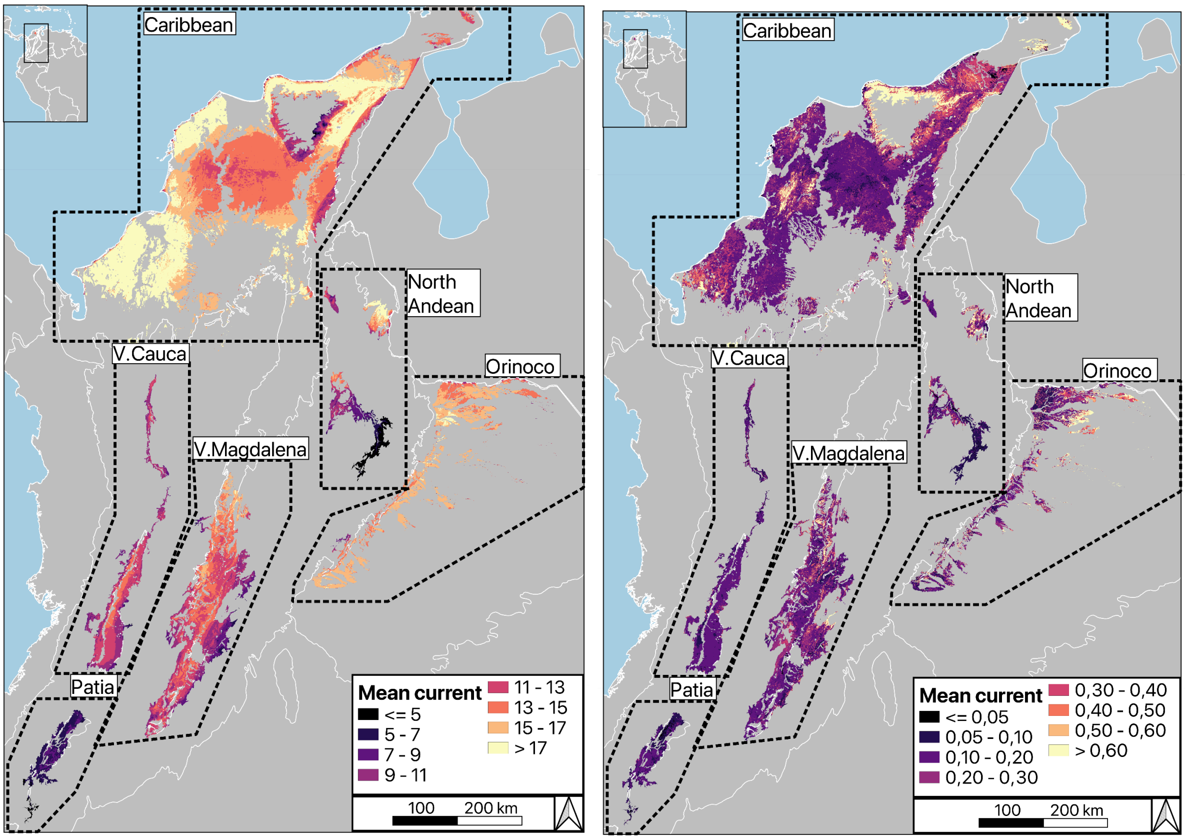
For GISFrag, three subregions with the largest mean distance values by 2020 were Cauca River Valley, Orinoco and Caribbean. While for Omniscape the subregions with the largest mean current flow were Orinoco, Caribbean and Magdalena River valley, with the North Andean subregion with really close values to the third subregion in both connectivity metrics (Appendix 7). Thus, regardless of the methodology, Orinoco and Caribbean regions had the largest connectivity values when considering only pixels with habitat areas larger than 10% of the 100m pixel.

(a) Mean distance to edges (b) Mean current; for hypothetical base year (left) and 2020 (right)





(a)


Caribbean
North
Andean
V.Cauca
Orinoco
V.Magdalena
Patia
Mean current
<= 5
5 - 7
7 - 9
9 - 11
11 - 13
13 - 15
15 - 17
> 17
100
200 km
Caribbean
North
Andean
V.Cauca
Orinoco
V.Magdalena
Patia
Mean current
<= 0,05
0,05 - 0,10
0,10 - 0,20
0,20 - 0,30
0,30 - 0,40
0,40 - 0,50
0,50 - 0,60
> 0,60
100
200 km

(b)

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