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An Ecological Modelling Approach to Support Peru Wildlife Conservation Planning Based on Geospatial Datasets and Remote Sensing Information

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ABSTRACT

Aim: Peru, a megadiverse country, has developed conservation plans for some threatened wildlife species. This study produced spatially explicit data integrating Species Distribution Models (SDMs) into a geospatial analysis of connectivity within the protected areas (PAs) network. In addition, a deforestation analysis around selected PAs was performed evaluating the related conservation implications. The use of lidar-derived vegetation vertical structure metrics from the spaceborne Global Ecosystem Dynamics Investigation (GEDI) mission was tested as an innovative data source to support ecological modelling. This country-level analysis is a useful approach to support conservation in high-biodiversity areas.

Location: Peru.

Methods: Occurrence data of seven threatened wildlife species were used to compute SDMs in MaxEnt using three variable sets: (i) bioclimatic and topographic, (ii) GEDI vegetation structure metrics joined with Normalized Difference Vegetation Index (NDVI), and (iii) a combination of both. MaxEnt was explicitly calibrated by testing 126 candidate models per species across feature-class and regularization multiplier combinations. SDMs combined with auxiliary data were used to identify core areas, then connected through main ecological corridors (ECs) using geospatial analysis. Deforestation rates were computed in the buffer zones (BZ) of Protected Natural Areas (PNAs) identified as core areas. GEDI lidar-derived data were also used to compare forest degradation between two PNAs and their BZ.

Results: This ecological modelling effort identified several core conservation areas, as well as the main ecological corridors interconnecting them. The study showed that highly suitable habitats are currently poorly represented by the present Peru protected areas network, particularly for primates. Test Area Under Curve (AUC) values ranged from 0.867 to 0.995; the *Biotopveg* set, integrating bioclimatic, topographic, GEDI, and NDVI variables was optimal for three species and the bioclimatic-topographic set for four, suggesting a species-specific contribution of vegetation structural data. GEDI data were used to detect forest degradation gradients, in accordance with known anthropogenic impacts. Deforestation analysis showed that even if indirect use protected areas resulted in less affected by deforestation in their surroundings, notable exceptions occur, calling for additional measures to support human-wildlife coexistence.

Main Conclusions: Ecological modelling based on SDMs and spatial analyses can support species conservation plans and landscape connectivity at broader planning scales. GEDI provides valuable data as input in SDMs and supports detecting forest degradation.

1 | Introduction

Peru is one of the 10 megadiverse countries in the world; 17.7% of its territory is included in the Protected Areas (PAs) network, which faces serious threats due to deforestation, agriculture expansion, extensive livestock, illegal mining, poaching, and forest fires (SERNANP 2021a, 2021b). The habitat for endemic and endangered species is fragmented and reduced, and the implementation of wildlife conservation plans is urgent especially for those umbrella or key species that support overall biodiversity conservation and regulate wild populations along the entire food chain (Crespo-Gascón and Guerrero-Casado 2019). In the last decade, the National Forest and Wildlife Service of Peru (SERFOR) has developed conservation plans for some of the most threatened species, such as: the spectacled bear (*Tremarctos ornatus*, SERFOR 2016), several primates (including *Lagothrix flavicauda, Lagothrix lagothricha lagothricha, Alouatta seniculus, and Ateles chamek*, SERFOR 2020), the mountain tapir (*Tapirus pinchaque*, SERFOR 2021), and the jaguar (*Panthera onca*, SERFOR 2022). For *L. flavicauda*, the yellow-tailed woolly monkey, a bill for its habitat conservation was just approved. Most of the mentioned species require urgent action according to the International Union for the Conservation of Nature (IUCN), the Convention on International Trade in Endangered Species, and the International Primatological Society (SERFOR 2018). Spatially explicit data are crucial for decision-making in animal conservation (Zurell et al. 2020): Fajardo et al. (2014) detected severe conservation data gaps in the Coastal and Andean regions based on SDMs and connectivity analysis; the same was observed by Ramirez-Villegas et al. (2014) for the Paramo, Puna, and Andean montane forests; recently Fajardo et al. (2023) observed unbalanced representation across taxa in the Andean region, raising concern over under-represented groups. The species here addressed are those for which conservation plans were officially published by SERFOR (2021), including: the spectacled bear (*Tremarctos ornatus*), the jaguar (*Panthera onca*), and the mountain tapir (*Tapirus pinchaque*); plus four species out of the fifteen included in the Primate plan, namely those having available occurrence data (*Lagothrix flavicauda, Lagothrix lagothricha lagothricha, Alouatta seniculus, and Ateles chamek*). The seven target species occur in six different ecoregions, covering most of the country.

The published conservation plans for wildlife Peru species were developed using occurrence data and theoretical species ecology knowledge; these plans are lacking spatially explicit habitat information, data on areas of conservation priority, or information on how the species are represented in the existing protected areas network. Habitat-level information is essential to facilitate effective conservation, management, and proper planning at the national level. Habitat spatially explicit information can be produced using species distribution models (SDMs), that serve to identify areas with suitable environmental conditions for a given species. The SDMs use as input species occurrence data and environmental variables, enabling the production of models for large regions and the assessment of anthropic disturbance or vegetation changes (He et al. 2015; Wilson et al. 2013). Many different models have been developed over the years (Norberg et al. 2019); among the widely adopted SDMs, there is the Maximum Entropy (MaxEnt) algorithm, that estimates a probability distribution based on conditions similar to those at known occurrence sites (Phillips et al. 2006; Valavi et al. 2022). MaxEnt addresses the lack of absence or pseudo-absence data by using background samples, comparing the distribution of presences with randomly selected reference points within the study area (Gomes et al. 2018). In Peru, the effectiveness of this modelling approach has already been shown to model the habitat of the spectacled bear (Meza et al. 2020; Falconi et al. 2023), the jaguar (Maffei et al. 2021), the mountain tapir (More et al. 2022) and various primates (Shanee et al. 2015; Zarate et al. 2023). It is recognized that the model algorithm can have impacts on outcomes (Qiao et al. 2015; Thuiller et al. 2019); to align with previous Peru wildlife studies allowing comparability, and considering its evaluation in several past researches (Elith et al. 2006; Kaky et al. 2020; Valavi et al. 2022), the MaxEnt algorithm was selected for this ecological modelling approach, that can be replicated testing additional modelling algorithms.

Spatially explicit species distribution models are valuable because they support national and local conservation planning, and can serve as input in specific tools to detect priority conservation areas and connectivity routes, such as the well-known Zonation or Linkage Priority tools (Gallo and Greene 2018; Moilanen et al. 2005, 2022). Preserving connectivity routes is an effective strategy to combat habitat fragmentation, to support the viability of wildlife populations and species movement (Beita et al. 2021; Miranda et al. 2021), for metapopulation dynamics (Iannella et al. 2024), and to maintain the balance of species inside and outside PAs (Sabogal 2023). The importance of habitat connectivity has been widely recognized also by the United Nations Convention on Biological Diversity, and in the establishment of new PAs, the areas suited for connectivity are considered among the most important ones (Riva et al. 2024). Previous efforts in this respect occurred worldwide, with examples from the South America region including the detection of avifauna connectivity habitats in dry neotropical forests (Prieto-Torres et al. 2018), of connectivity pathways for the puma and the jaguar in the Brazilian Atlantic forest (Castilho et al. 2015), for the spectacled bear in Peru (Cotrina Sánchez et al. 2022), and the definition of potential corridors connecting Colombia's protected area network (Pineda-Zapata et al. 2024).

Remote sensing provides essential data for conservation, allowing the monitoring of valuable habitats at multiple scales, of anthropic and climate impacts on resources, of species diversity, and providing environmental predictors useful in SDMs modelling procedures/frameworks (Duan et al. 2020; Garzon-Lopez et al. 2024; Nagendra et al. 2013; Wang et al. 2024). Data from satellite passive sensors, recording the sunlight energy reflected by a target (e.g., vegetation), are popular to monitor protected areas, but cannot be acquired with cloud cover presence. Examples of this data use are the detection of forest cover changes in indigenous territories of the Brazilian Amazon (Qin et al. 2023), or the monitoring of long-term ecosystem loss in the tropical Andes (Comer et al. 2022). In Peru passive sensors data were used the for the identification of critical habitats for endangered bird species in the Andes (Benham et al. 2011), or to assess forest loss and land use and land cover (LULC) changes within and outside PAs (Scullion et al. 2014; Asner and Tupayachi 2017); and as input for a platform developed by Peru's Ministry of the Environment (MINAM) to detect early deforestation alerts, supporting conservation monitoring (Vargas et al. 2019). Less popular and tested are data from space-based active sensors, that rely on their own sources of radiation to 'illuminate' objects so that the energy reflected and returned to the sensor may be measured, even in case of cloud cover presence. Active sensors were also used for conservation and monitoring purposes, either in combination with passive data for conservation planning in the Amazon rainforest and Andean landscapes (Higgins et al. 2012; Curatola Fernández et al. 2023) or independently. For instance, Synthetic Aperture Radar (SAR) data from ALOS PALSAR were used to map forest disturbances in PAs and chestnut concessions (Joshi et al. 2015), while Sentinel-1 data were used to support deforestation monitoring (Vargas et al. 2021), and as input for an alert system to monitor illegal gold mining in Indigenous territories and PAs (Becerra et al. 2024).

The recent availability of satellite LiDAR (Light Detection and Ranging) data represents a chance to further improve conservation monitoring and planning efforts based on vegetation structure information, or to refine species distribution models (Bakx et al. 2019; Moudrý et al. 2022). LiDAR is an active sensor that can penetrate the canopy, providing detailed information on its vertical structure, such as canopy height, vegetation density, or the full vertical forest profile. With the capability to measure fine-scale variations of forest structure, LiDAR is especially useful to detect forest degradation phenomena (Kent et al. 2015), that in Peru are linked to agriculture and oil palm expansion, livestock breeding, and illegal mining activities (Vijay et al. 2018; Móstiga et al. 2024). Despite its large potential, its use to enhance the predictive power of SDMs in different ecosystems, or to support forest status monitoring, has been poorly explored (Acebes et al. 2021). The Global Ecosystem Dynamics Investigation (GEDI) spaceborne LiDAR mission opens new opportunities to quantitatively describe forest ecosystems across large scales, providing vertical structure metrics with moderate resolution (25 m diameter per footprint) between 51.6°N and S latitude (Dubayah et al. 2020). GEDI data applications in the context of SDMs have been demonstrated only for bird species (Burns et al. 2020; Vogeler et al. 2023), and for the development of wildlife occupancy models (Killion et al. 2023).

The present study has the primary main goal to develop an ecological modelling approach to support Peru wildlife conservation planning based on geospatial datasets and innovative remote sensing information. In this framework, the following spatially explicit information was also produced: (a) SDMs for selected Peru wildlife species; (b) examples of 'safe' ecological corridors, avoiding zones of recurrent forest loss around protected areas; (c) deforestation information for selected areas. In this context, the usefulness of GEDI data as input in SDMs, and as a tool in monitoring forests degradation in the buffers of selected Protected Natural Areas was also assessed. The results of this study are discussed in view of the integration of remote sensing information in conservation, and in the light of the potential improvements of Peru conservation strategy and plans.

2 | Materials and Methods

2.1 | Study Area

The study area encompasses six ecoregions ranging from lowland rainforest (< 800 m a.s.l.) to highland Puna (6768 m a.s.l.) and covers 1,130,125.23 km^2 (Figure 1). The six ecoregions host diverse ecosystems (Brack Egg 1986) and include: Equatorial dry forest (56,037.54 km^2) Amazon rainforest (595,338.36 km^2), Paramo (1595.95 km^2), Puna (266,591.40 km^2), Palm Savannah (621.99 km^2), and Yungas upper jungle (208,077.44 km^2). There are 227 protected areas (PAs) instituted by National Service of Natural Protected Areas by the State (SERNANP), including 58 Definitive Protected Natural Areas (PNA), 6 Reserved Zones (RZ), 28 Regional Conservation Areas (RCA), and 135 Private Conservation Areas (PCA). The PAs network covers 228,106.13 km^2. PNAs are further classified in indirect and direct use (except for RZ which are not categorized): indirect use refers to areas where only scientific, recreational, and tourism activities are permitted, while in direct use areas resource exploitation and extraction are allowed, priority for local populations (Congreso de la República del Perú 1997).

2.2 | Datasets and Preprocessing

To produce SDMs to support Peru wildlife conservation plans, also testing the usefulness of GEDI data as SDMs input, different models were developed using species occurrence records and three sets of environmental variables (Tables S1 and S2 in Appendix S1). (i) the *Biotop* set includes 19 bioclimatic and topographic (elevation and derived slope) variables extracted from WorldClim 2.1 (Fick and Hijmans 2017) plus the Environmental Rasters for Ecological Modelling—ENVIREM dataset, that includes 16 climatic and two topographic variables not available in WordlClim 2.1 (Title and Bemmels 2018). (ii) the *Veg* set includes vertical structure metrics from GEDI data at 6 km spatial resolution (Burns et al. 2024), namely canopy height, canopy cover, plant area index (PAI), foliage height diversity (FHD), plant area volume density (PAVD), and aboveground biomass; plus the Normalized Difference Vegetation Index (NDVI) based on the Moderate Resolution Imaging Spectroradiometer averaged for the 2000–2023 period (Didan 2021). (iii) the *Biotopveg* set combines the variables from the previous groups. All the environmental variables were resampled with the nearest neighbour algorithm to 1 km^2 grid.

Species occurrence data for SDMs were mainly obtained from the Global Biodiversity Information Service (GBIF 2024: https://www.gbif.org/; accessed on 8 July 2024), which contributed with 5496 records (74.4%). Additional data were obtained by: the Peru Ministry of the Environment geoserver, with 1565 records (21.2%) (https://geoservidor.minam.gob.

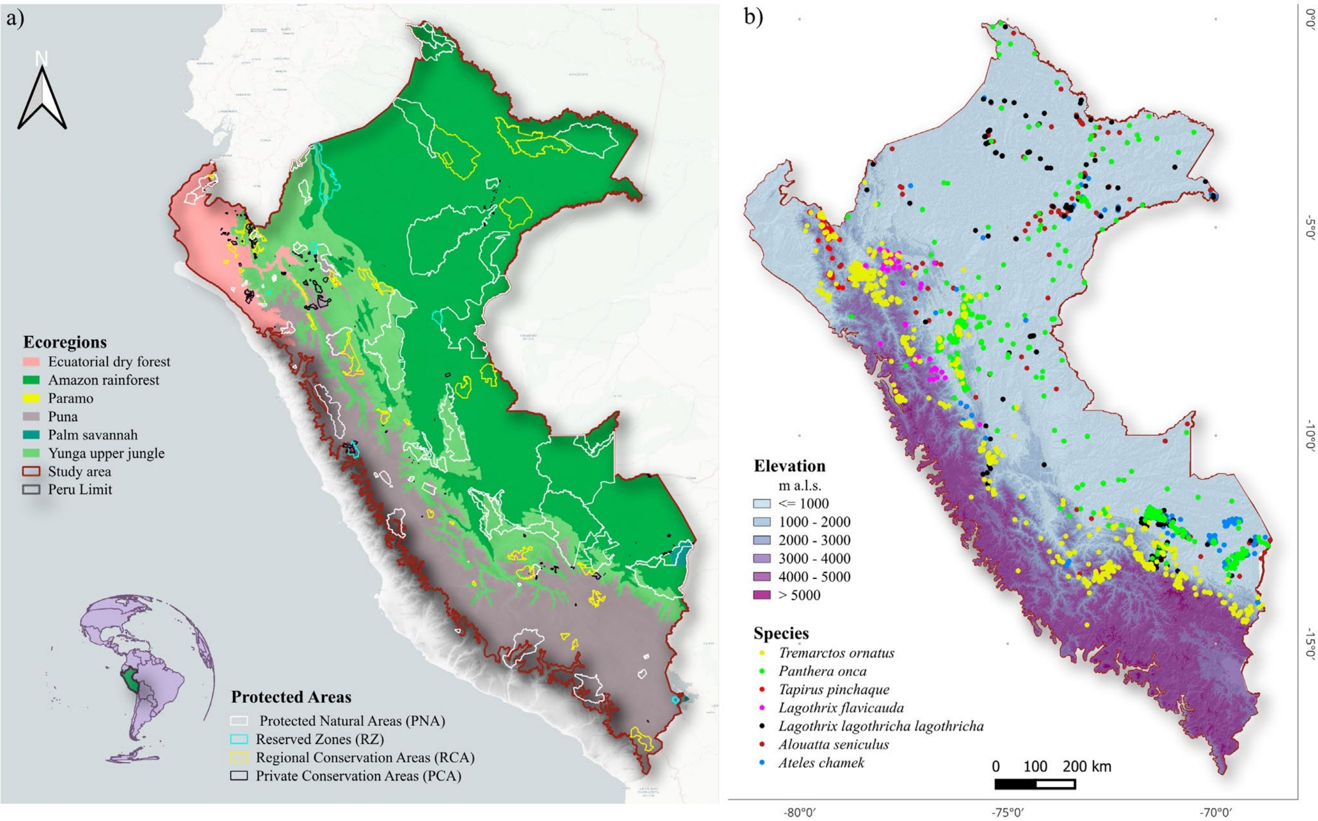

FIGURE 1 | The study area, including the six Peru ecoregions and the protected areas network, is shown in (a); the species occurrence records and the elevation information in (b).

pe/; accessed on 24/04/2024); the photo trapping tapir dataset by More et al. (2022) with 251 records (3.4%); and the jaguar dataset by Maffei et al. (2021), with 78 records (1.1%). Data located outside the six ecoregion's boundaries were removed, and only one record per cell of the 1 km^2 grid was retained to prevent oversampling (Boria et al. 2014). Then, the value of the environmental variables in the cells of occurrence data were reviewed: when the value exceeded 3.5 standard deviations the data was disregarded, for representing locations at unusual environmental conditions for the species (Bunn et al. 2015). In total, 2049 occurrence records were used in modelling (Table S1, in Appendix S1). To avoid multicollinearity, the Variance Inflation Factor (VIF) was computed -per each species- at species occurrence locations using the 'usdm' package (Naimi and Araújo 2016) in R (R Core Team 2023), retaining only environmental variables with VIF < 10, following Naimi et al. (2014). This threshold has also been applied in other SDM studies, specifically those integrating GEDI data (Burns et al. 2020; Elliott et al. 2024). Based on the VIF results, more than 70% of the predictors were excluded, with the number of retained variables ranging from 11 (*A. chamek, L. flavicauda*) to 16 (*L. lagothricha*), *19* (*T. pinchaque*), *20* (*P. onca*), *and* 23 for *A. seniculus* and *T. ornatus*. Similar ranges of predictors have been commonly used in SDM studies for these species: 9–14 variables for *A. chamek* and *L. flavicauda* (Rabelo et al. 2020; Guzman et al. 2022; Zarate et al. 2023), 10–15 for *T. pinchaque* (More et al. 2022; Mestanza-Ramón et al. 2021), 12–19 for *T. ornatus* (Meza et al. 2020; Rodríguez et al. 2022), and 7–17 for *P. onca* (Jędrzejewski et al. 2018; Machado-Aguilera et al. 2024). A detailed description of each retained predictor, including its relative contribution and ecological relevance for each species is provided in Tables S2–S8 of the Appendix S1.

To monitor forest status and especially degradation, vegetation structure information was used: metrics from GEDI data at 1 km spatial resolution (Burns et al. 2024), including canopy height, canopy cover, PAI, FHD, PAVD, and aboveground biomass, were extracted for comparison purposes from selected protected areas and in their external buffer zones.

To identify potential ecological corridors connecting priority conservation areas, that are not only suited for the target species but also represent relatively safe areas for conservation, the SDMs results were used, together with additional relevant information such as a land use/land cover change (LULC) map from Sentinel 2 data (ESRI 2024); the map of Peru Protected Areas (PAs; https://geo.sernanp.gob.pe/visorsernanp/, accessed on 8 July 2024); and a resistance raster here produced using elevation, slope, LULC from Brown et al. (2022), PAs map, and distance from hydrological and road networks obtained from the Spatial Data Infrastructure Portal of Peru (IDEP; https://www.geoidep.gob.pe/; accessed on 10 July 2024). All these variables were weighted through an Analytical Hierarchy Process (AHP; Vaidya and Kumar 2006), a multicriteria analysis based on pairwise comparison, using weights according to Morandi et al. (2020) and Santos et al. (2018) and considering a consistency ratio < 0.1.

Variables were reclassified in the 1–100 range (Table S9 in Appendix S1), and the resistance values were multiplied by their respective weights, as identified by AHP.

The analysis of historical forest loss around protected areas was based on data from the Global Forest Change dataset v1.11 (2001–2023), at 30 m spatial resolution (Hansen et al. 2013).

2.3 | Methodological Steps

2.3.1 | SDMs and the Monitoring of Forest Status

The initial step included the production of SDMs and corresponding maps; in this context, the use of GEDI data was tested. The potential distribution of the seven selected key species (*A. seniculus, A. chamek, L. flavicauda, L. lagothricha lagothricha, T. ornatus*, *P. onca*, and *T. pinchaque*) was modelled using the Maximum Entropy algorithm implemented in MaxEnt software v3.4.4 (Phillips et al. 2006). SDMs inputs included species occurrence data and three sets of environmental variables after selection for VIF < 10 (Tables S2–S8 in Appendix S1). Occurrence data were randomly partitioned into 75% and 25% training and validation sets, respectively, and models were fitted using 10 bootstrap replicates over 500 iterations. A total of 10,000 random background points, following the default strategy in MaxEnt (Phillips et al. 2006), were generated within the study area to characterize the environmental background, a configuration that is widely used in presence-only SDMs and provides stable model behaviour, with increases in background sample size beyond this threshold typically resulting in marginal or negligible changes in model performance (Song et al. 2025).

Following the model calibration and selection framework described by Anjita et al. (2026), MaxEnt was calibrated by explicitly testing feature-class combinations and regularization multipliers. Feature classes were defined as linear (L), quadratic (Q), product (P), threshold (T), and hinge (H), enabling MaxEnt to capture simple to complex species-environment relationships (Phillips and Dudík 2008). For each species, a total of 126 candidate models were evaluated, resulting from the combination of three environmental-variable subsets (*Biotopveg*, *Biotop*, and *Veg*) across seven feature-class configurations (L, LQ, H, LQP, LQH, LQPH, and LQPTH) and six regularization multipliers (RM = 0.5, 1.0, 2.0, 3.0, 4.0, and 5.0), yielding 42 parameterisations per variable subset ($3 \times 42 = 126$), and including MaxEnt's default configuration (LQPH with RM = 1.0). Model selection was performed using a composite score built from metrics rescaled to 0–1 (global min–max across all 126 models per species). The score integrated both discrimination ability and model stability: test AUC and test gain (Phillips et al. 2006) were treated as benefits, whereas AUC standard deviation, AUC gap (the difference between training and test AUC, as a measure of overfitting; Radosavljevic and Anderson 2014), test omission range, and mean test omission based on the maximum training sensitivity plus specificity (MTSS) threshold (Liu et al. 2005) were treated as costs. The selected model was thus optimized for a balance between model fit, generalization, and complexity. In cases where the second-ranked candidate showed comparable performance (Δscore ≤ 0.03 relative to the top model), a parsimony criterion was applied (Radosavljevic and Anderson 2014): the model with the higher RM was prioritized, or, if RMs were equal, the one with fewer feature classes, to further mitigate overfitting.

The ODMAP (Overview, Data, Model, Assessment and Prediction) protocol developed by Zurell et al. (2020) was followed to ensure transparency and reproducibility (Appendix S2). Based on the continuous probability distribution raster generated by MaxEnt, which ranges between 0 and 1 (Phillips 2005), the SDMs rasters outputs were reclassified using fixed threshold values into four potential habitat suitability classes: 'high' (> 0.6), 'moderate' (0.4–0.6), 'low' (0.2–0.4), and 'no potential' (< 0.2), following a threshold-based reclassification approach (Zhang et al. 2019). This reclassification was used exclusively to quantify and compare the spatial extent of habitat suitability classes among species, while the original continuous suitability rasters were retained for spatial prioritization and subsequent connectivity analyses.

To monitor forest status, especially with respect to degradation, different GEDI forest structure metrics from Burns et al. (2024) dataset at 1 km layer were extracted within two protected natural areas (PNAs) and from their buffer zones (BZ). The first is the Cordillera Azul PNA, where resource extraction in the BZ is high due to the concessions for wood extractions and strong impacts occur due to the high population density (Wali 2016; Rojas et al. 2021); the second is the Sierra del Divisor PNA, where wood concessions are present in the BZ but population density is low, as the PNA is located in a remote region of the Amazonian lowlands (SERNANP 2023). These areas served as a methodological example, representing PNAs located in areas with high and low population density. Forest areas were filtered to exclude other cover types, often occurring in the buffer zones after deforestation, using the Hansen et al. (2013) v1.11 (2001–2023) dataset; then, similarly to Ceccherini et al. (2023), the FHD, PAI, PAVD, total canopy cover, and Relative Heights (RH_50 and RH_98) metrics were extracted from all the GEDI pixels available in each PNA and buffer zones for comparison purposes; the analysis was done using Google Earth Engine (Gorelick et al. 2017). For Cordillera Azul PNA, only the western buffer zone was considered for being located in the same ecoregion of the PNA (Yunga upper jungle), differently from the eastern buffer that is geographically included in the Amazon rainforest ecoregion, which hosts forests with different structural characteristics. Descriptive statistics were computed and metrics extracted from PNAs and buffer zones were compared, after testing normality distribution; the analyses were carried out using the 'SciPy' Python package.

2.3.2 | Ecological Corridors and Forest Loss

To identify ecological corridors, first the priority conservation areas were selected using the Zonation 5 software v2.1 (Moilanen et al. 2022). Zonation 5 produces a ranked landscape that allows prioritizing areas for conservation and ecological corridors (ECs) to connect them (Hilty et al. 2020). Input data included the continuous single species SDMs raster layers, weighted according to IUCN threat categories (CR = 8; EN = 6; VU = 4; and NT = 2), adopting similar weights to those used in the Global Protected Area Network

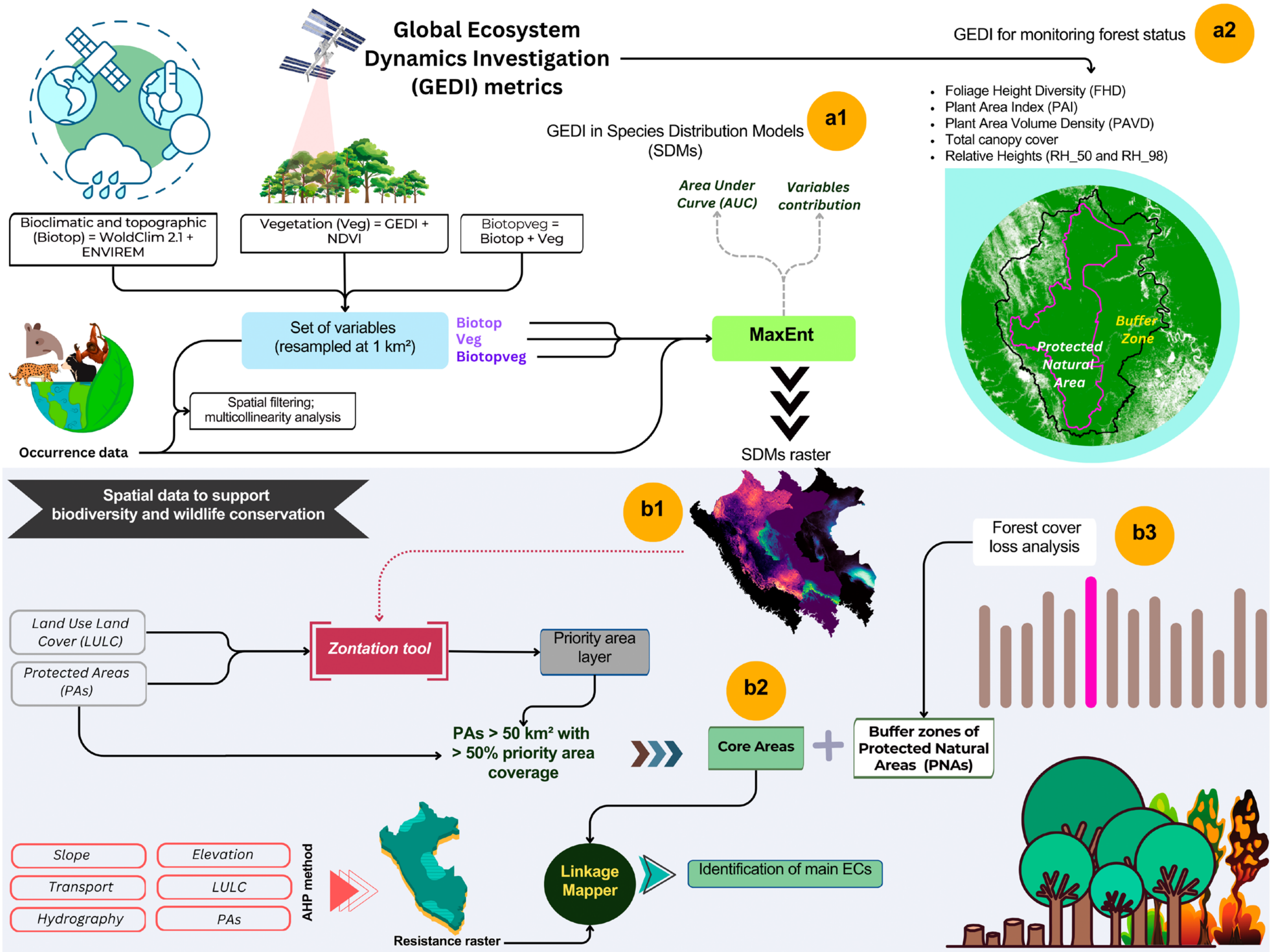

FIGURE 2 | Workflow diagram.

analysis (Montesino Pouzols et al. 2014; Kullberg et al. 2015). Additional information, relevant for effective identification of ecological corridors, was also used in Zonation 5: habitat degradation information, based on a binary reclassification of the LULC map by Brown et al. (2022) with forests classified as non-degraded (1), while all other categories (e.g., bare soil, crops, urban areas, water bodies) as degraded (0); and the conservation legal status based on the PAs network. In Zonation 5, the Core Area Zonation (CAZ1) marginal loss rule option was selected to give higher value to areas with high species richness (Moilanen et al. 2022). The output was a raster with cells in the 0–1 range: priority areas were defined as those scoring >0.6, a robust threshold encompassing core and contiguous areas according to Jalkanen et al. (2020). PAs having an amount of priority area > 50% in their extent, and an extension $>50\,\text{km}^2$, which is the amount needed to support the movements of species such as *T. ornatus* and *P. onca* (Cavalcanti and Gese 2009; Morrell et al. 2021) were identified as 'core' areas to be connected with ecological corridors, using the Linkage Mapper tool (LM; Gallo and Greene 2018). LM identifies normalized least cost routes by summing the cost weighted distance between two areas and subtracting the least cost path distance (Brodie et al. 2015); input layers to LM were the core areas and the resistance raster. The ecological corridors were mapped considering a buffer equal to 2.8 km around each side of the route (total width 5.6 km), representing 10% of the averaged distance of all least cost paths (28.09 km), similarly to what was done by Santos et al. (2018).

The historical forest loss (deforestation rate) was calculated in buffer zones around the core areas for the 2001–2023 period using the Global Forest Change dataset updated to 2023 (Hansen et al. 2013).

The methodology is visually depicted in Figure 2.

3 | Results

3.1 | SDMs and Forest Status Monitoring

The *Biotopveg* variable set, combining GEDI-derived structural metrics, NDVI, and bioclimatic information, yielded the highest test AUC values for three species (*A. seniculus*, *L. lagothricha*, and *T. ornatus*), while the bioclimatic-topographic set (*Biotop*) performed best for the remaining four species (*A. chamek*, *L. flavicauda*, *P. onca*, and *T. pinchaque*; Table 1; Figure S1 in Appendix S1). Among all species, *A. chamek* exhibited the largest discrepancy among variable sets, with a difference of 0.13 in test AUC between the *Biotop* and *Veg*

TABLE 1 | Performance summary of the best-fitting MaxEnt models selected for each of the seven study species, showing the optimal variable set, feature class combination, regularization multiplier, and discrimination metrics (training and test AUC, test gain, and omission rates).

Metric	*A. seniculus*	*A. chamek*	*L. flavicauda*	*L. lagothricha lagothricha*	*Panthera onca*	*Tapirus pinchaque*	*Tremarctos ornatus*
Set of variables	Biotopveg	Biotop	Biotop	Biotopveg	Biotop	Biotop	Biotopveg
Feature class combination	LQP	LQPH	LQ	LQPH	H	LQP	LQH
Regularization multiplier	2.0	1.0	2.0	4.0	0.5	1.0	5.0
Training AUC	0.9067	0.9549	0.9875	0.8816	0.9229	0.9942	0.9088
Test AUC	0.9079	0.9490	0.9864	0.8671	0.9138	0.9945	0.9062
Test gain	1.4728	2.0801	3.3633	1.1175	1.6158	4.2290	1.3587
Regularized training gain	1.2292	1.8551	3.0042	0.8230	1.5490	4.0755	1.2170
AUC standard deviation	0.0176	0.0134	0.0052	0.0219	0.0110	0.0008	0.0067
Training omission rate min	0.0526	0.0206	0.0000	0.0469	0.1020	0.000	0.0233
Training omission rate max	0.1579	0.1134	0.0513	0.1562	0.2194	0.0011	0.0698
Training omission rate avg	0.1114	0.0629	0.0077	0.1000	0.1533	0.0011	0.0426
Test omission rate min	0.0541	0.0312	0.0000	0.0476	0.1538	0.0000	0.0269
Test omission rate max	0.2162	0.1562	0.0833	0.1905	0.2154	0.0033	0.0699
Test omission rate avg	0.1459	0.0812	0.0250	0.1405	0.1846	0.0033	0.0452

sets. Overall, differences among models fitted with different variable sets were generally small, typically not exceeding the second decimal place, as detailed in Tables S10–S16 in Appendix S1, although the *Veg* variable set, comprising vegetation structural and greenness variables alone, consistently yielded the lowest test AUC values across all species compared to the *Biotop* and *Biotopveg* sets. Among bioclimatic predictors, temperature and precipitation metrics were the most consistently influential variables. Elevation was particularly important for *A. seniculus* and *T. pinchaque*, whereas topographic wetness index was a key predictor for *T. ornatus* and *L. flavicauda*. Among the GEDI-derived variables, the most useful were foliage height diversity and canopy cover, acting as key predictors for *L. lagothricha* and *P. onca*, with permutation contributions of 35.1% and 18.3% respectively; the other variables had contribution < 7.4% to model performance (Tables S2–S8 in Appendix S1, illustrating the contribution of single variables).

The two PNAs and their surrounding buffer zones, selected as sites to test GEDI capability to monitor forest status, are covered with abundant 1 km gridded valid data (Burns et al. 2024): Cordillera Azul (CA) with 80.63% in PNA and 49.99% in the western buffer, and Sierra del Divisor (SD) with 84.73% in PNA and 91.12% in buffer zone, respectively. The amount of sampled area and extracted GEDI pixels, together with metrics mean and CoV values, are reported in Table 2.

The GEDI metrics, including 6 metrics for each PNA for inside area and for buffer zones (total 24 metrics), were not normally distributed according to the Shapiro test results. Consequently, differences in distributions were evaluated using the Mann–Whitney test and the Kolmogorov–Smirnov test.

In Cordillera Azul for all the six GEDI metrics significant differences ($p < 0.001$) were found between PNA and the western buffer zone (Figure 3, a panel); differences are present in mean values but also evidenced by the CoV ranges, lower in the PNA (0.05–0.25) than in the BZ (0.13–0.44) (Table 2). The metrics that mostly differ are cover %, RH_50 and RH 98, thus related to forest cover, stratification and maximum height. In Sierra del Divisor, significant differences ($p < 0.001$) were also observed between PNA and BZ for all the GEDI metrics, except for PAVD (Figure 3, b panel); however the mean values are often similar, and CoV ranges resulted also similar between PNA (0.02–0.16) and the BZ (0.03–0.19).

TABLE 2 | Descriptive statistics for GEDI metrics in protected natural areas (PNA) and their buffer zones (BZ), including pixel count and percentage of coverage for each metric.

Protected natural area (PNA) and buffer zone (BZ)				GEDI metrics											
				Cover (%)		FHD		PAI (m^2/m^2)		PAVD (m^3/m^2)		RH_50 (m)		RH_98 (m)	
Name	Ecoregion	Area km^2	# GEDI Pixel	Mean	CoV	Mean	CoV	Mean	CoV	Mean	CoV	Mean	CoV	Mean	CoV
Cordillera Azul	PNA—Yunga	13,531.91	10,911	0.84	0.12	3.16	0.05	3.92	0.19	14.37	0.18	15.66	0.25	30.57	0.18
	BZ—Yunga	8325.17	4153	0.76	0.31	3.02	0.13	3.43	0.39	13.30	0.26	13.69	0.44	27.67	0.32
Sierra del Divisor	PNA—Amazon	13,544.85	11,477	0.86	0.07	3.22	0.02	4.07	0.13	14.52	0.14	16.90	0.16	32.08	0.11
	BZ—Amazon	6224.64	5672	0.85	0.09	3.21	0.03	4.00	0.16	14.50	0.15	16.46	0.19	31.25	0.13

3.2 | Connectivity Routes and Forest Loss

The potential distribution maps for each species (Figure 4) were generated using the best-fitting model and variable set per species (Table 1), and the resulting suitability surfaces were partitioned into three habitat suitability classes (low, moderate, and high), according to the probability distribution raster generated by MaxEnt, which ranges between 0 and 1. The suitable area for *T. pinchaque* is extremely small in extent (4035 km^2); of limited size is also the suitable area for *L. flavicauda* (46,205 km^2); for *A. chamek*, high quality habitat is restricted to the southeastern region of the country; while for *T. ornatus*, the suitable range is found only at high elevation in the Andean region; other species (*L. lagothricha*, *P. onca*, and *A. seniculus*) show broader ranges and less restricted habitat requirements (Figure 4; Table S17 in Appendix S1). The amount of high quality suitable area included in the network of Peru PAs is overall low for the seven considered species, ranging only from 9.5% to 18.5% and concentrated within the Palm savannah, Yungas upper jungle, and Paramo ecoregions (Tables S18 and S19 in Appendix S1).

To identify connectivity routes, a resistance raster had first to be produced: the AHP multicriteria analysis here returned a consistency ratio equal to 0.09, with LULC having the highest weight (49%), followed by protected areas (18%) and slope (13%) layers. According to the results of Zonation 5, the land having priority covers 462,165.06 km^2, and 57 'core' areas resulted after intersecting the priority land with PAs larger than 50 km^2 (114,280.06 km^2). The 'core' areas to be connected are included into 29 Definitive Protected Natural Areas (PNAs), 14 Regional Conservation Areas (RCAs), 11 Private Conservation Areas (PCAs), and 3 Reserved Zones (RZs) (Figure 5a). Buffer zones are present only around PNAs and RZs. Linkage Mapper identified 56 corridors (Figure 5b) to ensure connectivity among 'core' areas, with route length from 0.5 to 209.70 km. A buffer of 2.8 km per side (Figure 5b1) along the routes resulted in a total area of 591.57 km^2 of ecological corridors.

PNAs are divided into direct use (total buffer zone = 36,730.01 km^2), indirect use (53,808.96 km^2) areas, plus one not categorized area (Santiago Comaina; 1171.42 km^2); the forest loss in buffer zones, between 2001 and 2023, is higher for buffers of direct use PNAs, where resource extraction activities are allowed. A notable exception is Cordillera Azul PNA (Figure 6) that lost 16% of the forests in the buffer zone (3685.49 km^2). Excluding Cordillera Azul, the amount of forest loss in the period is much lower around indirect use PNAs (877.54 km^2) than around direct use PNAs (2470.26 km^2).

4 | Discussion

4.1 | SDMs and Monitoring Forest Status

The SDMs fitted with different input variable sets showed very limited differences in accuracy according to AUC values. Although AUC has limitations (Lobo et al. 2008), it remains the most widely accepted metric for assessing SDM performance, allowing comparability with other similar studies (Phillips et al. 2006; Elith et al. 2011). Across all tested variable sets, test AUC values ranged from 0.867 to 0.995, with

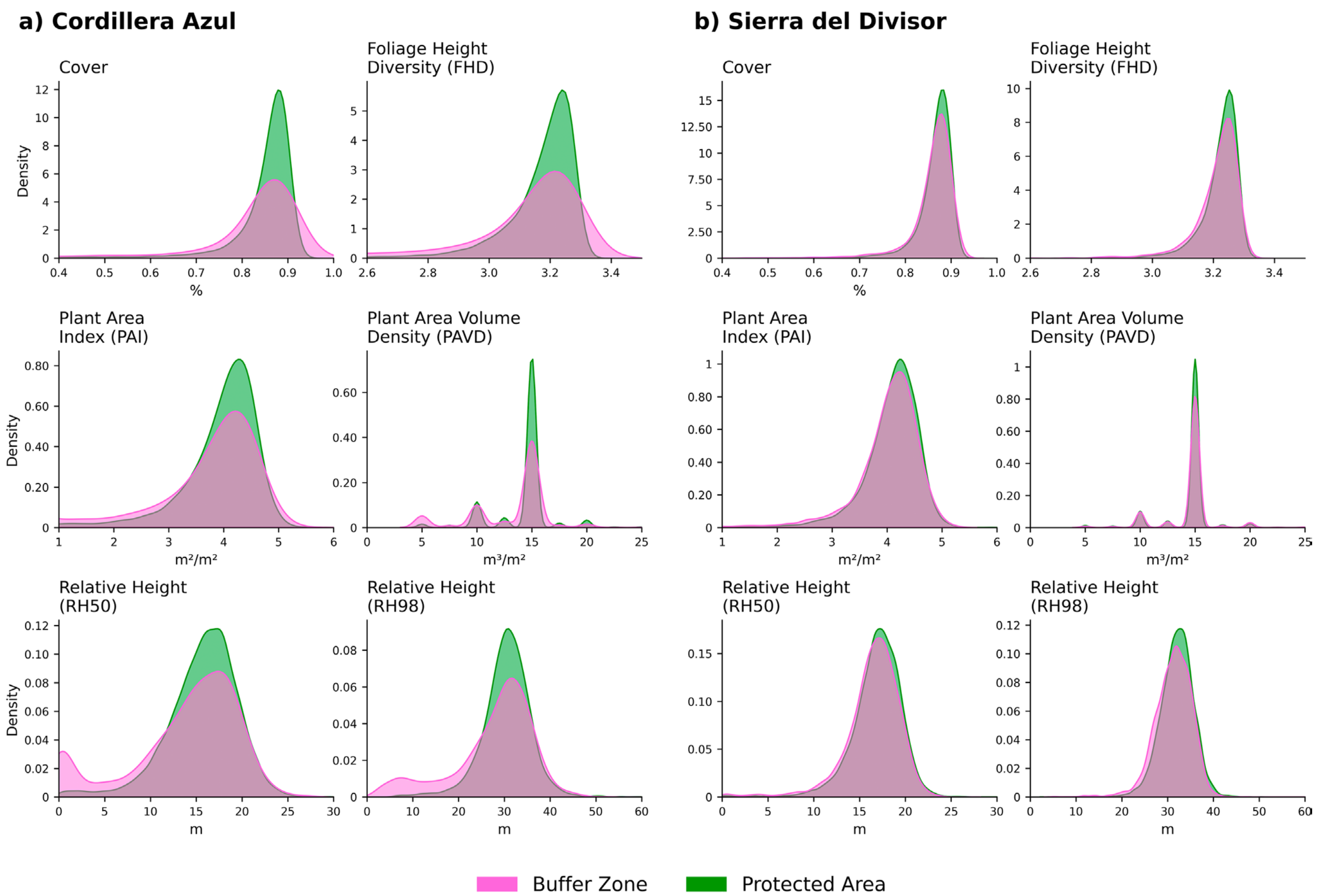

FIGURE 3 | Density plots comparing GEDI metrics inside the protected area (green) and in buffer zones (purple): (a) Cordillera Azul PNA; (b) Sierra del Divisor PNA.

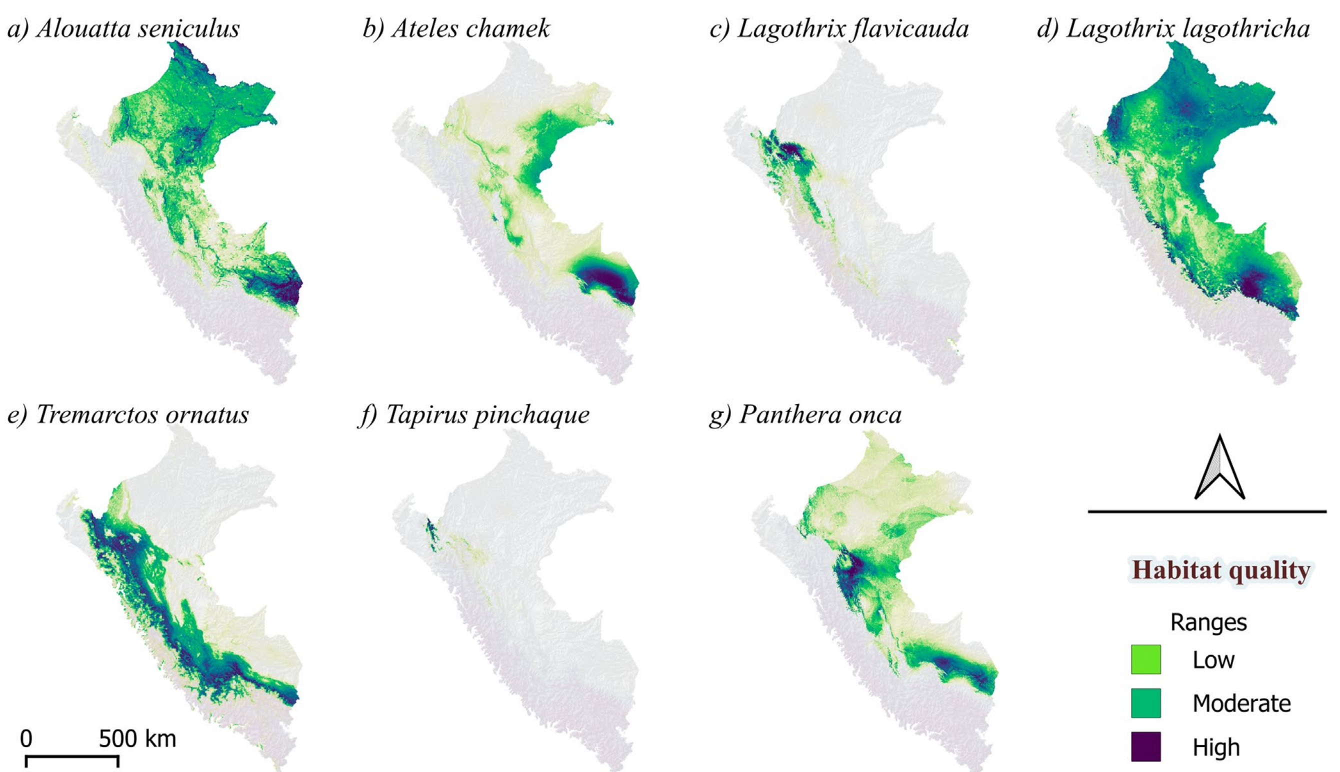

FIGURE 4 | Potential species distributions for each species, with continuous SDM outputs reclassified into three ranges of habitat quality using fixed suitability thresholds.

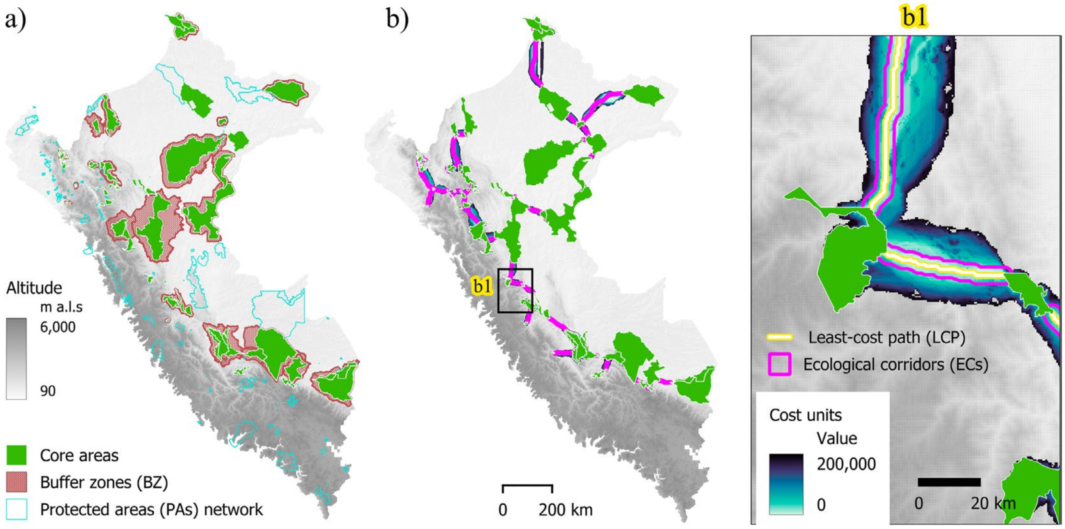

FIGURE 5 | (a) The 57 'core' areas; (b) the 56 ecological corridors linking the 'core' areas; (b1) details of the corridors showing both the LCP and ECs. The background colour gradient represents cost units from the resistance surface, where lighter tones indicate low movement cost and darker tones indicate high movement cost.

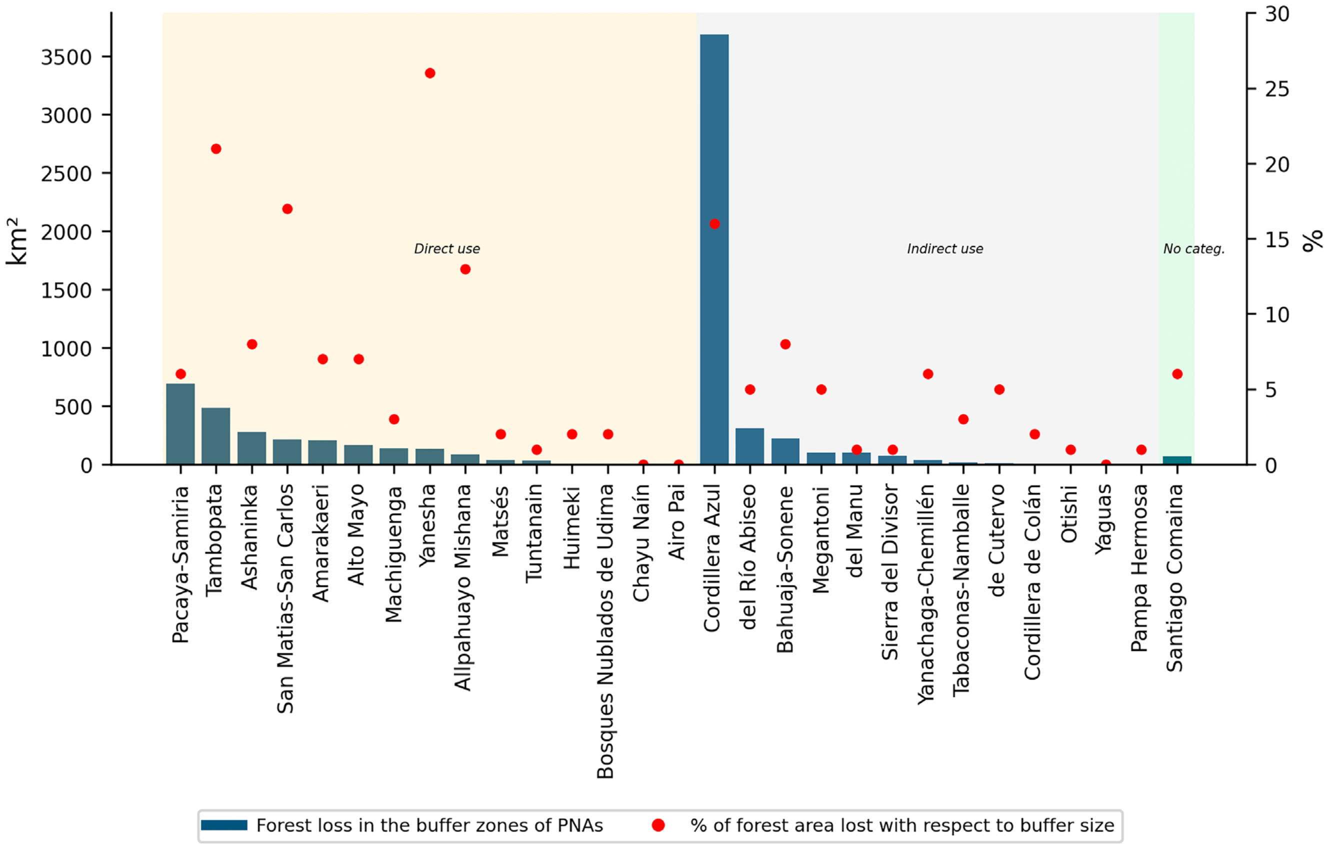

FIGURE 6 | Amount of forest loss (blue bars, in km^2) in the 2001–2023 period in the buffer zones around 57 PNAs considered as 'core' areas; PNAs are divided into direct (cream colour rea), indirect use (grey area), and not categorized (light green area); the % of forest loss (red bullets) is computed with respect to the buffer zone size.

the best-fitting models consistently showing strong discrimination ability regardless of the variable set employed (Table 1). Although the *Veg* set yielded the lowest discrimination across all species (Tables S10–S16), the combination of GEDI and NDVI with bioclimatic and topographic variables confirmed the complementary value of these data sources for certain species. Notably, the *Biotopveg* set was selected as optimal for three species (*A. seniculus*, *L. lagothricha*, and *T. ornatus*), whereas the *Biotop* configuration was favoured for the remaining four, indicating that the added value of vegetation structural information was species-specific rather than universal. This confirms the importance of vegetation structure and cover information for species distribution, and the usefulness of the GEDI dataset at 6 km spatial resolution in this context, as derived from models implemented using the MaxEnt algorithm. To our knowledge, this represents the first evaluation of the usefulness of GEDI data for mapping distribution in tropical ecosystems or for mammals in South America, while future studies could further assess this approach using alternative modelling algorithms. With GEDI simulated data, Burns et al. (2020) examined the impact of canopy structure variables over 25 bird species in California, with those variables resulting the second most important group of predictors after climate variables at fine scale of analysis (250 m); however, the improvement brought by GEDI data on 19 SDMs was minimal (max 0.04 in AUC). Vogeler et al. (2023) reported that GEDI metrics brought minimal improvement (0.001–0.007 in AUC) in SDMs of three woodpecker species in western U.S. states. Consistent with these findings, GEDI metrics did not substantially improve overall SDM discrimination in the present study; however, for two species (*L. lagothricha* and *P. onca*), GEDI-derived variables, particularly foliage height diversity and canopy cover emerged as critical predictors, contributing 35.1% and 18.3% to model performance, respectively. Thus, this structural information can be important for multiple analyses, and its use in conservation and monitoring has to be further tested.

The relatively high number of predictors retained after VIF filtering reflects a balance between reducing multicollinearity and capturing ecological complexity relevant for species distribution. While collinearity limits the interpretability of individual predictors and therefore requires caution in inference, its influence on predictive performance is less critical when the objective is spatial prediction rather than explanation (Dormann et al. 2013). Therefore, more conservative VIF thresholds or species-specific variable selection could be explored in future studies to further improve model interpretability. In addition to predictor selection, SDM performance and spatial predictions may nevertheless be influenced by modelling choices such as MaxEnt parameterization (e.g., regularization strength and feature classes) and background point selection strategies (Anderson and Gonzalez 2011; Merow et al. 2013; Syfert et al. 2013), as well as by background point selection strategies that account for uneven sampling effort (Kramer-Schadt et al. 2013; Barber et al. 2022). To address this, MaxEnt was explicitly calibrated following the framework of Anjita et al. (2026), systematically evaluating 126 candidate models per species across seven feature-class configurations and six regularization multipliers (RM = 0.5–5.0). Model selection was based on a composite score integrating discrimination ability (test AUC and test gain) and model stability (AUC standard deviation, AUC gap, and omission rates), with a parsimony criterion applied when top candidates showed comparable performance (Δscore ≤ 0.03). The selected models departed from MaxEnt default settings in most species: regularization multipliers ranged from 0.5 (*P. onca*) to 5.0 (*T. ornatus*), and optimal feature-class combinations varied from simple hinge-only (H; *P. onca*) to more complex configurations such as LQP (*A. seniculus; T. pinchaque*), LQPH (*A. chamek; L. lagothricha*), and LQH (*T. ornatus*), consistent with findings from other calibration studies showing that default settings are not universally optimal (Morales et al. 2017; Wiltshire and Tanner 2020). This explicit parameterisation reduces the risk of overfitting and improves model transferability compared to uncritical application of default configurations. Nevertheless, bias-aware background strategies and fully species-specific occurrence filtering represent valuable directions for further refinement. Such refinements could be further facilitated by dedicated SDM frameworks enabling systematic parameter tuning and ensemble evaluation, including R-based MaxEnt implementations (Muscarella et al. 2014; Phillips et al. 2017).

The analysis of the contribution of different variables as model input can support the prioritization of landscape features in conservation planning. The topographic wetness index resulted to be a critical variable in *T. ornatus* and *L. flavicauda* distribution models, and Sánchez-Mercado et al. (2014) considered that this index may influence both key food resources and the use of microsites by bears, as also suggested by Nielsen et al. (2010). Elevation, and precipitation and temperature derivatives, were relevant in modelling the distribution of various species, such as the spectacled bear (Meza et al. 2020), the mountain tapir (More et al. 2022), the jaguar (Jędrzejewski et al. 2018) and—together with vegetation proxies—the yellow-tailed woolly monkey (Guzman et al. 2022; Zarate et al. 2023). Among GEDI metrics, the most relevant were FHD for *L. lagothricha* and canopy cover for *Panthera onca*; the first metric is related to the species preference for upper forest layers for movement, refuge, and feeding (Aquino and Encarnación 1994; Rimachi-Taricuarima et al. 2019); dense forest cover is critical for *P. onca*, as it enables camouflage and hunting efficiency (da Silva 2017; Maffei et al. 2021).

The relevance of the species distribution maps produced in this study relies on the potential to integrate the published species conservation plans with spatially explicit information. Nevertheless, caution should be used when considering models built with low representativity of occurrence data. Even if most of the available Peru records were exploited, primate data were mainly collected along the Amazonian water courses due to forest inaccessibility, and jaguar data are underrepresented in certain regions: the resulting maps reflect these biases. In this context, the use of background point strategies that account for sampling bias could help reduce the influence of such spatial biases in future applications. Where there is limited room for increasing field data collection there is an opportunity to exploit/use informally collected data, along with tools such as camera traps and GPS collars, as done for the spectacled bear in Peru (Falconi et al. 2023; Pillco Huarcaya et al. 2024), together with the support to citizen science programs in remote regions.

The analysis of species potential habitat in relationship to the protected areas network and the government conservation goals allows to derive considerations that can orient future efforts and policy revision. According to classification of SDMs into habitat of different quality, only 14.5% of the high quality habitat of the spectacled bear (mainly found in Paramo ecoregion) is currently under protection: increased human-related conflicts and habitat fragmentation (Rodríguez et al. 2019; Rojas-VeraPinto et al. 2022) call for the urgent establishment of new and connected protected areas, a conservation target set for 2036 for this species. For the mountain tapir, most of the valuable habitat is found in the Paramo, as also noted by Ortega-Andrade et al. (2015) in Ecuador and by Mena et al. (2020) in Peru. Instead More et al. (2022) found that the Yunga forest is the primary habitat for this species, based on rearranging the modelling results according to known areas of presence. Only 23.2% of total suitability habitat for the mountain tapir is included in the protected areas network, with similar values also found by More et al. (2022); the information provided here could contribute to meet the 2027 conservation target of > 80% of habitat set under protection and at least one corridor established. For the jaguar, the areas of high value are well represented in the Peru protected areas network (30%) in the Yungas, Palm Savannah, and Amazonian rainforest ecoregions; given the mentioned bias in jaguar occurrence data, and considering the reported species presence in mountain forests (Rengifo et al. 2019), further observations are needed, also to meet the conservation objective set by 2030 to identify 30 priority landscapes and corridors. The four Primate species here considered have very low percentages of high value habitat included in the Peru protected areas network, ranging from 9.7% to 18.5%. Even if SDMs results are certainly influenced by biases in occurrence data, Guzman et al. (2022) evidenced that only 22.6% of the area suited for *L. flavicauda* is protected. Developing detailed species plans, extending the protected areas and their connectivity, is essential to meet the aim set for 2029 by the government of reducing the threat category for at least 27% of the Primate species.

GEDI provides valuable data for protected areas management and monitoring (Wang et al. 2020), informing on the conservation status of the forests. The comparison of GEDI data inside PNAs and from buffer zones showed consistently higher values for metrics in PNAs, where forests are better conserved due to legal protection. GEDI metrics result highly variable in Cordillera Azul buffer zone (Table 2), where conserved forests alternate with degraded patches, resulting in high heterogeneity of the vertical structure caused by multiple anthropogenic activities driven by a high population density and concessions for timber extraction (Rodríguez et al. 2018). This high heterogeneity in GEDI vertical structure metrics is not occurring in Sierra del Divisor, a remote area where less human presence is found in the buffer zone (SERNANP 2023); still the difference in metrics inside PNA and in buffer is significant in this PNA due to the presence in the buffer area of logging concessions and roads for timber transport (MONGABAY 2019). These results, obtained over areas classified as forest in 2023 (Hansen et al. 2013), even if obtained from two buffer zones only, are an example that highlights the capability of this data to penetrate the canopy and capture differences in the vertical structure of forests due to disturbance phenomena, a task that cannot be carried out with traditional optical imagery. Ceccherini et al. (2023) evaluated the effectiveness of protected areas using 30 million GEDI shots in Europe, finding great canopy height variability in forests surrounding protected areas. The requirement of very high computation resources for using single shot data (Holcomb et al. 2024) justifies the use here of Burns et al. (2024) GEDI dataset at 1 km spatial resolution. In Peru GEDI has the potential to support the National Biodiversity Strategy (MINAM 2024) and complement the information included in PNAs master plans, that are actualized at regular intervals, providing forest degradation data.

4.2 | Connection Routes and Forest Loss

The identification of corridors performed here has to be considered an exercise to show a methodological approach: based on open access data, it can be carried out at multiple scales with limited computational effort, with the aim of implementing the government plans for species conservation, that include: the identification of 3 corridors for threatened Primates (SERFOR 2020); 3 for *T. ornatus* (SERFOR 2016), 2 for *P. onca* (SERFOR 2022), and one for *T. pinchaque* (SERFOR 2021). The northwestern sector of Peru, less impacted by deforestation and where unique ecoregions and fragmented populations of threatened species are found, is possibly the area where ecological corridors are more needed and could be effective. In this region *T. pinchaque* populations are currently distributed in 12 protected areas that need to be interconnected, with an international Peru-Ecuador corridor also suggested by More et al. (2022). In the present study, 26 corridors have been identified in the northwestern sector of Peru, based on 'core' areas having high conservation value for multiple species: these corridors represent a first attempt on which to argue on the topic. In fact, in the same region *L. flavicauda* is present, requiring additional conservation measures given its threatened status (Guzman et al. 2022; Zarate et al. 2023), and the identified connection routes can expand those previously delineated at local level for *T. ornatus* (Cotrina Sánchez et al. 2022). The corridors identification was based on the Least Cost Path algorithm, that provides a single optimal path between two points, making it great here to visualize the most efficient route. Nevertheless, other algorithms that account for alternative pathways worth being tested, such as those based on circuit theory that consider all possible routes and are useful for analysing connectivity at regional level (Simpkins et al. 2018; Unnithan Kumar and Cushman 2022). Comparable applications of LCP-based connectivity combined with corridor prioritization have been successfully implemented at national scales, for instance in Colombia, where Pineda-Zapata et al. (2024) integrated resistance surfaces and connectivity indices to identify high-priority ecological corridors for threatened mammals. Beyond single-algorithm implementations, future studies could further strengthen conservation planning by integrating SDM outputs and connectivity analyses to identify functionally suitable and connected areas, including stepping-stone patches that maximize long-term persistence, as highlighted by Serva et al. (2025).

Connection routes run by definition outside PAs, crossing areas where anthropic-induced impacts on biodiversity can be multiple. Monitoring these impacts in the buffer zone surrounding protected areas is thus fundamental to succeed in establishing a connectivity plan. The deforestation analysis, carried out over the 29 buffer zones surrounding PNAs, evidenced that forest loss surrounding indirect use PNAs is lower with respect to direct use areas, showing that the former areas are better suited to host potential corridors. But exceptions occur, such as in the case of Cordillera Azul PNA buffer, evidencing the need for continuous monitoring. The Cordillera Azul case also shows that PNAs' establishment has to be accompanied by measures to improve the coexistence of wildlife and human activities, such as local community involvement in conservation and the development of proper local policies. In addition to monitoring and conservation planning efforts, fostering intersectoral coordination among authorities, the private sector, and civil society seems a critical approach to effectively protect biodiversity in Peru.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that supports the findings of this study are openly available and stored in Dryad at: http://datadryad.org/stash/share/4m9iE8ViG1J7428EZa908sGstmNplgd4UkT-2ZXCNU4.

Peer Review

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Species common and scientific names; IUCN category; number of occurrence records. **Table S2:** Environmental variables with VIF < 10 used in the Biotopveg model for *Alouatta seniculus* and their relative contribution to the species' predictive model. **Table S3:** Environmental variables with VIF < 10 used in the Biotop model for *Ateles chamek* and their relative contribution to the species' predictive model. **Table S4:** Environmental variables with VIF < 10 used in the Biotop model for *Lagothrix flavicauda* and their relative contribution to the species' predictive model. **Table S5:** Environmental variables with VIF < 10 used in the Biotopveg model for *Lagothrix lagothricha* and their relative contribution to the species' predictive model. **Table S6:** Environmental variables with VIF < 10 used in the Biotopveg model for *Panthera onca* and their relative contribution to the species' predictive model. **Table S7:** Environmental variables with VIF < 10 used in the Biotopveg model for *Tapirus pinchaque* and their relative contribution to the species' predictive model. **Table S8:** Environmental variables with VIF < 10 used in the Biotopveg model for *Tremarctos ornatus* and their relative contribution to the species' predictive model. **Table S9:** Variables used to identify ecological corridors, with information used to reclassify them and to define the cost or resistance value. **Table S10:** Performance summary of the maxent models for *Alouatta seniculus*. **Table S11:** Performance summary of the maxent models for *Ateles chamek*. **Table S12:** Performance summary of the maxent models for *Lagothrix flavicauda*. **Table S13:** Performance summary of the maxent models for *Lagothrix lagothricha lagothricha*. **Table S14:** Performance summary of the maxent models for *Panthera onca*. **Table S15:** Performance summary of the maxent models for *Tapirus pinchaque*. **Table S16:** Performance summary of the maxent models for *Tremarctos ornatus*. **Table S17:** Potential distributions (in km^2) partitioned according to three ranges of habitat quality (High, Moderate, Low) for the seven species. **Table S18:** Potential distribution (in km^2 and percentage) of seven study species within protected areas, partitioned by habitat suitability class (High > 0.6, Moderate 0.4–0.6, Low 0.2–0.4). Only protected areas where each species is present (MaxEnt probability > 0.2) are included, and percentages are calculated relative to the total area of those protected areas. **Table S19:** Potential distributions (in percentage) area in each ecoregion, partitioned according to three ranges of habitat quality (High, Moderate, Low) for the seven species. In bold, the highest value per species of high quality habitat. **Figure S1:** Model tuning observations using multiple feature class combinations and regularization multipliers for optimal model selection. **Appendix S2:** Model tuning observations using mulitple feature class combinations and regularization multipliers for optimal model selection.